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The role of regional economic conditions in active traveler injury severity: Accounting for COVID-19 pandemic disruptions

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Abstract: Regional economic disparities contribute to a disproportionate number of fatal and severe crashes among active travelers (pedestrians and bicyclists) in economically disadvantaged areas. Such road safety inequalities may be further exacerbated by external shocks such as the COVID-19 pandemic, due to regional variations in safety resilience. However, few studies have examined how the determinants of injury severity vary across regions with differing economic conditions, while accounting for COVID-contributing temporal shifts. This study uses North Carolina as a case study, classifying counties into three groups (i.e., highly, moderately, and least distressed counties) based on four economic indicators, and defining three pandemic periods (i.e., before, during, and after the pandemic). A partially constrained random parameter multinomial logit model with heterogeneity in the means and variances is estimated for crashes in each county group. Results show that the effects of factors are more stable in the least distressed counties, suggesting stronger safety resilience under external shocks. Additionally, during the pandemic, alcohol-impaired driving significantly affected injury severity only in highly and moderately distressed counties. Out-of-sample predictions further suggest that the probability of severe injuries among active travelers increases with rising regional economic distress and after the pandemic. Moreover, compared to the least distressed counties, the reduced safety resilience in highly and moderately distressed counties is attributed to weaker recovery and resistance capacities, respectively. These findings provide valuable insights for formulating region-specific policies, detecting system vulnerabilities, and promoting equitable and sustainable active transportation systems.

Keywords: Active transportation safety; Injury severities; Regional economic disparities; Transportation resilience; Temporal instability; Partially constrained model.

1 Introduction

The continuously rising fatalities of pedestrians and cyclists, which increased by 0.7% and 13% respectively from 2021 to 2022, have remained a major concern for the development of active transportation (NHTSA, 2024). However, these fatal or severe injury crashes are disproportionately concentrated in economically disadvantaged areas. For instance, according to Smart Growth America (SGA), pedestrian fatality rates are more than four times higher in areas with median household incomes between $15,000 and $25,000 than in areas where incomes exceed $100,000 (SGA, 2024). Moreover, the rising number of disruptive events (i.e., public health crises and other special events) has further exacerbated road safety inequity, due to disparities in regional safety resilience, which refers to the capacity to resist, absorb, and recover from disruptions (Peng et al., 2024; Ma et al., 2025). Evidence from the COVID-19 pandemic shows that during 2020-2022, traffic fatalities in the most vulnerable 20% of U.S. counties increased more than twice those in the least vulnerable 20% of counties (AAA Foundation for Traffic Safety, 2024). This underscores the urgent need to investigate the crash mechanisms of active travelers (pedestrians and cyclists) across regions with varying economic conditions, and how these mechanisms are affected by external shocks like the COVID-19 pandemic.

Research indicates that economic conditions significantly influence various road safety-related factors, such as human behavior, infrastructure maintenance, and the adoption of advanced vehicle technologies (Behnood and Mannering, 2016; Mannering, 2018). Consequently, regional economic disparities contribute to variations in the underlying mechanisms of crash injury severity across regions. In economically disadvantaged areas, pedestrians and cyclists are often exposed to unsafe conditions due to insufficient or poorly maintained active transportation infrastructure (i.e., bike lanes, sidewalks, and streetlights), which forces them to share road space with motor vehicles or cross roads under inadequate lighting (Zhai et al., 2024; Zhu et al., 2024). Additionally, residents in these areas frequently rely on older vehicles lacking modern safety features, further exacerbating injury severity for active travelers involved in crashes (Nasri et al., 2022; Scarano et al., 2023). By contrast, prosperous regions generally have better-maintained roads and more advanced infrastructure. While these conditions enhance accessibility, they may also unintentionally encourage higher vehicle speeds, leading to more serious injuries among pedestrians and cyclists (Coughenour et al., 2017). Furthermore, travel patterns likewise differ across economic contexts. In affluent regions, walking and cycling are typically recreational activities (e.g., exercise or dog walking), allowing individuals to avoid unsafe routes (Dumbaugh et al., 2023). Conversely, individuals in economically disadvantaged regions often rely on these vulnerable modes for essential travel, such as commuting to work or shopping, due to limited access to private vehicles (Merlin et al., 2020). However, prior research has mainly focused on economically disadvantaged areas (Younes et al., 2023; Zhu et al., 2024) or compared higher- and lower-income areas (Coughenour et al., 2017; Dumbaugh et al., 2023; Gedamu et al., 2024; Jafari and Persaud, 2025), often overlooking transitional economic areas that may exhibit distinct injury severity patterns. Moreover, regions with similar economic conditions are also more likely to share some unobserved characteristics, which can introduce heterogeneity and lead to biased parameter estimates (Mannering et al., 2016; Liu and Sharma, 2017). Therefore, it is essential to consider unobserved heterogeneity and investigate the non-transferability of injury severity determinants across regions grouped by economic conditions to derive deeper insights.

Temporal variations in the determinants of injury severity have been widely reported (Mannering, 2018; Song et al., 2025; Wang et al., 2025b). However, a growing number of disruptions (i.e., public health crises and other special events) can cause abrupt changes and challenge the reliable operation of transportation systems (Lee et al., 2023; Peng et al., 2024; Ma et al., 2025). In particular, the COVID-19 pandemic significantly contributed to an economic recession and triggered behavioral shifts, such as increased risk-taking among drivers (Islam et al., 2023; Wang et al., 2025b) and a surge in active travelers, including cyclists and pedestrians (Alnawmasi and Mannering, 2023; Marshall et al., 2023). Consequently, these changes resulted in significant shifts in crash mechanisms. For instance, Peng et al. (2024) found that the importance of human perception factors influencing crash severity varied significantly across different phases of the pandemic, with four key factors in the post-pandemic stage recovering to pre-pandemic levels. Barbour et al. (2024) reported that the influence of variables on nighttime pedestrian injuries changed more significantly than those on daytime injuries, and pedestrian injuries became more severe after the COVID-19 pandemic. Similarly, Rahman et al. (2025) also raised concerns about the increased severity of fixed-object passenger car crashes in the post-pandemic period. These findings not only reveal temporal instability but also reflect the evolution of risk factors and transportation safety conditions under external shocks. Therefore, examining the temporal changes in contributing factors and risk levels throughout the pandemic is crucial for understanding regional transportation safety resilience, identifying vulnerable components, and informing long-term development strategies.

This study explores the impact of regional economic conditions on active traveler injury severities, while accounting for COVID-contributing temporal shifts and revealing regional disparities in safety resilience. Specifically, this study investigates the following research questions: 1) What factors influence active traveler injury severity across counties with varying economic conditions? 2) How do collective crash risk and the effects of contributing factors evolve across different stages of the COVID-19 pandemic? 3) How does the system resist disruptions, maintain stability, and recover over time in different regions? To this end, the pedestrian and bicyclist-vehicle crash data from North Carolina are collected, and counties are classified into three county groups (i.e., highly, moderately, and least distressed counties) based on four economic indicators (quantified by four economic variables). In addition, three pandemic periods (i.e., before, during, and after the pandemic) are defined according to changes in traffic volume and pandemic control policies. Then, the partially constrained random parameter multinomial logit model with heterogeneity in the means and variances is estimated for crashes in each county group to obtain statistically stable parameters over time. Additionally, out-of-sample prediction is adopted to trace the evolution of collective crash risk across different pandemic periods and quantify shifts in aggregate effects across counties.

2 Literature review

2.1 Factors affecting pedestrian and cyclists' injury severities

Many studies have investigated the factors affecting pedestrian- and/or cyclist-vehicle crash injury severities, including human, vehicle, environmental, roadway, crash, and temporal characteristics. Table 1 summarizes the significant variables and corresponding findings. To better understand the influence of these factors on injury severity, researchers have compared differences across various groups, such as street patterns (Rifaat et al., 2011), party at fault (Salon and McIntyre, 2018), day of the week (Li et al., 2021), seasons (Sun et al., 2022; Abdulrazaq and Fan, 2026), age groups (Liu et al., 2024), genders (Barbour and Abdel-Aty, 2024), time of the day (Alnawmasi and Mannering, 2023; Barbour et al., 2024), posted speed limits (Phuksuksakul et al., 2024), roadway location (Marcoux et al., 2024), quarters of the year (Phuksuksakul et al., 2025) and rural versus urban areas (Wang and Fan, 2025b).

Previous studies have also shown that economic conditions play a critical role, with crash locations in lower-income areas tending to have higher injury severities (Traynor, 2009; Mansfield et al., 2018; Younes et al., 2023). In addition, Jafari and Persaud (2025) categorized neighborhoods into high-income and low-income groups based on residents' annual incomes and found that certain variables, such as speed limit and horizontal curve, exert differing impacts on crash severity across the two groups. Gedamu et al. (2024) compared crash patterns between low-income and high-income cities, classified based on per capita income, and found that roadway- and traffic-related factors contribute to differences in road traffic safety. Dumbaugh et al. (2023) categorized census block groups into high- and low-income groups based on median household income and poverty rate and found that limited safe access to household-supporting destinations in low-income areas and recreation and nightlife activities in high-income areas are associated with higher pedestrian deaths and injuries, respectively. However, current research has not sufficiently examined how risk factors influence active traveler injury severity across regions with different economic conditions, particularly in regions with transitional economies, while also accounting for unobserved heterogeneity and disruptions caused by the COVID-19 pandemic. Examining COVID-contributing temporal shifts across regions with different economic conditions can provide valuable insights into regional disparities in injury severity determinants and safety resilience.

Table 1 Influencing factors of pedestrian and cyclist injury severities.

Factor	Dependent variable	Effect on dependent variable	Study
Active traveler characteristics			
Age	Cyclist injury severity	Cyclists aged over 75 years	Scarano et al. (2023)
	Cyclist injury severity	Cyclists aged over 65 years	Eriksson et al. (2022)
	Pedestrian injury severity	Pedestrians aged over 65 years	Zeng et al. (2023)
	Pedestrian injury severity	Pedestrians aged under 15 years	Salehian et al. (2023)
Gender	Both	Male pedestrians and cyclists	Liu et al. (2021); Scarano et al. (2023)
	Pedestrian injury severity	Female pedestrians	Islam and Jones (2014)
Alcohol	Both	Alcohol-impaired pedestrians and cyclists	Phuksuksakul et al. (2025)
Driver characteristics			
Age	Pedestrian injury severity	Drivers aged over 60	Nasri et al. (2022)
	Cyclist injury severity	Drivers aged between 25 and 65	Scarano et al. (2023)
	Both	Drivers aged under 25	Liu et al. (2021)
Gender	Both	Male drivers	Sun et al. (2022); Phuksuksakul et al. (2025)
Alcohol	Both	Alcohol-impaired driving	Song et al. (2020); Lin and Fan (2021)
Distraction	Both	Distraction behaviors	Liu et al. (2024); Intini et al. (2024)
Vehicle characteristics			
Vehicle type	Both	Large vehicles (i.e., light trucks, buses, and SUVs)	Monfort and Mueller (2023); Sun et al. (2022)
Environmental characteristics			
Lighting condition	Both	Dark conditions with or without streetlights	Younes et al. (2023)
	Both	Dawn/dusk conditions	Du et al. (2024)
Weather condition	Cyclist injury severity	Rainy weather (negative effect)	Barbour and Abdel-Aty (2024)
	Pedestrian injury severity	Rainy weather	Zhai et al. (2019)
	Both	Clear weather	Islam and Hossain (2015)
Rural or urban	Both	Rural areas	Agheli and Aghabayk (2024); Gutierrez et al. (2025)
Land use	Both	Commercial land use	Liu et al. (2021)
	Cyclist injury severity	Park/green space/nature reserve areas	Du et al. (2024)
	Pedestrian injury severity	Industrial land use	Song et al. (2021)
Economic condition	Both	Poor regional economic conditions	Traynor (2009); Mansfield et al. (2018);

			Younes et al. (2023)
Roadway characteristics			
Speed limit	Both	Speed limits above 50 MPH	Phuksuksakul et al. (2024)
	Pedestrian injury severity	Speed limits above 60 MPH	Salehian et al. (2023)
Intersection or not	Both	Intersection	Nasri et al. (2022); Intini et al. (2024)
	Both	Road segments	Eriksson et al. (2022); Sun et al. (2019)
Roadway geometry	Cyclist injury severity	Sloped roadway	Robartes and Chen (2017)
	Both	Curved roadway	Robartes and Chen (2017); Li et al. (2021)
Road surface	Both	Wet surface roadway	Verzosa and Miles (2016); Samerei et al. (2021)
Number of lanes	Both	Four or more lanes	Lin and Fan (2021); Barbour et al. (2024)
Traffic control	Both	Signalized intersection (negative effect)	Verzosa and Miles (2016); Alnawmasi and Mannering (2023)
Pedestrian and bicycle facilities	Pedestrian injury severity	Crosswalks (negative effect)	Younes et al. (2023)
	Cyclist injury severity	Cycle lanes (negative effect)	Robartes and Donna Chen (2018)
Crash characteristics			
Hit-and-run	Both	Hit-and-run crashes	Song et al. (2020); Jiang et al. (2021)
Crossing the roadway	Both	Crossing the roadway	Sun et al. (2019); Hosseini et al. (2022)
Temporal characteristics			
Season	Both	Fall and winter	Sun et al. (2023) Hosseinpour et al. (2021)
Day of week	Both	Weekends	Younes et al. (2023); Agheli and Aghabayk (2024)
Time of day	Both	Night	Hosseinpour et al. (2021); Chakraborty et al. (2024)
	Both	Peak hour period	Hosseinpour et al. (2021); Liu et al. (2024)

Note: All listed factors have a positive effect on injury severity unless otherwise specified.

2.2 Crash injury severity modeling approaches

For crash injury severity modeling methods, machine learning models (i.e., tree-based ensemble models, neural networks, association rules, and support vector machines) and statistical models (i.e., generalized additive models, Bayesian models, random parameters logit models, ordered probit/logit) are widely used in current research (Mannering et al., 2020; Song et al., 2020; Alnawmasi and Mannering, 2023; Gutierrez et al., 2025; Wang et al., 2025a; Wang and Fan, 2025a). While machine learning models often achieve superior predictive accuracy, the 'black box' nature makes it difficult to explore causal relationships (Mannering et al., 2020). Although some post-hoc interpretation methods (i.e., SHAP and LIME) improve model explainability, they still struggle to illustrate unobserved heterogeneity and temporal variations (Wei et al., 2024).

