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Effects of speed difference on injury severity of freeway rear-end crashes: Insights from correlated joint random parameters bivariate probit models and temporal instability

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A B S T R A C T

Rear-end crashes particularly on freeways are the most frequent type of collisions causing many injuries, damage and congestion. This paper investigates the impact of varying speed differences between following and leading vehicles on injury severity in two-vehicle rear-end crashes. It develops three groups of correlated joint random parameters bivariate probit models with heterogeneity in means. The rear-end crash data from 2019 to 2021 on Interstate freeways in Florida are utilized, and categorized into periods before, during, and after the COVID-19 pandemic. The study considers two potential injury severity outcomes: no injury and injury/fatality, for both drivers involved in these crashes. The findings indicate that a range of variables, including driver, vehicle, roadway, environmental, crash, and temporal attributes, significantly influence the injury severity outcomes for drivers in both following and leading vehicles. Demonstrating superior goodness-of-fit, the proposed approach sheds light on interactive unobserved heterogeneity, captured through heterogeneity in means and significant correlations among random parameters. The study observes critical influences on the injury severity outcomes of both drivers, with significant factors such as gender, age, vehicle type, weather conditions, lighting, and time of day. Furthermore, the results substantiate the heightened risk outcomes associated with greater speed differences and the period of the COVID-19 pandemic. These findings yield further insights into the risk mechanisms of two-vehicle rear-end crashes and offer guidance for the development of effective safety countermeasures.

1. Introduction

Globally, traffic crashes cause injuries, fatalities and massive property damages each year, creating substantial safety and economics concerns (WHO, 2018). According to a report by NHTSA (2019), there were 36,096 fatalities caused by traffic crashes in the U.S in 2019. Despite a reduction in traffic volume due to the impact of COVID-19, the number of fatalities in traffic crashes remained high in 2020, reached 38,824 (NHTSA, 2020). It should be noted that even with a temporal decrease in traffic volume, the injury outcomes of traffic crashes remained elevated, with a rise by 7.6 % in fatality numbers from 2019 to 2020. Rear-end crashes, which present the leading crash type in the U.S, accounted for 27.8 % of all reported crashes in 2020 (NHTSA, 2020). Therefore, further investigation of the risk factors and the development of effective countermeasures are critical in mitigating the risks and outcomes associated with rear-

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end crashes.

A growing body of research has explored various perspectives on the risk factors, including following behaviors, and interactive patterns of rear-end crashes. For instance, Meng and Qu (2012) analyzed the time-to-collision data to establish a potential relationship between the exposure to traffic conflicts and the frequency of rear-end crashes in road tunnels. Lao et al. (2014) developed a generalized linear model-based approach to examine the determinants of the rear-end crash occurrences. King et al. (2016) explored the association between crash propensity and micro-scale driving behavior by developing a link-based Geographic Information System (GIS) environment. Dimitriou et al. (2018) captured car-following characteristics and vehicle interactions using loop detector data to investigate their effects on potential rear-end crashes. Wu et al. (2018) conducted a driving simulation experiment to analyze the impact of crash warning system on the occurrence of rear-end crashes under foggy conditions. Jo et al. (2019) utilized per-vehicle data from weight-in-motion sensors to estimate the risk probability of rear-end crashes involving heavy vehicles on freeways.