Unobserved heterogeneity, arising from undocumented factors such as traffic operations, vehicle maneuvers, and safety attitudes, can introduce variation in the effects of observed variables (Mannering et al., 2016; Liu et al., 2024). Common approaches to address this issue include the random parameters model, the latent-class model, and the Markov switching model (Behnood and Mannering, 2016; Mannering et al., 2016). Among these approaches, the random parameters logit model with heterogeneity in the means and variances is the most popular, as its enhanced ability to capture unobserved factors results in greater predictive accuracy and improved model fit (Behnood and Mannering, 2019; Alnawmasi and Mannering, 2023). Besides, temporal instability, which can bias parameter estimates, is another important consideration (Mannering, 2018). To solve this problem, previous research usually adopted a temporally unconstrained parameter approach by estimating separate models for different time periods, which allows the parameters to be different from one time period to the next (Behnood and Mannering, 2019; Li et al., 2021). However, this approach cannot identify variables with significant stable effects over time, thus temporally stabilized impacts of factors are ignored. Recently, Alnawmasi and Mannering (2023) proposed a partially constrained temporal modeling approach that simultaneously captures both temporal variations and stabilities with greater precision and flexibility. Besides, compared with the temporally unconstrained parameter approach, the partially constrained temporal modeling approach is designed based on the entire time period dataset, thus its integrated structure can simplify model results (Song et al., 2025) and tackle the small sample size challenge (Rangaswamy et al., 2024). Given its ability to simultaneously capture time-varying effects and unobserved heterogeneity, this study adopts this framework to address critical challenges in crash severity modeling and further explore regional safety resilience.

3 Data and empirical setting

This study uses the police-reported active traveler (pedestrian and bicyclist)-vehicle crash data collected from 2019 to 2022 in North Carolina. To isolate the potential impacts of the COVID-19 pandemic, this study examines fluctuations in vehicle miles traveled and pandemic-related policy responses in North Carolina, following the approach of prior studies (Barbour et al., 2024; Rahman et al., 2025; Song et al., 2025). North Carolina recorded its first COVID-19 case on March 3, 2020, and entered a state of emergency on March 10. To prevent the spread of COVID-19, a series of statewide executive orders was issued to restrict gatherings and outdoor activities. Figure

1 illustrates how vehicle miles traveled (VMT) fluctuated in response to these policy changes. As the pandemic moved from its initial severe phase to a more stabilized stage, certain policies were implemented in two distinct phases, with a stricter Phase 1 (red segment) followed by a more relaxed Phase 2 (orange segment). During Phase 1, strict restrictions, including stay-at-home and the closure of restaurants and other non-essential businesses, led to an even sharper decline in VMT from March to May 2020. In Phase 2, some restrictions were partially relaxed, such as limited-capacity indoor operations and nighttime stay-at-home requirements, resulting in a smaller yet still noticeable reduction in VMT. VMT began to recover to normal levels in March 2021. Therefore, to accurately analyze the impact of the COVID-19 pandemic, three distinct periods are defined as follows: the first period (before the pandemic) is from March 2019 to February 2020; the second period is from March 2020 to February 2021 (during the pandemic); the third period is from March 2021 to February 2022 (after the pandemic). This classification aligns with previous studies (Barbour et al., 2024; Rahman et al., 2025). A total of 8,674 observations were obtained, and injury severities were divided into three categories: severe (incapacitating and fatal), minor (non-incapacitating), and no injury (no and possible).

Figure 1 Changes in traffic volume and pandemic control policy.

To classify counties into distinct groups, this study adopts the County Development Tier Designation issued by the North Carolina Department of Commerce (NC Commerce) to define levels of economic distress. This County Tiers method has been consistently used since 2007 (NC Commerce, 2025). Specifically, each county was assigned a rank from 1 to 100 for each of the four economic indicators (average unemployment rate, median household income, population growth percentage, and adjusted property tax base per capita), yielding a maximum possible County Rank Sum of 400 and a minimum of 4. Based on the total Rank Sum, counties were then ordered from most to least economically distressed, with the top 40 classified as Highly Distressed Counties (HDC), the next 40 as Moderately Distressed Counties (MDC), and the remaining 20 as Least Distressed Counties (LDC). To more reliably distinguish counties with different economic levels, we directly use the County Ranks provided by NC Commerce for 2019-2021 and compute the three-year average. It is important to note that the County Rank is calculated using calendar-year data rather than the three pandemic periods defined in this research. This approach allows the ranking to capture the structural economic conditions of counties rather than pandemic-driven fluctuations. Moreover, the use of calendar-year indicators for determining county distress levels has long served as the standard methodology guiding the allocation of multiple statewide programs in North Carolina. The spatial distribution of the economic distress groups is presented in Figure 2. Figure 3 shows the distribution of active traveler injury severity across county groups over three periods. It is clear that as economic conditions worsen, the total number of crashes tends to decrease, while the proportion of severe injuries increases markedly. This highlights the disproportionate concentration of severe crashes in economically disadvantaged areas. Additionally, although overall crash counts declined during the pandemic, the proportion of crashes involving severe injuries rose significantly and remained at a higher level after the pandemic compared with before.

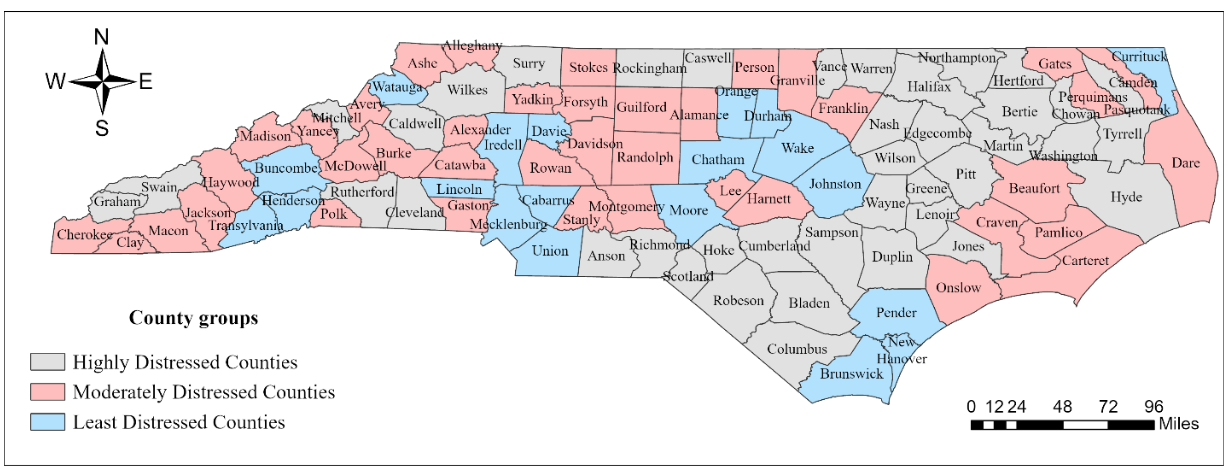

Figure 2 Spatial distribution of North Carolina counties (in total of 100) by economic distress groups.

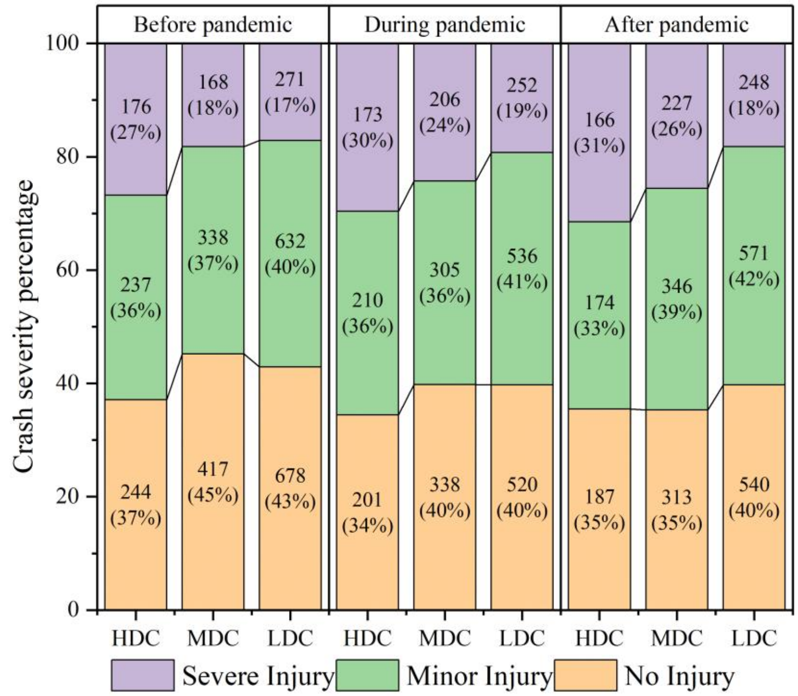

Figure 3 Distribution of active traveler injury severity by county groups across three pandemic periods.

Besides, Chi-square tests are used to further assess the practicality of categorizing counties into three types based on these four economic indicators (Wang et al., 2025b). As shown in Table 2, the results of the Chi-square test indicate that the null hypothesis that the injury severity distribution of active travelers across different county groups in the three periods is the same can be rejected under a high confidence level (>99.99 %). Besides, the results of the pairwise Chi-square test indicate that only 1 out of 9 tests has a confidence level below 95%. Thus, these tests can confirm that the segmentation of the data into three groups for each period is reasonable. Besides, six characteristics are collected, as shown in Table 3.

Table 2 Results of Chi-square tests for injury severity distribution.

	Before the pandemic		During the pandemic		After the pandemic	
	Chi-square	Confidence level	Chi-square	Confidence level	Chi-square	Confidence level
All groups	32.005 (4)	>99.99%	27.587 (4)	>99.99%	43.682 (4)	>99.99%
Highly/moderately distressed counties	18.96 (2)	>99.99%	6.434 (2)	>95.99%	7.378 (2)	>97.50%
Highly/least distressed counties	27.166 (2)	>99.99%	24.879 (2)	>99.99%	39.938 (2)	>99.99%
Moderately/least distressed counties	2.769 (2)	>74.96%	9.429 (2)	>99.10%	17.673 (2)	>99.99%

Table 3 Descriptive statistics of the explanatory variables for different county groups and periods in active traveler (pedestrian and bicyclist) -vehicle crashes. (BP: Before the pandemic; DP: During the pandemic; and AP: After the pandemic; Values are the percentage distribution of variables)

Variable Description	Highly distressed counties			Moderately distressed counties			Least distressed counties		
	BP	DP	AP	BP	DP	AP	BP	DP	AP
Active traveler Characteristics									
Young active traveler (1 if the active traveler is under 25 years old, 0 otherwise)	0.26	0.22	0.21	0.32	0.25	0.25	0.29	0.26	0.28
Middle-aged active traveler (1 if the active traveler is 25-65 years old, 0 otherwise)	0.65	0.70	0.69	0.60	0.65	0.65	0.63	0.66	0.64
Elderly active traveler (1 if the active traveler is over 65 years old, 0 otherwise)	0.08	0.07	0.09	0.08	0.09	0.10	0.08	0.08	0.08
Female active traveler (1 if the driver gender is female; 0 otherwise)	0.24	0.25	0.29	0.29	0.28	0.30	0.33	0.27	0.29
Alcohol-impaired active traveler (1 if the active traveler is alcohol-impaired; 0 otherwise)	0.14	0.13	0.13	0.09	0.09	0.11	0.07	0.10	0.07
Driver and vehicle Characteristics									
Young driver (1 if the driver is under 25 years old, 0 otherwise)	0.14	0.15	0.14	0.14	0.15	0.14	0.15	0.15	0.18
Middle-aged driver (1 if the driver is 25-65 years old, 0 otherwise)	0.74	0.76	0.72	0.72	0.71	0.73	0.75	0.76	0.71
Elderly driver (1 if the driver is over 65 years old, 0 otherwise)	0.12	0.10	0.13	0.14	0.14	0.13	0.10	0.10	0.11
Female driver (1 if the driver gender is female; 0 otherwise)	0.34	0.32	0.32	0.36	0.32	0.31	0.36	0.30	0.33
Alcohol-impaired driver (1 if the driver is alcohol-impaired; 0 otherwise)	0.03	0.04	0.03	0.02	0.03	0.02	0.03	0.02	0.03
Passenger car (1 if the vehicle type is passenger car, 0 otherwise)	0.47	0.48	0.45	0.51	0.50	0.48	0.50	0.49	0.47
Sport utility vehicle (1 if the vehicle type is sport utility vehicle, 0 otherwise)	0.16	0.14	0.17	0.19	0.20	0.20	0.20	0.20	0.22
Pickup (1 if the vehicle type is pickup, 0 otherwise)	0.15	0.15	0.13	0.14	0.13	0.15	0.11	0.12	0.12
Van (1 if the vehicle type is van, 0 otherwise)	0.04	0.03	0.03	0.04	0.04	0.03	0.05	0.05	0.05
Truck (1 if the vehicle type is truck, 0 otherwise)	0.02	0.03	0.02	0.02	0.03	0.02	0.03	0.03	0.03
Crash Characteristics									

Ambulance rescue (1 if ambulance is requested after the crash occurs; 0 otherwise)	0.78	0.73	0.68	0.78	0.65	0.72	0.69	0.64	0.65
Hit-and-run (1 if crash is hit-and-run; 0 otherwise)	0.22	0.26	0.25	0.20	0.23	0.23	0.21	0.25	0.23
Crossing roadway - vehicle not turning (1 if active traveler is struck while crossing the roadway by a vehicle traveling straight through; 0 otherwise)	0.16	0.12	0.19	0.15	0.14	0.15	0.14	0.16	0.16
Crossing roadway - vehicle turning (1 if active traveler is struck while crossing the roadway by a vehicle turning; 0 otherwise)	0.07	0.07	0.05	0.12	0.08	0.10	0.17	0.14	0.14
Active traveler in roadway (1 if active traveler is in the roadway; 0 otherwise)	0.04	0.12	0.11	0.05	0.10	0.10	0.04	0.07	0.06
Dash/dart-out (1 if active traveler suddenly entered the roadway (dashing/darting); 0 otherwise)	0.04	0.09	0.06	0.07	0.09	0.07	0.08	0.07	0.08
Active traveler failed to yield (1 if the active traveler failed to properly yield to the motorist at a signalized intersection; 0 otherwise)	0.07	0.05	0.05	0.06	0.04	0.05	0.05	0.06	0.06
Motorist overtaking (1 if the crash occurs while the motorist was overtaking the active traveler; 0 otherwise)	0.08	0.06	0.08	0.07	0.05	0.06	0.04	0.05	0.05
Motorist failed to yield (1 if the motorist failed to properly yield to the active traveler at a signalized intersection; 0 otherwise)	0.05	0.03	0.03	0.07	0.04	0.04	0.07	0.04	0.05
Motorist turning (1 if the crash occurs while the motorist was turning; 0 otherwise)	0.02	0.03	0.02	0.03	0.05	0.04	0.06	0.06	0.07
Locality and Roadway Characteristics									
Intersection (1 if crash occurs at an intersection; 0 otherwise)	0.35	0.32	0.35	0.44	0.40	0.39	0.51	0.51	0.53
Crosswalk area (1 if crash occurs in crosswalk area; 0 otherwise)	0.10	0.10	0.10	0.19	0.18	0.19	0.30	0.30	0.29
Travel lane (1 if crash occurs in vehicle travel lane; 0 otherwise)	0.69	0.73	0.74	0.62	0.68	0.68	0.54	0.60	0.61
Bike lane (1 if crash occurs in bike lane; 0 otherwise)	0.03	0.11	0.09	0.04	0.10	0.07	0.05	0.07	0.05
Mountain region (1 if crash occurs in mountains region; 0 otherwise)	0.14	0.11	0.14	0.09	0.07	0.07	0.08	0.08	0.07
Piedmont region (1 if crash occurs in piedmont region; 0 otherwise)	0.09	0.08	0.11	0.70	0.75	0.73	0.79	0.80	0.79

Coastal region (1 if crash occurs in coastal region; 0 otherwise)	0.77	0.81	0.74	0.21	0.18	0.20	0.13	0.12	0.14
Urban area (1 if crash occurs in urban area; 0 otherwise)	0.54	0.62	0.61	0.66	0.75	0.73	0.84	0.85	0.85
Residential area (1 if crash occurs in residential area; 0 otherwise)	0.38	0.38	0.38	0.38	0.40	0.37	0.34	0.40	0.38
Commercial area (1 if crash occurs in commercial area; 0 otherwise)	0.35	0.33	0.37	0.45	0.43	0.44	0.55	0.49	0.50
Institutional area (1 if crash occurs in institutional area; 0 otherwise)	0.01	0.01	0.01	0.03	0.01	0.01	0.03	0.02	0.02
Farms, woods, pastures area (1 if crash occurs in farms, woods, pastures area; 0 otherwise)	0.26	0.28	0.25	0.14	0.16	0.17	0.07	0.09	0.10
Curved roadway (1 if road geometry is curved roadway; 0 otherwise)	0.05	0.04	0.05	0.07	0.07	0.06	0.04	0.05	0.04
Level (1 if crash occurs on a level roadway; 0 otherwise)	0.86	0.83	0.84	0.83	0.84	0.84	0.83	0.85	0.84
Grade (1 if crash occurs on a grade roadway; 0 otherwise)	0.11	0.13	0.12	0.12	0.11	0.12	0.13	0.12	0.13
Hillcrest (1 if crash occurs on a hillcrest roadway; 0 otherwise)	0.02	0.03	0.04	0.04	0.04	0.04	0.03	0.03	0.03
US route (1 if road class is US route; 0 otherwise)	0.13	0.14	0.15	0.11	0.08	0.10	0.06	0.06	0.07
Interstate route (1 if road class is interstate route; 0 otherwise)	0.01	0.02	0.01	0.01	0.03	0.04	0.04	0.03	0.03
State route (1 if road class is state route; 0 otherwise)	0.12	0.11	0.12	0.10	0.09	0.10	0.04	0.05	0.06
State secondary route (1 if road class is state secondary route; 0 otherwise)	0.20	0.20	0.21	0.15	0.18	0.16	0.09	0.10	0.09
Local street (1 if road class is local street; 0 otherwise)	0.51	0.49	0.35	0.59	0.59	0.52	0.74	0.72	0.68
Public vehicular area (1 if crash occurs on public vehicular area; 0 otherwise)	0.04	0.04	0.16	0.04	0.02	0.08	0.03	0.03	0.07
One-way, not divided (1 if the road configuration is one-way not divided; 0 otherwise)	0.05	0.04	0.17	0.05	0.05	0.09	0.07	0.07	0.11
Two-way, not divided (1 if the road configuration is two-way not divided; 0 otherwise)	0.79	0.78	0.70	0.77	0.78	0.76	0.71	0.74	0.70
Two-way, divided (1 if the road configuration is two-way divided; 0 otherwise)	0.16	0.18	0.13	0.19	0.17	0.15	0.22	0.20	0.19
Dry road condition (1 if the road condition is dry; 0 otherwise)	0.90	0.85	0.90	0.89	0.86	0.88	0.88	0.85	0.89
Wet road condition (1 if the road condition is wet; 0 otherwise)	0.09	0.15	0.10	0.11	0.14	0.11	0.12	0.14	0.10

Number lanes below 3 (1 if the number of lanes is less than 3; 0 otherwise)	0.63	0.61	0.67	0.59	0.63	0.61	0.53	0.58	0.57
Number lanes between 3 and 4 (1 if the number of lanes is between 3 and 4; 0 otherwise)	0.20	0.21	0.20	0.24	0.21	0.23	0.30	0.27	0.29
Number lanes over 4 (1 if the number of lanes is greater than 4; 0 otherwise)	0.17	0.18	0.13	0.17	0.16	0.17	0.17	0.15	0.14
Speed limit below 30 MPH (1 if posted speed limit is below 30 MPH; 0 otherwise)	0.17	0.35	0.40	0.23	0.29	0.34	0.28	0.35	0.41
Speed limit between 30 and 50 MPH (1 if posted speed limit is between 30 and 50 MPH; 0 otherwise)	0.58	0.40	0.40	0.63	0.56	0.51	0.63	0.57	0.51
Speed limit over 50 MPH (1 if posted speed limit is greater than 50 MPH; 0 otherwise)	0.26	0.24	0.20	0.14	0.15	0.15	0.09	0.08	0.08
No control present (1 if there is no control present; 0 otherwise)	0.56	0.63	0.66	0.50	0.53	0.57	0.53	0.53	0.54
Traffic sign (1 if the traffic control type is traffic sign; 0 otherwise)	0.13	0.11	0.06	0.13	0.10	0.09	0.13	0.14	0.13
Traffic signal (1 if the traffic control type is traffic signal; 0 otherwise)	0.11	0.08	0.09	0.20	0.17	0.15	0.26	0.23	0.25
Double yellow line, no-passing zone (1 if crash occurs within no-passing zone with double yellow line; 0 otherwise)	0.19	0.18	0.19	0.17	0.18	0.18	0.07	0.09	0.08
Human control (1 if the type of traffic control is human control; 0 otherwise)	0.01	0.00	0.00	0.00	0.02	0.01	0.01	0.01	0.01
Environment and Temporal Characteristics									
Peak hour (1 if crash occurs between 6:00–9:00 or 17:00–19:00 period; 0 otherwise)	0.30	0.26	0.28	0.34	0.32	0.29	0.36	0.34	0.31
Weekday (1 if crash occurs during weekday; 0 otherwise)	0.75	0.75	0.74	0.78	0.75	0.72	0.76	0.75	0.74
Spring (1 if crash occurs in spring; 0 otherwise)	0.24	0.25	0.24	0.24	0.18	0.24	0.24	0.21	0.24
Summer (1 if crash occurs in summer; 0 otherwise)	0.26	0.22	0.25	0.25	0.25	0.27	0.23	0.25	0.24
Fall (1 if crash occurs in fall; 0 otherwise)	0.29	0.30	0.30	0.28	0.31	0.27	0.31	0.28	0.31
Winter (1 if crash occurs in winter; 0 otherwise)	0.21	0.24	0.21	0.22	0.26	0.22	0.23	0.27	0.21
Daylight (1 if light condition is daylight; 0 otherwise)	0.49	0.42	0.44	0.55	0.50	0.48	0.59	0.56	0.57
Dawn/dusk light (1 if light condition is dawn/dusk light; 0 otherwise)	0.04	0.04	0.04	0.05	0.06	0.05	0.04	0.04	0.04

Dark lighted roadway (1 if light condition is lighted roadway; 0 otherwise)	0.18	0.19	0.21	0.21	0.22	0.22	0.21	0.23	0.23
Dark roadway not lighted (1 if light condition is dark roadway not lighted; 0 otherwise)	0.29	0.35	0.31	0.18	0.22	0.25	0.15	0.17	0.16
Clear (1 if the weather condition is clear; 0 otherwise)	0.84	0.79	0.86	0.82	0.79	0.82	0.80	0.78	0.83
Cloudy (1 if the weather condition is cloudy; 0 otherwise)	0.10	0.11	0.08	0.10	0.11	0.10	0.10	0.12	0.11
Rain (1 if the weather condition is raining; 0 otherwise)	0.06	0.10	0.06	0.08	0.09	0.07	0.09	0.09	0.06

4 Methodology

4.1 Random parameter multinomial logit model with heterogeneity in mean and variance

This study uses the random parameters multinomial logit model with heterogeneity in means and variances to model the severity of injuries sustained by active traveler (pedestrian and bicyclist) involved in active traveler-vehicle crashes. The linear injury severity function determining the specific injury severity k (k = 1, 2, 3) for individual i is defined as follows (Washington et al., 2020):

$$U_{ki} = \beta_k X_{ki} + \varepsilon_{ki} \quad (1)$$

Where U_{ki} is an active traveler injury severity function that determines injury severity level k in crash observation i, X_{ki} denotes the vector of explanatory variables for crash observation i with injury severity level k, β_k represents the vector of estimated parameters for injury severity level k in crash observation i, and ε_{ki} is an error term. If the error term is assumed to be generalized extreme-value distributed, a multinomial logit model can be defined as follows (Washington et al., 2020):

$$P_i(k) = \int \frac{exp(\beta_k X_{ki})}{\sum_{\forall k} exp(\beta_k X_{ki})} f(\beta_k|\varphi_k) d\beta_k \quad (2)$$

Where $P_i(k)$ is the probability of injury severity level k in crash observation i, and $f(\beta_k|\varphi_k)$ denotes the probability density function of random parameters β_k and φ_k is the corresponding distribution parameters that describe the density function (mean and variance). If the heterogeneity in means and variance exists among random parameters, the β_{ki} can be defined as (Behnood and Mannering, 2019):

$$\beta_{ki} = \beta_k + \delta_{ki} Z_{ki} + \sigma_{ki} exp(\omega_{ki} W_{ki}) v_{ki} \quad (3)$$

Where β_k is the mean parameter estimate across all crashes, Z_{ki} is a vector of explanatory variables capturing heterogeneity in the mean for injury severity level k, W_{ki} denotes a vector of explanatory variables capturing heterogeneity in the variance (the standard deviation σ_{ki}) for injury severity level k, δ_{ki} and ω_{ki} represent the corresponding coefficient vector of estimable parameters, and v_{ki} is the error term.

In this study, simulated maximum likelihood estimation method was used to estimate models, with 1000 Halton draws employed to ensure the accuracy and stability of the parameters (Alnawmasi and Mannering, 2023; Se et al., 2024). Besides, random parameters were assumed to follow a normal distribution due to its appropriateness for modeling random effects, in comparison with alternatives such as log-normal, Weibull, uniform, and exponential distributions.(Barbour et al., 2024; Wei et al., 2024). Additionally, marginal effects were computed to evaluate how a one-unit change in each explanatory variable influences the probabilities of different injury severity outcomes for active travelers.

4.2 Partially constrained temporal modeling

In partially constrained temporal modeling approach, certain parameters are merged to illustrate temporal stability across multiple time periods, and others are permitted to vary over time (Alnawmasi and Mannering, 2023). Thus, this method is helpful in identifying individual variables with temporal stability and instability. To estimate this model, three periods of data with defined variables for each period are used, which is the same as assessing models on divided data by pandemic period. Subsequently, a series of likelihood ratio tests is conducted to identify parameters that vary significantly across one or more periods. This likelihood ratio test can be written as:

$$X^2 = -2[LL(\beta_C) - LL(\beta_U)] \tag{4}$$

Where $LL(\beta_U)$ is the log-likelihood at convergence of the model with unconstrained parameters (the coefficients of a given variable are allowed to vary in each period) and $LL(\beta_C)$ is the log-likelihood at convergence of the model with constrained parameters (where a given variables is constrained to have the same parameter value for several consecutive time period). The value X^2 follows χ^2 distribution with degrees of freedom equal to the difference in the number of estimated parameters and can be used to assess whether the null hypothesis that the constrained and unconstrained models are equal can be rejected. If the null hypothesis cannot be rejected with high confidence (more than 90 % confidence), the tested individual parameter from different periods can be combined (using one parameter for two or more time periods rather than individual stage parameters). This procedure is performed for every variable included in the model.

Additionally, to confirm that the partially constrained models and unconstrained models are not significantly different, the following likelihood ratio test was conducted:

$$X^2 = -2\left[LL(\beta_{PC}) - LL\left(\beta_{U,before}\right) - LL\left(\beta_{U,during}\right) - LL\left(\beta_{U,after}\right)\right] \tag{5}$$

Where $LL(\beta_{PC})$ represents the log-likelihood at convergence of the model with partially constrained parameters, where certain variables are constrained to have the same parameter value across different periods. $LL\left(\beta_{U,before}\right)$, $LL\left(\beta_{U,during}\right)$, and $LL\left(\beta_{U,after}\right)$ are the log-likelihood at convergence of the model with unconstrained parameters, where all the variables are allowed to vary for each time period. Similarly, the value X^2 follows χ^2 distribution with degrees of freedom equal to the difference in the number of parameters estimated.

5 Transferability tests and out-of-sample prediction

5.1 Transferability tests

To ascertain the effects of factors are significantly varied throughout the three county groups and periods, two groups of likelihood ratio tests are employed: one for temporal instability across periods, and one for spatial non-transferability across county groups. Besides, two types of likelihood ratio tests, global and pairwise, are employed within each group, as demonstrated in (Washington et al., 2020; Hou et al., 2022).