Regarding the analysis of the injury severity outcomes, numerous contributing factors have been identified including driver behavior, driver demographics, vehicle attributes, roadway features, and environmental characteristics. The power model initially formulated by Nilsson (1981) established correlations between traffic speeds and safety in Sweden in 1981. Specifically, this model identified that increases in fatalities, serious causalities, and total causalities were linked to 8th, 6th, and 4th powers, respectively, of the increase in mean speed (Nilsson, 2004). Otherwise, real-time data, encompassing kinematic parameters like location, speed, and acceleration of individual vehicles, were used to assess the likelihood and severity of crash occurrences (Wang et al., 2021; Yu and Abdel-Aty, 2014; Zhang and Abdel-Aty, 2022). Significantly, historical crash data is instrumental in modeling injury severity, offering essential insights into understanding the key risk factors. For instance, Weng et al, (2014) found that the risk of rear-end crashes increases with greater traffic flow within work zones. Chen et al. (2016) indicated that two-vehicle rear-end crashes are the most common type that result in fatalities. Furthermore, the posted speed limit on the road where the crashes occurred is positively correlated with the severity of driver injuries (Moussa et al., 2022; Zhang and Hassan, 2019). It is important to note that driving at a high speed increases the risk of the inability to stop in time, leading to the occurrence of the rear-end crashes and subsequent injuries (Das and Abdel-Aty, 2011). The speed difference between the leading (struck) and following (striking) vehicles has also been found to affect the consequences of rear-end crashes (Chatterjee, 2016). Additionally, Li et al. (2021) indicated a higher risk of rear-end collision with greater speed differences. Thus, providing a wealth of information, including specific details at the time of the crash, historical crash data enables a thorough analysis of factors contributing to injury severity. Consequently, it holds significant potential for in-depth investigation into the relationship between the speed difference at the time of collision and the resulting injury severity outcomes in two-vehicle rear-end crashes.

Although drivers and vehicles involved in the same rear-end crashes share the same driving environment, the attributes of each driver (such as driving behaviors and demographics) and vehicle type can have an impact on the injury severity outcomes of the other driver. Therefore, it is important to recognize that the injury severity outcomes of both drivers are likely interrelated. Instead of analyzing them separately, it is necessary to model and examine the internal relationship between the injury severity outcomes of both drivers simultaneously, at the same level of aggregation. To date, several research efforts have focused on analyzing the injury severity outcomes of both drivers in the same rear-end crashes. For example, Chen et al. (2019) developed a random parameters bivariate ordered probit model to model rear-end crashes, while Song et al. (2023) proposed a random parameter bivariate probit model with heterogeneity in means for truck-car crashes. Building upon this previous work, the current study proposes a correlated joint random parameters bivariate probit model with the heterogeneity in means to analyze and model the injury severity of both drivers involved in a rear-end crash, specifically the drivers of the striking and struck vehicle.

Following the outbreak of COVID-19 pandemic, there have been significant changes in traffic mobility as a result of government-imposed requirements such as social distancing protocols, travel restrictions, and lockdowns (Lee et al., 2023; Koloushani et al., 2023). Despite an 11.0 % reduction in vehicle miles traveled, the mortality rate in 2020 increased by 23.4 % reaching 1.37 fatalities per million vehicle-miles traveled compared to 1.11 in 2019 (NHTSA, 2019; NHTSA, 2020). Owing to variations in traffic mobility and socio-demographic conditions, driving behaviors and patterns have likely undergone fundamental changes before, during, and after the pandemic. These changes can lead to variations in decision making, information processing and safety attitudes (Mannering, 2018), which have been extensively explored in recent studies (Alnawmasi and Mannering, 2019; Alnawmasi and Mannering, 2022; Islam and Mannering, 2020; Islam et al., 2023; Wang et al., 2022a; Wang et al., 2022b). Addressing and comprehending the issues emanating from the pandemic can provide critical insights into its impact on driver's driving patterns, behavior, psychological states, and other pertinent factors, as evidenced by the noted temporal fluctuations in crash occurrence and severity. Therefore, effective countermeasures can be designed to mitigate the increase in injuries or fatalities resulting from rear-end crashes, should similar pandemic situations arise in the future.

To address the existing gaps in knowledge, this study aims to achieve the following objectives: (a) Investigate the impact of speed differences between the leading (struck) and following (striking) vehicles on the severity of injuries sustained by each driver involved in two-vehicle rear-end crashes. (b) Assess the performance of a correlated joint random parameters bivariate probit model, considering the heterogeneity in means. (c) Estimate the temporal instability among three distinct analysis periods: before, during, and after the COVID-19 pandemic. Additionally, provide long-term strategies for mitigating the outcomes of freeway two-vehicle rear-end crashes.