For the temporal stability test, the likelihood ratio test is first applied to compare the joint model with separate period-specific models, and the statistical test can be defined as (Washington et al., 2020):

$${X_{t1}}^2 = -2\left[LL\left(\beta_{all\,periods,s}\right) - LL\left(\beta_{BP,s}\right) - LL\left(\beta_{DP,s}\right) - LL\left(\beta_{AP,s}\right)\right] \tag{6}$$

Where $LL\left(\beta_{all\,periods,s}\right)$ is the log-likelihood at convergence of the model estimated for each distressed county group s over all the periods; $LL\left(\beta_{BP,s}\right)$, $LL\left(\beta_{DP,s}\right)$ and $LL\left(\beta_{AP,s}\right)$ are the log-likelihood at convergence of the model estimated for before, during and after the pandemic in distressed county group s. The calculated value X^2 is χ^2 distributed and the degrees of freedom equal to the sum of the parameter number in the $\beta_{BP,s}$, $\beta_{DP,s}$ and $\beta_{AP,s}$ minus the parameter number in the $\beta_{all\,periods,s}$ model. For highly, moderately and least distressed counties crashes, the χ^2 values are 40.77, 45.93, and 61.34 with 21, 30 and 28 degrees of freedom, respectively. Thus, the null hypothesis that the parameters of before the pandemic, during the pandemic and after the pandemic models are equal in each county groups can be rejected at the 99% confidence level.

Additionally, the second likelihood ratio test assesses the temporal instability between models from two periods, with the statistical test expressed as (Washington et al., 2020):

$$X_{t2}^{\,2} = -2\left[LL\left(\beta_{y_2 y_1}\right) - LL\left(\beta_{y_1}\right)\right] \quad (7)$$

Where $LL\left(\beta_{y_2 y_1}\right)$ is the log-likelihood at convergence of a model containing converged parameters based on using period y_2 data, while using data from period y_1. $LL\left(\beta_{y_1}\right)$ is the log-likelihood at convergence of the model using data from period y_1 but the parameters are no longer restricted to the converged parameters from period y_2. This test was also reversed by using $LL\left(\beta_{y_1 y_2}\right)$ and $LL\left(\beta_{y_2}\right)$. The calculated value X^2 is χ^2 distributed (with degrees of freedom equal to the number of estimated parameters in the $\beta_{y_2 y_1}$ model) and can determine whether to reject the null hypothesis that the parameters are the same in period y_2 and y_1 (Alnawmasi and Mannering, 2023). Table 4 shows the pairwise test results between different periods for highly, moderately and least distressed counties crashes and the results indicate that the null hypothesis can be rejected with a 99.99% confidence level. Thus, the model should be estimated independently for each of the three periods.

Table 4 Likelihood ratio test results between different time periods.

y1	y2 Before the pandemic			During the pandemic			After the pandemic		
	Highly distressed counties	Moderately distressed counties	Least distressed counties	Highly distressed counties	Moderately distressed counties	Least distressed counties	Highly distressed counties	Moderately distressed counties	Least distressed counties
Before the pandemic				135.33(13) >99.99%	206.11(25) >99.99%	136.82(17) >99.99%	153.16(17) >99.99%	129.2(19) >99.99%	142.67(20) >99.99%
During the pandemic	82.56(13) >99.99%	206.26(18) >99.99%	125.45(22) >99.99%				133.11(17) >99.99%	135.78(19) >99.99%	110.89(20) >99.99%
After the pandemic	127.68(13) >99.99%	192.84(18) >99.99%	112.42(22) >99.99%	115.37(13) >99.99%	207.43(25) >99.99%	102.21(17) >99.99%			

For the spatial stability tests, the first likelihood ratio test can be defined as:

$$X_{s1}{}^2 = -2\left[LL\left(\beta_{all\ counties,t}\right) - LL\left(\beta_{HDC,t}\right) - LL\left(\beta_{MDC,t}\right) - LL\left(\beta_{LDC,t}\right)\right] \tag{8}$$

Where $LL\left(\beta_{all\ counties,t}\right)$ denotes the log-likelihood at convergence of the model estimated for each period t over all the counties; $LL\left(\beta_{HDC,t}\right)$, $LL\left(\beta_{MDC,t}\right)$ and $LL\left(\beta_{LDC,t}\right)$ are the log-likelihood at convergence of the model estimated for each distressed county group at corresponding period t, respectively. Similarly, the degrees of freedom equal to the sum of the parameter number in the $\beta_{HDC,t}$ $\beta_{MDC,t}$ and $\beta_{LDC,t}$ model minus the parameter number in the $\beta_{all\ counties,t}$ model. The χ^2 values for before pandemic, during pandemic and after pandemic models are 40.46, 61.34, and 95.68 with 20, 22 and 30 degrees of freedom, respectively. These results indicate that the null hypothesis that the model parameters of highly, moderately and least distressed counties crashes are equal in each period can be rejected at the 99% confidence level. Another likelihood ratio test can be defined as:

$$X_{s2}{}^2 = -2[LL(\beta_{mn}) - LL(\beta_n)] \tag{9}$$

Where $LL(\beta_{mn})$ is the log-likelihood at convergence of a model containing converged parameters based on using the region m data, while using data from the region n. $LL(\beta_n)$ is the log-likelihood at convergence of the model using data from location n but the parameters are no longer restricted to the converged parameters from the location m. This test was also reversed by using $LL(\beta_{nm})$ and $LL(\beta_m)$. Table 5 shows the pairwise test results between different county groups for three periods of crashes, and the results indicate that the null hypothesis that the estimated parameters are transferable between the two county groups can be rejected with 99.99% (only 1 out of 18 tests produced confidence levels of less than 99.99%) confidence level.

Table 5 Likelihood ratio test results between different county groups.

m	n								
	Highly distressed counties			Moderately distressed counties			Least distressed counties		
	Before the pandemic	During the pandemic	After the pandemic	Before the pandemic	During the pandemic	After the pandemic	Before the pandemic	During the pandemic	After the pandemic
Highly distressed counties				83.9(18) >99.99%	126.83(25) >99.99%	121.78(19) >99.99%	24.17(22) >66.16%	78.84(17) >99.99%	80.47(20) >99.99%
Moderately distressed counties	96.63(13) >99.99%	295.95(13) >99.99%	258.20(17) >99.99%				64.14(22) >99.99%	137.62(17) >99.99%	95.09(20) >99.99%
Least distressed counties	216.64(13) >99.99%	373.72(13) >99.99%	266.25(17) >99.99%	294.5(18) >99.99%	233.92(25) >99.99%	176.31(19) >99.99%			

5.2 Out-of-sample predictions

As a supplement to likelihood ratio tests, out-of-sample predictions aim to evaluate the cumulative effects of variables on crash severity outcomes. Specifically, applying a model from an earlier period or a specific region to forecast crash injury severity probabilities for a later period or another region reveals the shifts in risk levels (Hou et al., 2022; Liu et al., 2024). Compared with within-sample observations, where parameters estimated from a specific period or region are applied to the same data, prediction-observation discrepancies reflect the direction and magnitude of risk changes rather than merely the estimated parameter deviations captured by likelihood ratio tests (Se et al., 2024). For instance, if a model estimated using before the pandemic crashes consistently underestimates injury severity during and after the pandemic crashes, it suggests a deterioration in baseline risk conditions. Therefore, tracking these collective shifts in prediction-observation discrepancies offers a clearer view of evolving risks and system safety status.

In this study, out-of-sample predictions are implemented from two aspects: temporal shifts and county group variations. Specifically, for the temporal instability, the parameters of highly, moderately and least distressed counties model from an earlier period are used to predict injury severities with data from the subsequent periods. For spatial instability, the parameters estimated from one group's crash (i.e., highly or moderately distressed counties) are used to predict injury severities with data from another group in the same period. Following previous research (Hou et al., 2022; Alnawmasi and Mannering, 2023), the simulation of individual crash injury probabilities requires the entire random parameter distribution and incorporates both the mean and variance of random parameters, avoiding the inaccurate probability estimates.

Table 6 illustrates the average differences between the forecasted probabilities and observed probabilities for highly, moderately and least distressed counties models across all periods, utilizing before the pandemic and during the pandemic as the baseline. To more directly capture the extent of the differences, relative changes by normalizing with the observed probabilities were calculated, following the approach used by (Barbour and Abdel-Aty, 2024; Barbour et al., 2024). Clearly, using the before pandemic parameter estimates to predict during parameter data yields an underestimation of both minor injuries (-0.0057, -0.0138, and -0.0146, respectively) and severe injuries (-0.0168, -0.0710, and -0.0300, respectively). This pattern suggests heightened risk during the pandemic, likely due to driver risk-taking and increased presence of active travelers (Islam et al., 2023; Liu et al., 2024). For highly distressed counties crashes, applying during the pandemic model to predict after the pandemic data underestimates severe injuries (-0.0244), whereas in moderately and least distressed counties crashes, it slightly overestimates them (0.0030 and 0.0021). This divergence implies that highly distressed counties face greater challenges in recovering from major shocks, due to insufficient social support and resources, such as limited access to vaccination (Xi et al., 2024). Interestingly, Table 2 shows that the injury severity distribution did not significantly differ between moderately and least distressed regions before the pandemic. However, severe injuries increased by 28.85% (0.0700/24.26%) in moderately distressed counties and 15.58% (0.0300/19.26%) in least distressed counties from before the pandemic to during the pandemic, indicating lower shock-absorption capacity in moderately distressed counties.

Moreover, the persistently elevated probability of severe injury observed in highly distressed counties may stem from long-standing infrastructure deficiencies and strained emergency medical resources, which weakened the system's recovery capability. This conclusion is also supported by our model estimation results, which show that wider roadways (e.g., number lanes between 3 and 4 indicator and number lanes over 4 indicator) and the ambulance rescue indicator are associated with higher injury severity during and after the pandemic period, as shown in Table 10. These wider roadways may lack adequate pedestrian or cycling facilities, exposing the growing number of active travelers to more hazardous environments. At the same time, COVID-19 induced pressures on medical resources and broader economic decline undermined the timeliness of post-crash emergency care, thereby worsening injury outcomes. Therefore, for highly distressed counties, enhancing targeted financial assistance, such as increasing funding for infrastructure upgrades and health-care resources, is essential for strengthening their safety resilience (Navarro-Moreno et al., 2023; Patwary et al., 2024). Conversely, for moderately distressed counties, the decreased probability of severe injury after the pandemic may imply that the deterioration in active travelers' safety observed during the pandemic was partially driven by COVID-19 disruptions, such as increases in alcohol-impaired driving and speeding behaviors. As the pandemic subsided, the risk of severe crashes began to recover toward levels observed before the pandemic. Therefore, these counties may benefit from strengthening emergency preparedness and response strategies, such as establishing community resilience networks and ensuring the stable supply of essential goods, which can reduce uncertainty and mitigate stress during disruptive events. Higher stress and uncertainty have been shown to increase risky driving behaviors, including drunk driving and speeding (Vingilis et al., 2020). This may help resist and absorb the safety disruptions caused by unexpected events.

Table 6 The average differences in the predicted probabilities between different periods

Base group	Injury Severity	Forecast group: During the pandemic – Highly distressed counties	During the pandemic – Moderately distressed counties	During the pandemic – Least distressed counties	After the pandemic – Highly distressed counties	After the pandemic – Moderately distressed counties	After the pandemic – Least distressed counties
Before the pandemic	NI	0.0225 (6.54%)	0.0838 (21.23%)	0.0447 (11.25%)	0.0343 (9.65%)	0.1069 (30.24%)	0.0415 (10.44%)
	MI	-0.0057 (-1.58%)	-0.0138 (-3.81%)	-0.0146 (-3.57%)	0.0232 (7.03%)	-0.0373 (-9.56%)	-0.0187 (-4.44%)
	SI	-0.0168 (-5.66%)	-0.0700 (-28.85%)	-0.0300 (-15.58%)	-0.0576 (-18.35%)	-0.0696 (-27.19%)	-0.0228 (-12.53%)
During the pandemic	NI	-	-	-	0.0093 (2.62%)	0.0080 (2.26%)	0.0025 (0.63%)
	MI	-	-	-	0.0151 (4.57%)	-0.0110 (-2.81%)	-0.0046 (-1.10%)
	SI	-	-	-	-0.0244 (-7.79%)	0.0030 (1.16%)	0.0021 (1.15%)

Table 7 shows the average differences in predicted probabilities when applying parameters from one county group's model (i.e., highly or moderately distressed counties) to predict outcomes with data from another group in the same period. Notably, the probability of severe injuries is consistently overestimated when applying the highly distressed counties model to predict moderately and least distressed counties crashes, and the moderately distressed counties model to least distressed counties crashes, throughout all three periods. This suggests that the probability of severe injuries rises progressively as the level of distressed counties grows. The reason for this may be due to higher distressed counties usually have poorer transportation facilities, lower intensity of enforcement measures, and more unsafe behaviors (Zhai et al., 2024). Notably, applying the highly distressed counties model to predict least distressed counties crashes increased severe injuries from 16.07% (0.0276/17.18%) before the pandemic to 24.30% (0.0443/18.23%) after the pandemic, while applying the moderately distressed counties model to predict least distressed counties crashes increased severe injuries from 1.92% (0.0033/17.18%) to 8.89% (0.0162/18.23%). This indicates that inequities in road safety have further widened after the pandemic.

Table 7 The average differences in the predicted probabilities between different county groups

Base group	Injury Severity	Forecast group					
		Moderately distressed counties			Least distressed counties		
		Before the pandemic	During the pandemic	After the pandemic	Before the pandemic	During the pandemic	After the pandemic
Highly distressed counties	NI	-0.0503 (-11.16%)	-0.0510 (-12.92%)	0.0149 (4.22%)	0.0169 (3.95%)	-0.0417 (-10.50%)	0.0274 (6.89%)
	MI	0.0096 (2.62%)	-0.0512 (-14.12%)	-0.0417 (-10.67%)	-0.0445 (-11.13%)	-0.1039 (-25.36%)	-0.0717 (-17.06%)
	SI	0.0407 (22.33%)	0.1022 (42.12%)	0.0267 (10.45%)	0.0276 (16.07%)	0.1456 (75.51%)	0.0443 (24.30%)
Moderately distressed counties	NI	-	-	-	0.0219 (5.11%)	0.0273 (6.87%)	0.0162 (4.07%)
	MI	-	-	-	-0.0252 (-6.30%)	-0.0360 (-8.79%)	-0.0323 (-7.69%)
	SI	-	-	-	0.0033 (1.92%)	0.0087 (4.51%)	0.0162 (8.89%)

6 Model results and discussion

Before estimating the model, stepwise regression is employed to select significant indicators, which can avoid the influence of multicollinearity. The estimation results of temporally unconstrained models using highly, moderately and least distressed counties crashes for three periods are listed in Appendix Tables A1 to A3. As shown in these tables, each model has a good statistical fit with McFadden Pseudo R^2 values varying from 0.1366 to 0.2013, and at least one or more random parameters are found in each model. Besides, heterogeneity in the means of random parameters is found in four models, while heterogeneity in the variances of the random parameters is only found in the moderately distressed counties model before the pandemic. Table 8 presents the results of the likelihood ratio test, indicating whether the partially constrained models differ significantly from their unconstrained counterparts. The X^2 values indicate that the null hypothesis can only be rejected with 85.78%, 57.49%, and 7.43% confidence in each county group, thus the partially constrained model is warranted. Therefore, this work focuses on partially constrained models to uncover how the effects of factors on active traveler injury severities change over three periods, and the results are listed in Tables 9-12.