The study commences by reviewing previous research findings on the impacts of speed attributes on rear-end crashes, as well as the impacts of the COVID-19 pandemic on traffic safety. Subsequently, information about the dataset and the methodological approaches utilized are presented. The study then focuses on undertaking a likelihood ratio test and out-of-sample prediction to examine the effects of speed difference and temporal instability. Following this, the results of model estimation are discussed to address changes in the injury-severity model. Finally, conclusions are drawn regarding the interpretation and implications of the findings, along with suggestions for future research directions.

2. Literature review

2.1. Review of influencing factors on injury severity outcomes of rear-end crashes

Nowadays, an extensive body of research efforts has examined the risk and severity of rear-end crashes, in terms of driver, vehicle, roadway, environmental, traffic, temporal, and crash characteristics. For instance, male drivers have been identified as being more frequently involved in fatal rear-end crashes within work zones (Zhang and Hassan, 2019). Moreover, Yu et al. (2020) found that the male drivers decrease the possible injury and injury likelihood. Young drivers with age below 25 years old is found to significantly decrease the injury likelihood than their counterparts (Yu et al., 2020). Heavy truck involvement has been recognized as a crucial factor in predicting driver fatalities (Chen et al., 2016). Approaching long curved segments is positively associated with an increased likelihood of severe injuries in rear-end crashes (Wang et al., 2022b). Additionally, windy weather conditions markedly escalate the severity of injuries sustained by occupants in rear-end crashes (Chen et al., 2015).

Table 1
A summary of findings regarding relationship between speed attributes and rear-end crashes.

Previous research efforts (Crash type or pattern)	Modeling Approach [a]	Data Source	Number of Observations	Findings
Farmer et al. (1997) (Passenger car struck passenger car)	Chi-square test and Logistic regression	NASS/CDS 1988–1992	4,226	A striking vehicle approaching from **a higher-speed** roadway should produce a more severe crash assuming some positive correlation between speed limits and travel speeds.
Wang and Abdel-Aty (2006) (Signalized intersections)	Generalized estimating equations with negative binomial link	Florida State 2000–2002	1,275	**Higher posted speed limit** on the major roadway was found to cause more rear-end crashes.
Yan and Radwan (2006) (Rear-end versus non-rear-end crashes)	Classification tree model	Florida State 2001	7,666	**The risk of the rear-end crashes** are over-presented in the higher speed limits.
Das and Abdel-Aty (2011) (Urban arterials)	Genetic Programming	Florida State 2004–2006	57,155	Crashes occurring **at higher speeds** would more likely lead to a severe crash. The frequency of crashes decreases with increase in the **maximum posted speed limit** for access related rear-end crashes.
Zhang and Hassan (2019) (Highway work zone)	Random parameter ordered probit model	Egypt 2010–2017	1,045	**Higher speed limit** tends to cause a severe rear-end crash.
Ahmadi et al. (2020) (Highway)	Multinomial logit, Mixed multinomial logit and Support vector machine	California state 2007–2011	9,468	**Speeding** is less likely to lead to fatality or severe injury compared to the situation where the driver is under influence of the alcohol.
Dabbour et al. (2020) (Highway)	Logistic regression model	North Carolina 2004–2015	451,662	**Higher speed limit** increases the injury severity of both striking and struck drivers, indicating consistent significance for striking drivers with not temporally consistent significance for the struck drivers.
Yu et al. (2020) (Work zone)	Random parameters logit model with heterogeneity in means and variances	North Carolina 2010–2013	12,477	A lower possibility of property damage only and a higher possibility of injury and possible injury was observed in 2012–13 on the highway with **a higher speed limit (i.e., 30–60 mph)**.
Liu and Fan (2022) (Large trucks involved)	Random parameters logit model	North Carolina 2005–2013	7,976	Roadways with **speed limit of more than 50 mph** can significantly increase the injury severity of large truck involved rear-end crashes at all injury levels.
Moussa et al. (2022) (Highway)	Deep residual neural networks	North Carolina 2010–2017	384,869	The injury severity of the drivers in rear-end crashes is correlated with **the posted speed limit** on the road where the crashes occurred.
Wang et al. (2022b) (Rear-end versus non-rear-end crashes)	Random parameters logit model with heterogeneity in means and variances	Jiangsu Province 2017–2019	2,251	**Higher operating speed of cars** consistently resulted in more severe injuries. The probability of minor, severe, and fatal injury rear-end crashes increased with higher **speed difference of cars with adjacent segment** in 2019.
Wang et al. (2022d) (Five types of crash pattern)	Random parameters logit model with heterogeneity in means and variances	Jiangsu Province 2017–2019	1,596	The greater **operating speed of trucks** has a higher propensity of more medium/severe injury outcomes of Car-Truck, Truck-Truck, and Truck-Car rear-end crashes. **Speed difference of cars with adjacent segment** increases the likelihood of medium/severe injury outcomes in Car-Car and Others rear-end crashes.
Yuan et al. (2023) (Vehicle strikes car/truck)	Random thresholds random parameters hierarchical ordered probit model	Fatality Analysis Reporting System 2017–2019	2,062	**Speed limit of more than 60 mile/h** is found to increase the likelihood of fatal injury by 0.0955.

Furthermore, many valuable and important findings have emerged that highlight the crucial role of speed attributes in risk of rear-end crashes. Table 1 presents related findings regarding relationship between speed attributes and rear-end crashes. A considerable number of studies have addressed the posted speed limit of the roadway for various crash types and patterns. Dabbour et al. (2020) indicated that the higher speed limit increases the injury severity of both striking and struck drivers showing temporal instability. Specifically, the speed limit of more than 60 mile/h was found to increase the likelihood of fatal injury by 0.0955 (Yuan et al., 2023). Besides, Wang et al. (2022b) found that higher operating speed of cars consistently caused more severe injuries. However, more research efforts should be devoted to analyzing the effects of the speed difference between the two vehicles involved in one collision on the injury severity levels.

Moreover, the injury levels of the most injured in the same collision was proposed to develop estimation models in most recent studies. Moreover, even with separated models developed for both parties (Dabbour et al., 2020), the specific correlation among the injury severity outcomes of both parties was unrevealed in the same rear-end crashes. It is noted that the correlation in injury outcomes among occupants involved in the same crash may stem from shared unobserved elements (Russo et al., 2014). Ineffective and biased estimation results might be contributed by excluding such potential relationships and heterogeneity (Abay et al., 2013). Consequently, it is essential to model and analyze the injury severities of both drivers involved in the same two-vehicle rear-end crash simultaneously, rather than evaluating them separately.

2.2. Review of methodical approach for injury severity

To account for unobserved heterogeneity (Mannering et al., 2016), a wide range of methodological approaches have been utilized for crash severity analysis, including models of generalized ordered logit (Yasmin et al., 2014), latent class ordered probit (Fountas et al., 2018b), grouped random parameters (Ahmed et al., 2020; Meng et al., 2021), correlated random parameters (Ahmed et al., 2021; Fountas et al., 2018a; Fountas et al., 2021), random thresholds (Fountas and Anastasopoulos, 2017; Yu et al., 2021), Bayesian random-effects (Song et al., 2020), Bayesian random-parameters (Ali et al., 2022), random parameters ordered probit (Khan et al., 2023), and random parameters logit with heterogeneity in means and variances (Alnawmasi and Mannering, 2023; Ren and Xu., 2023).

Showing the statistical superiority in terms of accuracy and reduced heterogeneity, the random parameters approaches providing much more flexibility in tracking the unobserved heterogeneity were widely used in recent studies (Alnawmasi and Mannering, 2019; Behnood and Mannering, 2017; Kim et al., 2013; Seraneeprakarn et al., 2017; Waseem et al., 2019). While both the potential correlation and unobserved heterogeneity were accommodated, the effects of variables might not be fixed (Mannering et al., 2016). Due to the discrete nature of crash injury severity outcomes and the potential heterogeneity underlying crash observations, discrete choice models, such as the random parameters multinomial logit model with heterogeneity in means (and variances), have been widely utilized (Alzaffin et al., 2023; Al-Bdairi et al., 2020; Wang et al., 2022c).