Table 8 Test results between partially constrained and temporally unconstrained models.

County groups	$LL(\beta_{PC})$	$\sum LL(\beta_U)$	X^2	Degree of freedom	Confidence level
Highly distressed counties	-1642.2732	-1636.1693	12.2078	8	85.78%
Moderately distressed counties	-2450.3869	-2448.4564	3.8610	4	57.49%
Least distressed counties	-3782.8489	-3779.2361	7.2256	14	7.43%

6.1 Insights from temporally stable parameters

As shown in Table 9, the least distressed counties model contains the highest number of temporally stable parameters, with four variables exhibiting consistent effects across all periods and another four variables showing stability in two of the three periods. In contrast, the other models contain only a limited number of variables with stable effects across two periods. This suggests that the active transportation systems in least distressed counties demonstrate greater safety resilience and shock-absorbing capacity compared to other regions.

In the highly distressed counties model, three variables exhibited consistently positive impact on severe injuries across two periods, namely ambulance rescue, speed limits over 50 MPH, and number lanes between 3 and 4. Notably, during and after the pandemic, ambulance rescue was associated with an approximately twofold increase in the marginal effect on severe injuries compared with before the pandemic (from 0.0245 to 0.0484), as shown in Table 10. The reason may be that the COVID-19 outbreak exacerbated the strain on medical resources, and that higher rescue costs and longer response times contributed to worse outcomes in crashes involving ambulance rescue. Furthermore, limited access to vaccination in such areas continued to burden local healthcare systems even after the pandemic (Xi et al., 2024). On wide roads with three to four lanes, drivers tended to lower their guard and increase speed due to reduced traffic volumes during the pandemic, thereby raising the risk of overlooking pedestrians and cyclists. Moreover, this increased risk persisted after the pandemic, possibly due to police staffing shortages that have hindered the restoration of patrol frequency to before the pandemic levels (PERF, 2021). These results reflect the system's low adaptive and recovery capacity in emergency response and traffic enforcement when faced with the COVID-19 shock. Interestingly, the speed limit over 50 MPH produced the same parameter before and after the pandemic, consistently increasing the likelihood of severe injuries. This may be because high-speed roads often pass through low-income regions, and travel restrictions during the pandemic reduced traffic volumes, thereby lowering active traveler exposure to the risks associated with these high-speed corridors (Zhu et al., 2024).

In the moderately distressed counties model, only two variables demonstrated the same effects over two periods. The urban areas indicator (before and during the pandemic) was associated with a higher probability of severe injury. However, this indicator contributed to a decreased probability of severe injury in the highly distressed counties model during the pandemic and in the least distressed counties model before the pandemic. This may be because the least distressed counties, despite having high traffic volumes and population density, are equipped with well-developed infrastructure and advanced management strategies that help mitigate the severity of crashes (Wang and Fan, 2025a). The highly distressed counties tend to have lower traffic volumes, reducing the complexity of the traffic environment. However, urban areas within moderately distressed counties tend to experience relatively high traffic volumes, while infrastructure may offer less effective protection compared to that in the least distressed counties, thereby increasing the probability of severe injury. The local street (during and after the pandemic) exhibited a higher likelihood of minor injury but a lower likelihood of severe injury. Due to the impact of COVID-19, people increasingly turned to walking and cycling for daily activities, resulting in a higher presence of active travelers on local roads. However, the relatively low driving speeds on these roads make active travelers less likely to sustain severe injury (Rifaat et al., 2011).

In the least distressed counties model, speed limit over 50 MPH, speed limit between 30 and 50 MPH, Interstate routes, and dark roadway not lighted exhibit consistently positive effects on severe injuries across all periods. These findings suggest that these crash mechanisms in this region were not significantly affected by the impact of COVID-19, demonstrating a strong resistance to external disturbances. Additionally, these risk factors may indicate issues related to excessive vehicle speeds facilitated by well-designed roads (Coughenour et al., 2017). High population density may also result in active travelers appearing in unexpected and poorly lit areas, raising the risk of severe injuries. Moreover, active travelers on roadways, alcohol-impaired drivers, and crossing roadway-vehicle not turning crashes consistently increased the likelihood of severe injury before and after the pandemic. This suggests that these mechanisms have returned to before the pandemic state after disruption caused by COVID-19. Notably, the marginal effects of crossing roadway-vehicle not turning indicator on severe injury were three and five times higher than those observed in highly and moderately distressed counties models, respectively. The elevated risk of high-speed crashes in the least distressed counties is likely attributable to drivers having greater difficulty noticing and yielding to active travelers in a timely manner (Coughenour et al., 2017). Interestingly, the effect of alcohol-impaired drivers was not significant during the pandemic, which contrasts with previous findings that suggested an increase in crashes caused by risky behaviors during this period (Marshall et al., 2023). During the pandemic, driver anxiety and stress were major contributors to alcohol-related crashes. However, drivers in economically advantaged areas were less likely to experience job loss or income reduction and had better access to community resources for stress relief. As a result, drivers in these regions were less affected by the pandemic's impact.

6.2 Insights from random parameters

In the highly distressed counties model, ambulance rescue, dark roadway not lighted, and local street were identified as random parameters. Ambulance rescue exhibited consistent means and standard deviations during and after the pandemic. Moreover, the proportion of observations resulting in minor injuries increased from 60.43% before the pandemic to 62.70% during and after the pandemic. Notably, before the pandemic, the random parameter had a higher mean when crashes occurred on dark lighted roadways. Dark roadway not lighted indicator was identified as a significant random parameter (mean: 1.2419; standard deviation: 2.0460) after the pandemic and as a fixed parameter before the pandemic. Thus, most active travelers (72.81%) tend to have a higher probability of severe injuries. The reason is poor lighting reduces drivers' reaction times, leading to more severe impacts (Zhai et al., 2024; Wang and Fan, 2025a). Local street indicator had a mean (standard deviation) of -3.5330(3.6577) after the pandemic, with 16.7% of the local street crashes being more likely to result in severe injury. This result is reasonable because poor road design may not provide adequate protection for active travelers in economically distressed counties, but the typically low vehicle speeds may prevent severe injury crashes (Rifaat et al., 2011).

In the moderately distressed counties model, random parameters include the travel lane indicator, winter indicator, speed limit over 50 MPH indicator, and elderly active traveler indicator. Travel lane indicator produced a statistically significant random parameter before the pandemic, with 54.6% of crashes increasing the probability of severe injuries among active travelers. This finding is consistent with Campos Ferreira et al. (2022), indicating that severe injury crashes are more likely to occur on facilities designed for active travelers. However, the mean value of random parameter was lower if the crashes occurred in urban areas. This may due to the more developed infrastructure in urban areas, reducing the probability of severe injuries among active travelers (Agheli and Aghabayk, 2024). Besides, the standard deviation of the travel lane parameter decreased when the crash involved ambulance rescue before the pandemic. During the pandemic, the winter indicator was a statistically significant random parameter (means: -1.0705, standard deviation: 1.5697), with 24.76% of active travelers tending to sustain severe injuries. Moreover, the random parameter mean was lower if crashes occurred on curved roadway and higher if crashes occurred on Interstate toute. This may be because drivers tend to reduce their speed on curved roadways, whereas the relatively straight interstate routes encourage higher speeds (Rangaswamy et al., 2024). Speed limit over 50 MPH was identified as a significant random parameter (means: 0.9419, standard deviation: 2.1337) during the pandemic, and as a fixed parameter after the pandemic. Thus, 67.06% of crashes that occurred on high-speed limit roadways linked to a higher probability of severe injury, and the average marginal effects increased after the pandemic. This may be attributed to active travelers becoming less attentive after the pandemic (Barbour et al., 2024). Elderly active traveler indicator was significant during and after the pandemic and was identified as a random parameter only after the pandemic. As shown in Table 11, the average marginal effects of severe injury decreased from 0.0043 and 0.0038. This may be due to decreased traffic during the pandemic, promoting elderly active travelers to travel more often, but they became more cautious once the traffic volume recovered.

In the least distressed counties model, the travel lane indicator, crosswalk area indicator, ambulance rescue indicator, and hit-and-run indicator were identified as significant random parameters. However, travel lane indicator exhibited a lower average marginal effect on severe injury (0.0058) compared with the moderately distressed counties model (0.0093). This may be attributed to the region's more prosperous economic conditions, which allow for better maintenance and management of travel lanes (Agheli and Aghabayk, 2024). The crosswalk areas indicator had a mean (standard deviation) of -0.5971(1.5340), with 34.85% of active travelers leading to minor injuries during the pandemic. Interestingly, after the pandemic, this variable became a fixed parameter and exhibited the opposite effect, increasing the likelihood of severe injuries, as indicated by the marginal effects. This may be due to the gradual restoration of traffic volume after the pandemic combined with relatively high vehicle speeds in this region, increasing the probability of severe injuries (Wang and Fan, 2025b). After the pandemic, the ambulance rescue indicator's random parameter was statistically significant, whereas it was a fixed parameter before or during the pandemic. Additionally, the hit-and-run indicator resulted in a random parameter, with its mean increased if the active traveler was dashing or darting out. This is because the sudden appearance of active travelers makes it difficult for drivers to react in time, and without timely rescue, the likelihood of severe injuries increases (Jiang et al., 2021).

6.3 Other fixed parameters

6.3.1 Human characteristics

Elderly active travelers were found to suffer a higher probability of severe injury in the highly, distressed counties model before the pandemic. The underlying reason may be that the decline in physiological functions makes the body more vulnerable (Sun et al., 2023; Zeng et al., 2023). Alcohol-impaired driver indicator was statistically significant in highly and moderately distressed counties models during the pandemic period and showed an increased probability of severe injury for active travelers. This may be because, during the pandemic, people experienced emotional anxiety, and individuals in economically disadvantaged counties faced additional financial burdens (Hosseini et al., 2022; Gutierrez et al., 2025). Some drivers turned to alcohol to cope with stress, which increased the likelihood of severe injury crashes (Marshall et al., 2023). The elderly driver indicator was statistically significant in the least distressed counties model before the pandemic and was associated with a higher likelihood of no injury. This may be due to their more conservative driving behavior and lower driving speed (Salehian et al., 2023).

6.3.2 Crash location and roadway characteristics

The indicator of Interstate route was statistically significant in the highly and moderately distressed counties models during the pandemic period, with a higher likelihood of severe injury and minor injury, respectively. This may uncover the regional variations in driver behavior. In highly distressed counties, reduced traffic volume during the pandemic may have led to more aggressive or speeding behavior, increasing likelihood of severe injuries (Song et al., 2025). In contrast, drivers in moderately distressed counties may have maintained more controlled speeds, resulting in relatively less severe outcomes.

The indicator of roads with more than four lanes was linked to a higher likelihood of severe injury in the highly distressed counties model for both during and after the pandemic, as well as in the least distressed counties model during the pandemic. Broad roadways are often associated with higher vehicle speeds and reduced driver awareness of active travelers (Agheli and Aghabayk, 2024). During the pandemic, the decline in traffic volumes may have reduced active travelers' caution on wide roadways, resulting in more frequent activity and an elevated risk of severe injury. Even after the pandemic period, as traffic volumes began to recover, active travelers in highly distressed counties may have continued these unsafe behaviors, thereby further increasing their vulnerability to severe injury.

The indicator of Piedmont areas was significant in the highly distressed counties model during the pandemic and in the moderately distressed counties model after the pandemic. However, the direction of the effect is inconsistent, showing an increased probability of severe injury in highly distressed counties and a reversed effect in moderately distressed counties. Piedmont areas usually have more curvy and hilly roads (Liu et al., 2021). However, in relatively affluent counties, effective maintenance and infrastructure investments can mitigate their risk, leading to a reduced likelihood of severe crashes.

6.3.3 Environmental and temporal characteristics

The dark lighted roadway indicator produced a significant parameter in the highly distressed counties model before the pandemic, the least distressed counties model during the pandemic, and the moderately distressed counties model after the pandemic, and was linked to a higher likelihood of severe injury. This finding is consistent with previous research (Zhai et al., 2024; Wang and Fan, 2025a). Poor lighting conditions reduce the visibility of both active travelers and drivers, potentially causing delayed braking or less effective evasive maneuvers by drivers, thereby increasing the severity of crashes.

Cloud weather was associated with a decreased likelihood of severe injuries in the highly distressed counties model after the pandemic. But rainy weather conditions showed the opposite result in the least distressed counties model before the pandemic. This could result from reduced visibility and decreased road surface friction during rainy conditions, which makes it more difficult for drivers to control their vehicles and thus leads to more severe collisions (Wei et al., 2024). Moreover, the fall season was associated with a higher probability of no injury in the moderately distressed counties model during the pandemic.

6.3.4 Crash characteristics

The ambulance rescue indicator was associated with an increased likelihood of both minor and severe injuries in the moderately distressed counties model. This may be because the high cost of medical services could deter individuals from requesting ambulance assistance unless the injuries are perceived as severe (Wang and Fan, 2025a). And the variation in effects across different pandemic phases highlights the temporal dynamics of the ambulance rescue indicator.

The indicator of crossing roadway-vehicle not turning was statistically significant in the highly distressed counties models during the pandemic, as well as the moderately distressed counties model before the pandemic, contributing to a higher likelihood of severe injury. A possible explanation is that vehicles moving straight typically travel at higher speeds, which can result in greater impact force during a crash (Yang et al., 2023).

The dash or dart-out indicator was statistically significant in the least distressed counties model both before and after the pandemic, as well as the moderately distressed counties model before the pandemic, increasing likelihood of severe injury. This is because the sudden appearance of active travelers left the driver with insufficient time to react, resulting in severe injuries (Wang and Fan, 2025a).

Motorists failed to yield indicator decreased the severe injury in the highly and moderately distressed counties models before the pandemic. This variable reflects whether the motorists yielded at a signalized intersection. This finding may result from drivers reducing their speed in advance when approaching intersections, thereby decreasing the severity of injuries (Wang et al., 2023). Similarly, the indicator of motorists turning behavior was associated with decreased likelihood of severe injury in the moderately distressed counties model during and after the pandemic, as well as in the least distressed counties model after the pandemic. This is also attributed to lower vehicle speeds.