However, the aforementioned model, despite its ability to capture unobserved heterogeneous characteristics, may overlook potential interactions among these characteristics and assume that they are independently distributed (Fountas et al., 2018a; Yan et al., 2022). Recognizing the potential interrelation between the injury severity outcomes of the two drivers, this study derives a correlated random parameters model that captures the interactive relationship among the random parameters. Consequently, this paper aims to contribute to the existing body of knowledge by examining the performance of a correlated joint random parameters bivariate probit model with heterogeneity in means.

2.3. Review of findings regarding the impact of COVID-19 pandemic on traffic safety

An extensive body of research has analyzed the impact of the COVID-19 pandemic on traffic safety (Stavrinos et al., 2020; Wagner et al., 2020; Islam et al., 2023; Lee et al., 2023). For instance, Doucette et al. (2021) found that the crash rate increased even with a reduction in vehicle mileage traveled and crash numbers. Alhajyaseen et al. (2022) reported that the rates of minor/major and fatal injuries per 1000 crashes increased during the highest restrictions period caused by the pandemic. Lee et al. (2023) observed significant reduction in peak-hour crashes (22 %), while no significant change was found in fatal crashes.

Despite a significant reduction in vehicle miles traveled due to the outbreak of COVID-19, the fatality rate per vehicle miles traveled experienced a 21 % increase from 2019 to 2020 in the U.S (NHTSA, 2019; NHTSA, 2020). Recent studies have identified the reduction in traffic volumes and potentially lower enforcement as critical factors contributing to the increase in the fatality rate during the pandemic (Islam et al., 2023). Substantial evidence has confirmed the link between the pandemic and risky driving behaviors (Lee et al., 2023; Tucker and Marsh, 2021). For example, Wagner et al. (2020) observed an increase in speeding behavior during the second quarter of 2020 compared to the same period in 2019. Additionally, the California Highway Patrol reported an 87 % increase in citations for speeds exceeding 100 mph (McGreevy, 2020). After the outbreak of COVID-19 in Florida, a remarkable increase was observed in risky driving behavior, including speeding, aggressive driving, and driving under the influence of drugs (Lee et al., 2023). Moreover, the widespread stress and anxiety induced by the pandemic could result in drivers becoming more distracted and aggressive, or making poor decisions on the road (Peng et al., 2024). Such significant factors arising from COVID-19 thus substantially escalated the risk of rear-end crashes.

Numerous studies have utilized approaches such as time series analysis (Shanthosh et al., 2020), propensity score matching (Kane et al., 2020), Empirical Bayesian (Lee et al., 2017), full Bayesian approaches (Sacchi et al., 2016) for conducting before-and-after safety evaluation. These techniques typically emphasize the immediate effects of specific interventions or changes. Nonetheless, temporal stability analysis, as underscored by Mannering (2018), is exceptionally valuable in unraveling the dynamics of how specific factors influencing injury severity outcomes evolve or maintain consistency under diverse conditions. It delves into shifts in driver behavior, traffic patterns, and environmental influences, offering insights that not only complement but also enhance the outcomes from before-and-after safety evaluations. This approach is geared towards identifying factors that consistently impact traffic safety and those that alter in different temporal contexts, thereby providing a more nuanced and dynamic perspective.

To prevent inadequate estimation results, erroneous conclusions, and the implementation of ineffective or potentially hazardous safety policies, many existing studies have focused on examining temporal stability (Mannering, 2018). Transferability tests, encompassing global and pairwise tests, are extensively employed to estimate parameter shifts (Washington et al., 2020). These tests have led to the identification of key factors that exhibit variations across different time periods, as underscored in research conducted by Behnood and Mannering (2015), Li et al. (2021), Meng et al. (2021), and others. Similarly, out-of-sample prediction is employed in temporal stability analysis by calculating the probability differences between the observed and predicted models. This approach entails utilizing a set of estimated parameters to predict outcomes in datasets from different periods, a method increasingly evidenced in recent scholarly literature (Alogaili and Mannering, 2022; Hou et al., 2022; Alnawmasi and Mannering, 2023).

Considering the significant impact of speeding behavior during the COVID-19 pandemic, the potential association between the outbreak of COVID-19 and injury outcomes of rear-end crashes remains uncertain. Thus, it is essential to gain a better understanding of the complex relationship between the pandemic and injury severities of rear-end crashes. An examination of the variations in injury outcomes of rear-end crashes before, during, and after the pandemic would offer valuable insights into the evolving circumstances and aid in the development of new strategies to enhance traffic safety.

3. Data description

Data for this study was collected from two-vehicle rear-end crashes that occurred on Interstate freeways in Florida over a three-year period spanning from January 1st, 2019, to December 31st, 2021. The dataset includes information on injury severity outcomes for both drivers involved in the leading (struck) and following (striking) vehicles, as well as detailed demographics, vehicle, roadway geometric, environmental and temporal characteristics of the crashes. Additionally, the operating speeds of both vehicles at the time of the collision were estimated by the police using various methods such as skid marks analysis, braking distance, vehicle data recorders, vehicle damage assessment, and time-distance analysis (Brach et al., 2022; Knill and Fawcett, 1981). In each rear-end crash, the speed difference ($\Delta \nu$) between the leading (struck) and following (striking) vehicles at the time of the collision was quantified. The dataset encompasses a total of 41,597 two-vehicle rear-end crashes, with driver's injury severity outcome categorized into three groups: fatality, injury, and no injury (property damage only). Owing to the relatively small proportion of fatalities (only 0.25 % and 0.11 % for drivers of leading (struck) and following (striking) vehicles, respectively), the categories of fatality and injury have been combined into a single category: Injury/Fatality.

Chi-square tests are conducted to ensure the validity of the study classifying speed difference ($\Delta \nu$) by three ranges: $\Delta \nu < 5$ mph, 5 mph $\leq \Delta \nu \leq 10$ mph, and $\Delta \nu > 10$ mph. The Chi-square test results are shown in Table 2, rejecting null hypothesis that the rear-end crashes caused by different $\Delta \nu$ for the two injury severity levels are the same under high confidence levels (>99.99 %) for the three periods.[1]

Significant differences are evident in the distribution of injury severity between the following and leading vehicles, as depicted in Fig. 1. With an increase in $\Delta \nu$, the incidence of rear-end crashes progressively rises from 5,178 for the subgroup with $\Delta \nu < 5$ mph to 8,164 for the subgroup with $\Delta \nu > 10$ mph. Within each subgroup, the proportion of injury/fatality crashes is higher in leading vehicles compared to following vehicles, indicating more severe injury outcomes for the leading (struck) vehicles. Notably, there is a 2.8 % and 2.3 % increase in the proportion of injury/fatality from the following vehicle to the leading vehicle within the speed difference range of 5 mph $\leq \Delta \nu \leq 10$ mph and $\Delta \nu > 10$ mph, respectively.

Such a phenomenon can be explained by the fact that drivers in the leading vehicle may have less time to react or brace for impact compared to those in the following vehicle, affecting their level of preparedness and potential injury outcomes. Additionally, the impact from the following vehicle tends to transmit more force and energy to the leading vehicle. Drivers of leading vehicles often experience a sudden and unexpected forceful impact, accompanied by a greater change in velocity and deceleration, potentially leading to a higher risk of injury or fatality.

Moreover, Fig. 2 indicates the statistical distribution of drivers' injury severity outcomes of following and leading vehicle by different ranges of $\Delta \nu$ before, during and after the COVID-19 pandemic. Fig. 2 illustrates the statistical distribution of driver's injury severity outcomes for following and leading vehicles across various ranges of $\Delta \nu$ before, during, and after the COVID-19 pandemic. As $\Delta \nu$ increases, the severity of driver's injuries in both the following and leading vehicles escalates, indicated by a higher proportion of injury and fatality crashes in each time period. This suggests the likelihood of a positive relationship between $\Delta \nu$ and injury severity

[1] The chi-square test was conducted separately for the injury severity outcomes for both the following and leading vehicles. Specifically, the χ^2 test for the following vehicle yielded a value of 17.597 with 4 degrees of freedom at a confidence level greater than 99.99% before COVID-19 (2019). Additionally, when gathering the injury severity outcomes for both following and leading vehicles within the same category, χ^2 test results of 42.358, 88.720, and 38.167 were obtained for the periods before, during, and after the pandemic, respectively. These tests had 10 degrees of freedom and were conducted at a confidence level greater than 99.99%.