Table 9 The results of partially temporally constrained models for highly, moderately and least distressed counties crashes (NI: no injury; MI: minor injury; SI: severe injury; BP: Before the pandemic; DP: During the pandemic; and AP: After the pandemic)

Significant variables	Highly distressed counties		Moderately distressed counties		Least distressed counties	
	Estimated Parameter	Z-Value	Estimated Parameter	Z-Value	Estimated Parameter	Z-Value
Constant [MI] [BP, DP, AP]	-1.18	-9.20				
Constant [SI] [BP, AP]	-2.62	-11.00				
Constant [SI] [DP]	-1.57	-5.26				
Constant [MI] [BP, AP]			-0.63	-4.87		
Constant [SI] [DP, AP]			-1.73	-7.92		
Constant [SI] [BP]			-4.43	-4.20		
Constant [MI] [BP]					-1.01	-7.76
Constant [MI] [DP]					-0.69	-5.54
Constant [MI] [AP]					-0.35	-3.16
Constant [SI] [BP, DP, AP]					-3.19	-17.86
Random parameters (normally distributed)						
Ambulance rescue (1 if ambulance is requested after the crash occurs; 0 otherwise) [MI] [DP, AP]	1.21	3.72				
Ambulance rescue indicator standard deviation	3.73	3.37				
Ambulance rescue (1 if ambulance is requested after the crash occurs; 0 otherwise) [MI] [BP]	0.63	1.79				

Ambulance rescue indicator standard deviation	2.40	2.08				
Dark roadway not lighted (1 if light condition is dark roadway not lighted; 0 otherwise) [SI] [AP]	1.24	2.91				
Dark roadway not lighted indicator standard deviation	2.05	2.15				
Local Street (1 if road class is local street; 0 otherwise) [SI] [AP]	-3.53	-1.97				
Local Street indicator standard deviation	3.66	1.84				
Travel Lane (1 if crash occurs in vehicle travel lane; 0 otherwise) [SI] [BP]			0.56	1.15		
Travel Lane indicator standard deviation			4.86	3.36		
Winter (1 if crash occurs in winter; 0 otherwise) [SI] [DP]			-1.07	-1.99		
Winter indicator standard deviation			1.57	1.71		
Speed limit over 50 MPH (1 if posted speed limit is greater than 50 MPH; 0 otherwise) [SI] [DP]			0.94	2.29		
Speed limit over 50 MPH indicator standard deviation			2.13	2.03		
Elderly active traveler (1 if the active traveler is over 65 years old, 0 otherwise) [SI] [AP]			0.50	1.73		
Elderly active traveler indicator standard deviation			2.59	2.00		
Travel lane (1 if crash occurs in vehicle travel lane; 0 otherwise) [MI] [BP]					0.36	2.35
Travel lane indicator standard deviation					1.30	2.15
Crosswalk area (1 if crash occurs in crosswalk area; 0 otherwise) [MI] [DP]					-0.60	-2.52
Crosswalk area indicator standard deviation					1.53	1.72
Ambulance rescue (1 if ambulance is requested after the crash occurs; 0 otherwise) [MI] [AP]					0.97	6.62
Ambulance rescue indicator standard deviation					1.26	2.12
Hit-and-run (1 if crash is hit-and-run; 0 otherwise) [SI] [AP]					0.59	1.69
Hit-and-run indicator standard deviation					1.17	1.72

Heterogeneity in the mean of the random parameters						
Ambulance rescue: Dark lighted roadway [MI] [BP]	0.92	1.76				
Travel Lane: urban areas [SI] [BP]			-1.59	-2.15		
Winter: curved roadway [SI] [DP]			-2.66	-2.00		
Winter: Interstate route [SI] [DP]			4.71	1.80		
Hit-and-run: Dash / Dart-Out [SI] [AP]					0.80	2.10
Heteroscedasticity of random parameters						
Travel Lane: Ambulance rescue [SI] [BP]			-3.44	-2.38		
Parameters maintained stable across two or more periods						
Ambulance rescue (1 if ambulance is requested after the crash occurs; 0 otherwise) [SI] [DP, AP]	2.69	10.74				
Speed limit over 50 MPH (1 if posted speed limit is greater than 50 MPH; 0 otherwise) [SI] [BP, AP]	1.04	4.55				
Speed limit over 50 MPH (1 if posted speed limit is greater than 50 MPH; 0 otherwise) [SI] [BP, DP, AP]					1.47	7.79
Speed limit between 30 and 50 MPH (1 if posted speed limit is between 30 and 50 MPH; 0 otherwise) [SI] [BP, DP, AP]					0.73	5.70
Number lanes between 3 and 4 (1 if the number of lanes is between 3 and 4; 0 otherwise) [SI] [DP, AP]	1.26	4.49				
Interstate route (1 if road class is interstate route; 0 otherwise) [SI] [BP, DP, AP]					1.69	6.83
Local Street (1 if road class is local street; 0 otherwise) [SI] [DP, AP]			-0.76	-4.63		
Urban areas (1 if crash occurs in urban area; 0 otherwise) [MI] [BP, DP]			-0.68	-6.08		
Crossing roadway - vehicle not turning (1 if active traveler is struck while crossing the roadway by a vehicle traveling straight through; 0 otherwise) [SI] [BP, AP]					1.29	8.08

Active traveler in roadway (1 if active traveler is in the roadway; 0 otherwise) [SI] [BP, AP]					1.27	5.39
Alcohol-impaired driver (1 if the driver is alcohol-impaired; 0 otherwise) [SI] [BP, AP]					1.90	6.51
Dark roadway not lighted (1 if light condition is dark roadway not lighted; 0 otherwise) [SI] [BP, DP, AP]					0.84	6.87
Elderly active traveler (1 if the active traveler is over 65 years old, 0 otherwise) [SI] [BP, DP]					0.88	4.81
Other fixed parameters						
Active traveler Characteristics						
Elderly active traveler (1 if the active traveler is over 65 years old, 0 otherwise) [SI] [BP]	0.86	2.28				
Elderly active traveler (1 if the active traveler is over 65 years old, 0 otherwise) [SI] [DP]			0.98	2.82		
Driver Characteristics						
Alcohol-impaired driver (1 if the driver is alcohol-impaired; 0 otherwise) [SI] [DP]	2.73	4.06	1.53	2.79		
Elderly driver (1 if the driver is over 65 years old, 0 otherwise) [MI] [BP]					-0.45	-2.13
Elderly driver (1 if the driver is over 65 years old, 0 otherwise) [SI] [BP]					-0.97	-3.09
Locality and Roadway Characteristics						
US route (1 if road class is US route; 0 otherwise) [MI] [AP]	-2.11	-2.49				
Interstate route (1 if road class is interstate route; 0 otherwise) [SI] [DP]	2.27	2.25				
Interstate route (1 if road class is interstate route; 0 otherwise) [MI] [DP]			1.87	2.73		
State route (1 if road class is state route; 0 otherwise) [MI] [DP]			0.99	3.31		
State route (1 if road class is state route; 0 otherwise) [MI] [AP]			0.76	2.42		

State route (1 if road class is state route; 0 otherwise) [SI] [AP]			1.04	2.91		
Local Street (1 if road class is local street; 0 otherwise) [SI] [BP]			-1.73	-4.33		
Local Street (1 if road class is local street; 0 otherwise) [SI] [AP]					-1.06	-5.55
Number lanes over 4 (1 if the number of lanes is greater than 4; 0 otherwise) [SI] [AP]	2.64	4.86				
Number lanes over 4 (1 if the number of lanes is greater than 4; 0 otherwise) [SI] [DP]	1.03	2.86			0.61	2.94
Speed limit over 50 MPH (1 if posted speed limit is greater than 50 MPH; 0 otherwise) [MI] [DP]			-0.67	-2.10		
Speed limit over 50 MPH (1 if posted speed limit is greater than 50 MPH; 0 otherwise) [SI] [AP]			0.45	1.83		
Bike lane (1 if crash occurs in bike lane; 0 otherwise) [SI] [DP]	-1.89	-3.75				
Travel lane (1 if crash occurs in vehicle travel lane; 0 otherwise) [MI] [BP]	0.56	2.43	0.29	1.90		
Travel lane (1 if crash occurs in vehicle travel lane; 0 otherwise) [SI] [BP]					0.73	4.19
Crosswalk area (1 if crash occurs in crosswalk area; 0 otherwise) [SI] [DP]					-1.20	-5.00
Crosswalk area (1 if crash occurs in crosswalk area; 0 otherwise) [MI] [AP]					-0.47	-3.04
Urban area (1 if crash occurs in urban area; 0 otherwise) [SI] [BP]					-0.90	-5.09
Urban area (1 if crash occurs in urban area; 0 otherwise) [SI] [DP]	-2.08	-6.88				
Residential areas (1 if crash occurs in residential area; 0 otherwise) [MI] [DP]			0.55	3.71		
Piedmont region (1 if crash occurs in piedmont region; 0 otherwise) [SI] [DP]	1.11	2.38				
Piedmont region (1 if crash occurs in piedmont region; 0 otherwise) [SI] [AP]			-0.85	-3.30		
Hillcrest (1 if crash occurs on a hillcrest roadway; 0 otherwise) [MI] [AP]					-0.91	-2.19

Curved roadway (1 if road geometry is curved roadway; 0 otherwise) [SI] [BP]			1.54	3.31		
Curved roadway (1 if road geometry is curved roadway; 0 otherwise) [MI] [DP]			-0.88	-2.48		
Environment and Temporal Characteristics						
Dawn/Dusk Light (1 if light condition is dawn/dusk light; 0 otherwise) [MI] [AP]	2.16	2.76				
Dawn/Dusk Light (1 if light condition is dawn/dusk light; 0 otherwise) [SI] [AP]	2.33	2.19				
Dark lighted roadway (1 if light condition is lighted roadway; 0 otherwise) [SI] [BP]	1.26	4.07				
Dark lighted roadway (1 if light condition is lighted roadway; 0 otherwise) [SI] [DP]					0.68	3.59
Dark lighted roadway (1 if light condition is lighted roadway; 0 otherwise) [SI] [AP]			0.96	4.29		
Dark roadway not lighted (1 if light condition is dark roadway not lighted; 0 otherwise) [SI] [BP]	1.54	6.15				
Dark roadway not lighted (1 if light condition is dark roadway not lighted; 0 otherwise) [MI] [AP]	1.14	2.83				
Dark roadway not lighted (1 if light condition is dark roadway not lighted; 0 otherwise) [SI] [AP]			1.18	5.43		
Cloudy weather (1 if the weather condition is cloudy; 0 otherwise) [SI] [AP]	-2.45	-3.23				
Rain (1 if the weather condition is raining; 0 otherwise) [MI] [BP]					-0.55	-2.32
Fall (1 if crash occurs in fall; 0 otherwise) [MI] [DP]			-0.92	-4.73		
Fall (1 if crash occurs in fall; 0 otherwise) [SI] [DP]			-0.88	-3.37		
Winter (1 if crash occurs in winter; 0 otherwise) [MI] [DP]			-0.65	-3.26		
Human control (1 if the type of traffic control is human control; 0 otherwise) [MI] [BP]					1.34	2.13

Double yellow line, no-passing zone (1 if crash occurs within no-passing zone with double yellow line; 0 otherwise) [SI] [DP]					1.02	4.37
Crash Characteristics						
Ambulance rescue (1 if ambulance is requested after the crash occurs; 0 otherwise) [MI] [BP]			0.84	5.21	1.09	7.57
Ambulance rescue (1 if ambulance is requested after the crash occurs; 0 otherwise) [SI] [BP]	1.70	6.60	3.93	3.79	1.46	7.91
Ambulance rescue (1 if ambulance is requested after the crash occurs; 0 otherwise) [MI] [DP]			1.07	6.62	1.43	8.95
Ambulance rescue (1 if ambulance is requested after the crash occurs; 0 otherwise) [SI] [DP]			2.45	9.41	1.94	10.76
Ambulance rescue (1 if ambulance is requested after the crash occurs; 0 otherwise) [MI] [AP]			1.30	8.23		
Ambulance rescue (1 if ambulance is requested after the crash occurs; 0 otherwise) [SI] [AP]			1.96	8.90	2.16	11.08
Crossing roadway - vehicle not turning (1 if active traveler is struck while crossing the roadway by a vehicle traveling straight through; 0 otherwise) [SI] [DP]	1.03	2.62			0.63	2.99
Crossing roadway - vehicle not turning (1 if active traveler is struck while crossing the roadway by a vehicle traveling straight through; 0 otherwise) [MI] [BP]			0.65	2.83		
Crossing roadway - vehicle not turning (1 if active traveler is struck while crossing the roadway by a vehicle traveling straight through; 0 otherwise) [SI] [BP]			1.80	3.59		
Crossing roadway - vehicle turning (1 if active traveler is struck while crossing the roadway by a vehicle turning; 0 otherwise) [SI] [DP]			-2.03	-3.06		

Crossing roadway - vehicle turning (1 if active traveler is struck while crossing the roadway by a vehicle turning; 0 otherwise) [MI] [AP]			-0.67	-2.65		
Crossing roadway - vehicle turning (1 if active traveler is struck while crossing the roadway by a vehicle turning; 0 otherwise) [SI] [AP]			-2.08	-2.27		
Dash / Dart-out (1 if active traveler suddenly entered the roadway (dashing/darting); 0 otherwise) [MI] [BP]			0.98	2.82	1.00	3.25
Dash / Dart-out (1 if active traveler suddenly entered the roadway (dashing/darting); 0 otherwise) [SI] [BP]			1.81	2.59	1.67	5.39
Dash / Dart-out (1 if active traveler suddenly entered the roadway (dashing/darting); 0 otherwise) [SI] [AP]					1.35	3.89
Motorist failed to yield (1 if the motorist failed to properly yield to the active traveler at a signalized intersection; 0 otherwise) [MI] [BP]			-0.68	-2.14		
Motorist failed to yield (1 if the motorist failed to properly yield to the active traveler at a signalized intersection; 0 otherwise) [SI] [BP]	-2.01	-1.91	-3.85	-2.04		
Motorist Turning (1 if the crash occurs while the motorist was turning; 0 otherwise) [SI] [DP]			-2.72	-1.99	-1.77	-2.41
Motorist Turning (1 if the crash occurs while the motorist was turning; 0 otherwise) [MI] [AP]			-1.40	-3.21		
Motorist Turning (1 if the crash occurs while the motorist was turning; 0 otherwise) [SI] [AP]			-2.08	-2.27		
Motorist Overtaking (1 if the crash occurs while the motorist was overtaking the active traveler; 0 otherwise) [SI] [BP]	-1.19	-2.61				
Active Traveler in Roadway (1 if active traveler is in the roadway; 0 otherwise) [MI] [DP]			0.92	2.49		