Table 2
Chi-square test results for the driver's injury severity among rear-end crashes caused by different ranges of $\Delta\nu$.

Period	Different range of $\Delta\nu$	Following vehicle			Leading vehicle		
		No Injury	Injury/ Fatality	Total	No Injury	Injury/ Fatality	Total
Before COVID-19 (2019)	$\Delta\nu < 5$ mph	1517	219	**1736**	1510	226	**1736**
	5 mph $\leq \Delta\nu \leq$ 10 mph	2033	283	**2316**	1938	378	**2316**
	$\Delta\nu >$ 10 mph	2619	489	**3008**	2451	557	**3008**
	χ^2 **test**	**17.597 (4) [> 99.99 %]**			**24.261 (4) [> 99.99 %]**		
During COVID-19 (2020)	$\Delta\nu < 5$ mph	1292	212	**1504**	1300	204	**1504**
	5 mph $\leq \Delta\nu \leq$ 10 mph	1344	233	**1577**	1319	258	**1577**
	$\Delta\nu >$ 10 mph	1646	418	**2064**	1587	477	**2064**
	χ^2 **test**	**30.127 (4) [> 99.99 %]**			**58.593 (4) [> 99.99 %]**		
After COVID-19 (2021)	$\Delta\nu < 5$ mph	1658	280	**1938**	1649	289	**1938**
	5 mph $\leq \Delta\nu \leq$ 10 mph	1926	306	**2232**	1876	356	**2232**
	$\Delta\nu >$ 10 mph	2549	543	**3092**	2489	603	**3092**
	χ^2 **test**	**17.078 (4) [> 99.99 %]**			**21.089 (4) [> 99.99 %]**		

Note: $\Delta\nu$ denotes the speed difference between the leading (struck) and following (striking) vehicles at the time of rear-end crashes. Moreover, degrees of freedom and confidence level are respectively shown in parenthesis and brackets.

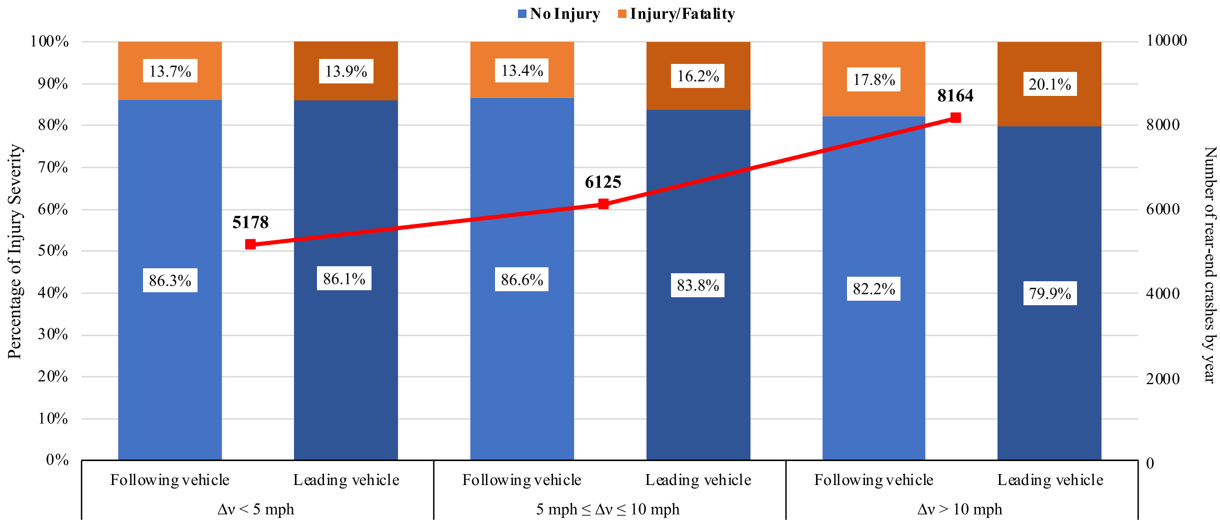

Fig. 1. Driver' injury severities of following and leading vehicle by different ranges of speed differences across all years (2019–2021).

outcomes.