Active Traveler in Roadway (1 if active traveler is in the roadway; 0 otherwise) [SI] [DP]			1.89	4.69		
Hit-and-run (1 if crash is hit-and-run; 0 otherwise) [MI] [AP]			-0.35	-1.88	-1.33	-2.82
Hit-and-run (1 if crash is hit-and-run; 0 otherwise) [SI] [AP]			-0.60	-2.32		
Model statistics						
Log-likelihood at convergence	-1642.27		-2450.39		-3782.85	
Log-likelihood at zero	-1942.35		-2920.11		-4666.91	
McFadden Pseudo R-squared	0.15		0.16		0.19	
Number of observations	1768		2658		4248	
Degree of freedom	35		58		45	

Table 10 Marginal effects of partially temporally constrained models for highly distressed counties crashes (bold values are constrained parameters)

Description	Highly distressed counties [BP]			Highly distressed counties [DP]			Highly distressed counties [AP]		
	NI	MI	SI	NI	MI	SI	NI	MI	SI
Active traveler Characteristics									
Elderly active traveler (1 if the active traveler is over 65 years old, 0 otherwise)	-0.0026	-0.0018	0.0044						
Driver Characteristics									
Alcohol-impaired driver (1 if the driver is alcohol-impaired; 0 otherwise)				-0.0026	-0.0020	0.0046			
Locality and Roadway Characteristics									
Travel lane (1 if crash occurs in vehicle travel lane; 0 otherwise)	-0.0120	0.0205	-0.0085						
Bike lane (1 if crash occurs in bike lane; 0 otherwise)				0.0038	0.0017	-0.0055			
Speed limit over 50 MPH (1 if posted speed limit is greater than 50 MPH; 0 otherwise)	**-0.0040**	**-0.0039**	**0.0079**				**-0.0040**	**-0.0039**	**0.0079**
Urban areas (1 if crash occurs in urban area; 0 otherwise)				0.0339	0.0144	-0.0483			

Number lanes between 3 and 4 (1 if the number of lanes is between 3 and 4; 0 otherwise)				**-0.0134**	**-0.0110**	**0.0245**	**-0.0134**	**-0.0110**	**0.0245**
Number lanes over 4 (1 if the number of lanes is greater than 4; 0 otherwise)				-0.0056	-0.0028	0.0084	-0.0070	-0.0040	0.0110
US route (1 if road class is US route; 0 otherwise)							0.0016	-0.0053	0.0037
Interstate route (1 if road class is interstate route; 0 otherwise)				-0.0009	-0.0007	0.0016			
Local Street (1 if road class is local street; 0 otherwise)							0.0023	0.0002	-0.0025
Piedmont region (1 if crash occurs in piedmont region; 0 otherwise)				-0.0022	-0.0015	0.0037			
Environment and Temporal Characteristics									
Dawn/dusk light (1 if light condition is dawn/dusk light; 0 otherwise)							-0.0013	0.0009	0.0004
Dark lighted roadway (1 if light condition is lighted roadway; 0 otherwise)	-0.0074	-0.0058	0.0132						
Dark roadway not lighted (1 if light condition is dark roadway not lighted; 0 otherwise)	-0.0175	-0.0138	0.0313				-0.0047	0.0016	0.0031
Cloudy (1 if the weather condition is cloudy; 0 otherwise)							0.0029	0.0011	-0.0040
Crash Characteristics									
Ambulance rescue (1 if ambulance is requested after the crash occurs; 0 otherwise)	-0.0335	0.0090	0.0245	**-0.0601**	**0.0118**	**0.0484**	**-0.0601**	**0.0118**	**0.0484**
Motorist overtaking (1 if the crash occurs while the motorist was overtaking the active traveler; 0 otherwise)	0.0025	0.0013	-0.0038						

Motorist failed to yield (1 if the motorist failed to properly yield to the active traveler at a signalized intersection; 0 otherwise)	0.0007	0.0003	-0.0010						
Crossing roadway - vehicle not turning (1 if active traveler is struck while crossing the roadway by a vehicle traveling straight through; 0 otherwise)				-0.0035	-0.0026	0.0061			

Table 11 Marginal effects of partially temporally constrained models for moderately distressed counties crashes (bold values are constrained parameters)

Description	Moderately distressed counties [BP]			Moderately distressed counties [DP]			Moderately distressed counties [AP]		
	NI	MI	SI	NI	MI	SI	NI	MI	SI
Active traveler Characteristics									
Elderly active traveler (1 if the active traveler is over 65 years old, 0 otherwise)				-0.0018	-0.0025	0.0043	-0.0019	-0.0019	0.0038
Driver Characteristics									
Alcohol-impaired driver (1 if the driver is alcohol-impaired; 0 otherwise)				-0.0012	-0.0016	0.0028			
Locality and Roadway Characteristics									
Travel lane (1 if crash occurs in vehicle travel lane; 0 otherwise)	-0.0103	0.0010	0.0093						
Speed limit over 50 MPH (1 if posted speed limit is greater than 50 MPH; 0 otherwise)				-0.0004	-0.0035	0.0039	-0.0017	-0.0030	0.0047
Urban areas (1 if crash occurs in urban area; 0 otherwise)	**0.0523**	**-0.0678**	**0.0155**	**0.0523**	**-0.0678**	**0.0155**			
Residential areas (1 if crash occurs				-0.0107	0.0159	-0.0052			

in residential area; 0 otherwise)									
Interstate route (1 if road class is interstate route; 0 otherwise)				-0.0012	0.0029	-0.0017			
State route (1 if road class is state route; 0 otherwise)				-0.0031	0.0057	-0.0026	-0.0020	0.0004	0.0016
Local Street (1 if road class is local street; 0 otherwise)	0.0111	0.0114	-0.0225	**0.0135**	**0.0179**	**-0.0314**	**0.0135**	**0.0179**	**-0.0314**
Curved roadway (1 if road geometry is curved roadway; 0 otherwise)	-0.0022	-0.0025	0.0048	0.0019	-0.0031	0.0012			
Piedmont region (1 if crash occurs in piedmont region; 0 otherwise)							0.0027	0.0045	-0.0072
Environment and Temporal Characteristics									
Dark lighted roadway (1 if light condition is lighted roadway; 0 otherwise)							-0.0050	-0.0072	0.0122
Dark roadway not lighted (1 if light condition is dark roadway not lighted; 0 otherwise)							-0.0078	-0.0122	0.0199
Fall (1 if crash occurs in fall; 0 otherwise)				0.0090	-0.0063	-0.0027			
Winter (1 if crash occurs in winter; 0 otherwise)				0.0049	-0.0045	-0.0004			
Crash Characteristics									
Ambulance rescue (1 if ambulance is requested after the crash occurs; 0 otherwise)	-0.0470	0.0010	0.0460	-0.0340	0.0040	0.0300	-0.0320	0.0096	0.0224
Motorist failed to yield (1 if the motorist failed to properly yield to the active traveler at a signalized	0.0017	-0.0012	-0.0005						

intersection; 0 otherwise)									
Crossing roadway - vehicle not turning (1 if active traveler is struck while crossing the roadway by a vehicle traveling straight through; 0 otherwise)	-0.0044	0.0002	0.0042						
Crossing roadway - vehicle turning (1 if active traveler is struck while crossing the roadway by a vehicle turning; 0 otherwise)				0.0011	0.0009	-0.0020	0.0030	-0.0015	-0.0015
Dash/dart-out (1 if active traveler suddenly entered the roadway (dashing/darting); 0 otherwise)	-0.0022	0.0008	0.0014						
Motorist turning (1 if the crash occurs while the motorist was turning; 0 otherwise)				0.0003	0.0005	-0.0008	0.0019	-0.0013	-0.0006
Active traveler in roadway (1 if active traveler is in the roadway; 0 otherwise)				-0.0026	-0.0012	0.0038			
Hit-and-run (1 if crash is hit-and-run; 0 otherwise)							0.0033	-0.0013	-0.0020

Table 12 Marginal effects of partially temporally constrained models for least distressed counties crashes (bold values are constrained parameters)

Description	Least distressed counties [BP]			Least distressed counties [DP]			Least distressed counties [AP]		
	NI	MI	SI	NI	MI	SI	NI	MI	SI
Active traveler Characteristics									
Elderly active traveler (1 if the active traveler is over 65 years old, 0 otherwise)	**-0.0035**	**-0.0039**	**0.0074**	**-0.0035**	**-0.0039**	**0.0074**			
Driver Characteristics									
Alcohol-impaired driver (1 if the	**-0.0029**	**-0.0034**	**0.0063**				**-0.0029**	**-0.0034**	**0.0063**

driver is alcohol-impaired; 0 otherwise)									
Elderly driver (1 if the driver is over 65 years old, 0 otherwise)	0.0022	-0.0011	-0.0012						
Locality and Roadway Characteristics									
Travel lane (1 if crash occurs in vehicle travel lane; 0 otherwise)	-0.0101	0.0043	0.0058						
Speed limit between 30 and 50 MPH (1 if posted speed limit is between 30 and 50 MPH; 0 otherwise)	**-0.0236**	**-0.0263**	**0.0499**	**-0.0236**	**-0.0263**	**0.0499**	**-0.0236**	**-0.0263**	**0.0499**
Speed limit over 50 MPH (1 if posted speed limit is greater than 50 MPH; 0 otherwise)	**-0.0103**	**-0.0129**	**0.0232**	**-0.0103**	**-0.0129**	**0.0232**	**-0.0103**	**-0.0129**	**0.0232**
Urban areas (1 if crash occurs in urban area; 0 otherwise)	0.0130	0.0125	-0.0255						
Number lanes over 4 (1 if the number of lanes is greater than 4; 0 otherwise)				-0.0020	-0.0025	0.0044			
Interstate route (1 if road class is interstate route; 0 otherwise)	**-0.0046**	**-0.0053**	**0.0099**	**-0.0046**	**-0.0053**	**0.0099**	**-0.0046**	**-0.0053**	**0.0099**
Local Street (1 if road class is local street; 0 otherwise)							0.0096	0.0092	-0.0187
Crosswalk area (1 if crash occurs in crosswalk area; 0 otherwise)				0.0042	-0.0010	-0.0031	0.0066	-0.0083	0.0017
Double yellow line, no passing zone (1 if crash occurs within no-passing zone with double yellow line; 0 otherwise)				-0.0023	-0.0032	0.0055			

Human control (1 if the type of traffic control is human control; 0 otherwise)	-0.0008	0.0010	-0.0002						
Hillcrest (1 if crash occurs on a hillcrest roadway; 0 otherwise)							0.0012	-0.0015	0.0003
Environment and Temporal Characteristics									
Dark lighted roadway (1 if light condition is lighted roadway; 0 otherwise)				-0.0030	-0.0038	0.0067			
Dark roadway not lighted (1 if light condition is dark roadway not lighted; 0 otherwise)	**-0.0102**	**-0.0127**	**0.0229**	**-0.0102**	**-0.0127**	**0.0229**	**-0.0102**	**-0.0127**	**0.0229**
Rain (1 if the weather condition is raining; 0 otherwise)	0.0021	-0.0030	0.0010						
Crash Characteristics									
Ambulance rescue (1 if ambulance is requested after the crash occurs; 0 otherwise)	-0.0303	0.0164	0.0139	-0.0277	0.0125	0.0153	-0.0247	0.0044	0.0203
Crossing roadway - vehicle not turning (1 if active traveler is struck while crossing the roadway by a vehicle traveling straight through; 0 otherwise)	**-0.0107**	**-0.0102**	**0.0209**	-0.0021	-0.0025	0.0046	**-0.0107**	**-0.0102**	**0.0209**
Dash/dart-out (1 if active traveler suddenly entered the roadway (dashing/darting); 0 otherwise)	-0.0028	0.0004	0.0024				-0.0016	-0.0031	0.0047
Motorist turning (1 if the crash occurs while the motorist was				0.0003	0.0005	-0.0008			

turning; 0 otherwise)									
Active traveler in roadway (1 if active traveler is in the roadway; 0 otherwise)	**-0.0034**	**-0.0040**	**0.0074**				**-0.0034**	**-0.0040**	**0.0074**
Hit-and-run (1 if crash is hit-and-run; 0 otherwise)							0.0014	-0.0017	0.0003

7 Conclusion and policy recommendations

Regional economic disparities have led to variations in human behavior, infrastructure maintenance, and social support across regions, contributing to a disproportionate number of fatal and severe crashes among active travelers in economically disadvantaged areas. Such road safety inequalities may be further exacerbated by abrupt events, such as the COVID-19 pandemic. However, few studies have investigated how the determinants of injury severity for active travelers vary across regions with different economic conditions, while accounting for COVID-contributing temporal shifts and revealing disparities in regional safety resilience. Using pedestrian and bicyclist-vehicle crash data from North Carolina as a case study, this research classified counties into three groups (i.e., highly, moderately, and least distressed counties) based on four economic indicators and defined three pandemic periods (i.e., before, during and after the pandemic) according to changes in traffic volume and pandemic control policies. Multiple random parameter multinomial logit models with heterogeneity in means and variance were then estimated for crashes in each county group to identify significant variables and capture unobserved heterogeneity. Subsequently, the partially constrained modeling approach was employed to capture individual variables with temporal stability across the three periods. Finally, the out-of-sample prediction was undertaken to evaluate the collective risk shifts.

The results of partially constrained models indicated that the least distressed counties model has four parameters (speed limits between 30 and 50 MPH, speed limits over 50 MPH, Interstate route, and dark roadways not lighted) with statistically consistent effects across all periods. In contrast, the highly and moderately distressed counties models exhibit only a few variables with consistent statistical effects across two periods. This suggests that the effects of variables are more stable in the least distressed counties, indicating stronger safety resilience under external shocks. Nevertheless, high driving speeds, facilitated by well-maintained road conditions, remain a key issue in these regions. Therefore, installing speed cameras or increasing police patrol frequency could effectively mitigate the severity of injuries resulting from high-speed driving. In addition, due to high population density, active travelers may be active on road segments without lighting. Therefore, it is essential to deploy portable lighting systems in high-crash, unlit areas to enhance nighttime visibility. Notably, alcohol-impaired driving exhibited a consistently positive effect on severe injury outcomes both before and after the pandemic. However, during the pandemic period, this effect remained statistically significant only in highly and moderately distressed counties. Thus, vehicles in the least distressed counties should be equipped with passive alcohol sensors that seamlessly analyze alcohol in a driver's breath, thereby preventing alcohol-impaired driving (DADSS, 2023). Additionally, implementing resilient and partial control policies may help alleviate the panic and economic strain triggered by abrupt events in economically disadvantaged regions, while also reducing risk behaviors such as alcohol-impaired driving (Lee et al., 2023).

For moderately distressed counties, urban areas consistently exhibited a positive impact on severe injuries both before and during the pandemic, whereas in other county groups, they were linked to a lower likelihood of severe injuries. This may be due to higher population density and mismatched infrastructure. Therefore, these areas warrant comprehensive traffic safety evaluations and the deployment of cost-effective interventions, such as curb extensions and speed humps. Moreover, the temporal shifts observed in the effect of speed limit over 50 MPH and state route variables may suggest a growing safety concern associated with these roadways. Therefore, it is imperative to implement educational programs that raise active travelers' awareness of the risks associated with high-grade roads, alongside expanding dedicated infrastructure to accommodate the growing demand for active travel.

For highly distressed counties, speed limits over 50 MPH consistently showed a positive association with severe injuries both before and after the pandemic. This may reveal a long-standing issue in these areas, where high-speed roads often pass through residential neighborhoods. Thus, traffic calming measures (e.g., raised crosswalks and speed humps) and physical separation (e.g., protected bike lanes and sidewalks) should be prioritized to safeguard active travelers. Moreover, the consistent effects of number lanes over 4 and the increasing impact of number lanes between 3 with 4 during and after the pandemic suggest that wide roads pose significant risks for active travelers when crossing. Thus, refuge islands on wide streets are recommended to improve crossing safety (Dumbaugh et al., 2023; Agheli and Aghabayk, 2024). Lastly, temporal shifts in the effect of the ambulance rescue variable reveal a shortage of medical resources in this region.

During and after the pandemic, the overwhelmed healthcare system was unable to provide a timely emergency response, contributing to a surge in severe injury crashes. Such shortages are likely to recur following future major events. Thus, counties should strengthen regional cooperation, for example by sharing EMS vehicle dispatch centers, to build resource redundancy during routine operations, thereby enhancing resilience against major events.

Out-of-sample predictions suggest that active travelers in highly and moderately distressed counties are more likely to suffer severe injuries. This underscores the urgent need to advance complete streets initiatives that create inclusive travel environments for active travelers, along with comprehensive safety education programs for all road users in economically disadvantaged areas. Moreover, the probability of severe injuries has increased after the pandemic in all regions. This means that certain factors become more hazardous over time, though the increase may also partly reflect changes in behavior and self-selection bias in crash data (Islam et al., 2023). Besides, the evolution of collective risk further reveals disparities in regional safety resilience. Specifically, highly distressed counties face the highest risk of severe injuries, with an upward trend that continues even after the pandemic. In moderately distressed counties, the post-pandemic decline in severe injuries is insufficient to offset the sharp increase observed during the pandemic. Consequently, the weak recovery in highly distressed counties and the limited resistance in moderately distressed counties have further exacerbated regional safety inequalities. These findings suggest that targeted financial assistance, particularly for strengthening medical resources, is imperative to enhance the recovery capacity of highly distressed counties. Additionally, designing redundant systems can bolster the resilience of moderately distressed counties to external shocks. For example, allocating additional space for active travelers can effectively prevent them from moving on to high-speed and major roads, which typically pose greater safety risks.

Nevertheless, this study has certain limitations. First, the reliability of the findings is highly dependent on data quality, even though the mixed logit model is inherently robust. Police-reported crash data tend to overrepresent more severe crashes and omit important variables such as driver behavior and impact speed, which could affect the model results. Moreover, the limited sample size in highly distressed counties could result in less precise parameter estimates. Future research should consider incorporating multi-source datasets, such as video surveillance and vehicle insurance claims, to improve real-time accuracy and capture underreported crashes. Second, although certain factors have a similar impact on injury severity for both pedestrians and cyclists, these two road-user groups still exhibit differences in characteristics such as travel speed. Future work should therefore explore these differences in greater depth. Finally, county distress levels in this study are designated based on a specific region (North Carolina). Thus, these findings may not directly apply to other regions due to variations in traffic conditions and regional economic characteristics. Incorporating data from multiple regions could overcome this limitation.

CRediT authorship contribution statement

Zehao Wang: Conceptualization, Methodology, Software, Validation, Writing - original draft, Visualization. **Wei Fan**: Data curation, Supervision, Writing - review & editing.

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.

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Appendix

Table A1 Temporally unconstrained parameter estimation results for highly distressed counties crashes.

Variables' List	Before the pandemic		During the pandemic		After the pandemic	
	Estimated Parameter	Z-Value	Estimated Parameter	Z-Value	Estimated Parameter	Z-Value
Constant [MI]	-1.55	-5.41	-0.71	-2.44	-1.10	-5.12
Constant [SI]	-3.05	-8.12	-1.34	-3.71	-2.65	-5.48
Random parameters (normally distributed)						
Ambulance rescue [MI]	0.78	1.89	1.45	3.67	0.95	2.06
Ambulance rescue indicator standard deviation	2.35	1.96	2.99	2.06	3.38	2.20
Dark roadway not lighted [SI]					1.18	2.53
Dark roadway not lighted indicator standard deviation					2.29	1.93

Local Street [SI]					-3.69	-1.97
Local Street indicator standard deviation					3.72	1.82
Heterogeneity in the mean of the random parameters						
Ambulance rescue: Dark lighted roadway [MI]	0.93	1.78				
Non-random parameters						
Active traveler Characteristics						
Elderly active traveler [SI]	0.84	2.21				
Driver Characteristics						
Alcohol-impaired driver [SI]			2.62	3.85		
Locality and Roadway Characteristics						
Travel Lane [MI]	0.90	2.88				
Bike Lane [SI]			-1.87	-3.71		
Speed limit over 50 MPH [SI]	0.94	3.49			1.16	2.62
Urban areas [SI]			-2.16	-6.93		
Number lanes between 3 and 4 [SI]			1.06	3.21	1.65	2.87
Number lanes over 4 [SI]			0.94	2.62	2.67	4.15
US route [MI]					-1.76	-1.99
Interstate route [SI]			2.38	2.40		
Piedmont region [SI]			1.10	2.42		
Environment and Temporal Characteristics						
Dawn/Dusk Light [MI]					2.09	2.62
Dawn/Dusk Light [SI]					2.25	2.07
Dark lighted roadway [SI]	1.27	3.91				
Dark roadway not lighted [SI]	1.50	5.58				
Dark roadway not lighted [MI]					1.15	2.61
Cloudy weather [SI]					-2.57	-3.15
Crash Characteristics						
Ambulance rescue [SI]	1.75	5.43	2.61	7.31	2.64	5.43
Motorist overtaking [SI]	-1.25	-2.71				
Motorist failed to yield [SI]	-2.01	-1.90				
Crossing roadway - vehicle not turning [SI]			1.01	2.57		
Model statistics						
Log-likelihood at convergence	-623.16		-532.65		-480.36	
Log-likelihood at zero	-721.79		-641.59		-578.97	
McFadden Pseudo R-squared	0.13		0.17		0.17	
Number of observations	657		584		527	
Degree of freedom	13		13		17	

Table A2 Temporally unconstrained parameter estimation results for moderately distressed counties crashes.

Variables' List	Before the pandemic		During the pandemic		After the pandemic	
	Estimated Parameter	Z-Value	Estimated Parameter	Z-Value	Estimated Parameter	Z-Value
Constant [MI]	-0.78	-3.58			-0.54	-3.31
Constant [SI]	3.94	3.79	-1.54	-4.72	-2.06	-5.74

Random parameters (normally distributed)						
Travel Lane [SI]	0.57	1.15				
Travel Lane indicator standard deviation	4.82	3.34				
Winter [SI]			-1.06	-2.06		
Winter indicator standard deviation			1.55	1.84		
Speed limit over 50 MPH [SI]			0.80	1.98		
Speed limit over 50 MPH indicator standard deviation			2.08	2.01		
Elderly active traveler [SI]					0.51	1.73
Elderly active traveler indicator standard deviation					2.59	1.89
Heterogeneity in the mean of the random parameters						
Travel Lane: urban areas [SI]	-1.54	-2.09				
Winter: curved roadway [SI]			-2.66	-2.03		
Winter: interstate route [SI]			4.61	2.01		
Heteroscedasticity of random parameters						
Travel Lane: Ambulance rescue [SI]	-0.72	-1.82				
Non-random parameters						
Active traveler Characteristics						
Elderly active traveler [SI]			0.96	2.84		
Driver Characteristics						
Alcohol-impaired driver [SI]			1.52	2.85		
Locality and Roadway Characteristics						
State route [MI]			1.05	3.64	0.74	2.28
State route [SI]					1.14	3.06
Interstate route [MI]			1.90	3.05		
Local Street [SI]	-1.70	-4.26	-0.98	-4.08	-1.15	-1.97
Curved roadway [MI]			-0.88	-2.50		
Curved roadway [SI]	1.53	3.28				
Speed limit over 50 MPH [MI]			-0.70	-2.23		
Speed limit over 50 MPH [SI]					0.51	1.99
Urban areas [MI]	-0.61	-3.61	-0.72	-4.58		
Residential areas [MI]			0.56	3.65		
Travel Lane [MI]	0.34	2.09				
Piedmont region [SI]					-0.87	-3.19
Environment and Temporal Characteristics						
Fall [MI]			-0.91	-4.70		
Fall [SI]			-0.90	-3.41		
Winter [MI]			-0.64	-3.11		
Dark lighted roadway [SI]					1.13	3.78
Dark roadway not lighted [SI]					1.36	5.31
Crash Characteristics						
Ambulance rescue [MI]	0.92	4.78	1.09	6.47	1.23	6.91
Ambulance rescue [SI]	3.94	3.79	2.41	7.57	2.12	6.88
Crossing roadway - vehicle not turning [MI]	0.66	2.83				

Crossing roadway - vehicle not turning [SI]	1.80	3.58				
Dash / Dart-Out [MI]	0.96	2.77				
Dash / Dart-Out [SI]	1.79	2.58				
Motorist failed to yield [MI]	-0.63	-1.97				
Motorist failed to yield [SI]	-3.83	-2.01				
Crossing roadway - vehicle turning [MI]					-0.66	-2.62
Crossing roadway - vehicle turning [SI]			-2.00	-2.94	-2.48	-3.66
Active traveler in roadway [MI]			0.92	2.58		
Active traveler in roadway [SI]			1.88	4.87		
Motorist Turning [MI]					-1.42	-3.20
Motorist Turning [SI]			-2.75	-2.37	-2.11	-2.30
Hit-and-run [MI]					-0.39	-2.00
Hit-and-run [SI]					-0.65	-2.30
Model statistics						
Log-likelihood at convergence	-847.42		-766.23		-834.81	
Log-likelihood at zero	-1014.02		-932.72		-973.37	
McFadden Pseudo R-squared	0.16		0.18		0.14	
Number of observations	923		849		886	
Degree of freedom	18		25		19	

Table A3 Temporally unconstrained parameter estimation results for least distressed counties crashes.

Variables' List	Before the pandemic		During the pandemic		After the pandemic	
	Estimated Parameter	Z-Value	Estimated Parameter	Z-Value	Estimated Parameter	Z-Value
Constant [MI]	-1.03	-7.79	-0.67	-5.30	-0.36	-3.19
Constant [SI]	-3.35	-9.31	-2.97	-11.23	-3.34	-9.52
Random parameters (normally distributed)						
Travel Lane [MI]	0.36	2.26				
Travel Lane indicator standard deviation	1.40	2.29				
Crosswalk area [MI]			-0.61	-2.57		
Crosswalk area indicator standard deviation			1.54	1.71		
Ambulance rescue [MI]					0.98	6.64
Ambulance rescue indicator standard deviation					1.28	2.01
Hit-and-run [SI]					0.58	1.69
Hit-and-run indicator standard deviation					1.17	1.71
Heterogeneity in the mean of the random parameters						
Hit-and-run: Dash / Dart-Out [SI]					0.80	2.09
Non-random parameters						
Active traveler Characteristics						
Elderly active traveler [SI]	0.70	2.66	1.04	4.03		
Driver Characteristics						
Elderly driver [MI]	-0.45	-2.11				
Elderly driver [SI]	-0.95	-2.98				

Alcohol-impaired driver [SI]	1.87	4.62			2.04	4.55
Locality and Roadway Characteristics						
Interstate route [SI]	2.11	5.18	1.42	3.30	1.43	3.06
Local Street [SI]					-0.97	-4.59
Number lanes over 4 [SI]			0.59	2.81		
Speed limit between 30 and 50 MPH [SI]	0.80	3.20	0.69	3.41	0.69	3.10
Speed limit over 50 MPH [SI]	1.41	3.89	1.46	4.81	1.61	4.76
Crosswalk area [MI]					-0.47	-3.06
Crosswalk area [SI]			-1.24	-5.14		
Travel Lane [SI]	0.77	3.86				
Urban areas [SI]	-0.95	-4.43				
Hillcrest [MI]					-0.92	-2.18
Environment and Temporal Characteristics						
Rain [MI]	-0.56	-2.30				
Dark lighted roadway [SI]			0.65	3.28		
Dark roadway not lighted [SI]	0.72	3.50	0.90	4.49	0.92	3.86
Traffic Control Types						
Human control [MI]	1.37	2.14				
Double yellow line, no-passing zone [SI]			0.91	3.80		
Crash Characteristics						
Ambulance rescue [MI]	1.10	7.61	1.41	8.79		
Ambulance rescue [SI]	1.55	6.88	1.76	8.32	2.29	8.15
Crossing roadway - vehicle not turning [SI]	1.50	6.83	0.58	2.76	1.11	4.50
Active traveler on roadway [SI]	1.42	4.08			1.21	3.61
Dash / Dart-Out [MI]	1.01	3.25				
Dash / Dart-Out [SI]	1.73	5.39			1.33	3.70
Motorist Turning [SI]			-1.81	-2.47		
Hit-and-run [MI]					-1.31	-2.77
Model statistics						
Log-likelihood at convergence	-1387.33		-1180.20		-1211.71	
Log-likelihood at zero	-1736.91		-1436.98		-1493.01	
McFadden Pseudo R-squared	0.20		0.18		0.19	
Number of observations	1581		1308		1359	
Degree of freedom	22		17		20	

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