Furthermore, even with lowest number of rear-end crashes in each range of $\Delta\nu$, the injury severity outcomes during the pandemic are basically the most severe in proportion compared with those before and after the pandemic,[2] indicating the serious safety issues during the COVID-19 pandemic. This observation suggests significant safety concerns during the COVID-19 pandemic, underscoring the need for increased research efforts and assistance in developing new strategies to enhance traffic safety.

In addition, Appendix A presents the descriptive statistics for the explanatory variables associated with the estimated two-vehicle rear-end crashes, categorized by different ranges of $\Delta\nu$ and segmented into periods before, during, and after the COVID-19 pandemic, encompassing driver, vehicle, roadway, environmental, crash, and temporal characteristics.

4. Methodology

The unobserved heterogeneity in two-vehicle rear-end crashes are addressed by considering factors that vary across observations (random parameters), the correlation among these parameters, and factors influencing the means of these random parameters. The present paper employs a correlated joint random parameters bivariate probit model, which accounts for heterogeneity in means, to examine the determinants influencing the injury severity outcomes of both drivers. As an extension of the univariate model, the

[2] Notably, the only exception is the subgroup with a $\Delta\nu$ of less than 5 mph. In this subgroup, the injury severity outcomes during the COVID-19 pandemic (2020) were more severe compared to those before the pandemic (2019), yet they were less severe than those recorded after the pandemic (2021).

a) Δv < 5 mph

b) 5 mph ≤ Δv ≤ 10 mph

c) Δv > 10 mph

Fig. 2. Driver' injury severities of following and leading vehicle by different ranges of $\Delta\nu$ before, during and after COVID-19 pandemic.

bivariate probit model can be specific as follows (Washington et al., 2020),

$$S_{i,1} = \beta_{i,1}\mathbf{X}_{i,1} + \varepsilon_{i,1}, s_{i,1} = 1 if S_{i,1} > 0, 0 otherwise$$

$$S_{i,2} = \beta_{i,2}\mathbf{X}_{i,2} + \varepsilon_{i,2}, s_{i,2} = 1 if S_{i,2} > 0, 0 otherwise \tag{1}$$

Consider a bivariate normal distribution based on the error terms $\varepsilon_{i,1}$ and $\varepsilon_{i,2}$:

$$\boldsymbol{\varepsilon} = \begin{pmatrix} \varepsilon_{i,1} \\ \varepsilon_{i,2} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right] \tag{2}$$

The vector $\mathbf{X}$ is intended to capture the relationship between explanatory factors and driver's injury severity outcomes in rear-end crashes, while the vector β represents the corresponding estimable parameters. The binary outcomes $s_{i,1}$ and $s_{i,2}$ characterize the injury severity outcomes for the following and leading vehicles, respectively, while $S_{i,1}$ and $S_{i,2}$ represent the corresponding latent variables. Assuming a normal joint distribution, the errors $\varepsilon_{i,1}$ and $\varepsilon_{i,2}$ have a mean of 0 and a variance of 1, respectively. The correlation coefficient ρ denotes the cross-equation error correlation, and the cumulative bivariate function following normal probability distribution could be expressed as (Bhat, 2018; Song et al., 2023),

$$\Phi\left(S_{i,1}, S_{i,2}; \rho\right) = \frac{\exp\left[-\frac{\left(S_{i,1}{}^2 + S_{i,2}{}^2 - 2\rho S_{i,1}S_{i,2}\right)}{2-2\rho^2}\right]}{\left[2\pi\sqrt{(1-\rho^2)}\ \right]} \tag{3}$$

The bivariate selection joint probability for $s_{i,1} = 1$ and $s_{i,2} = 1$ in the bivariate probit model is expressed as follows (Washington et al., 2020),

$$\begin{aligned} P\left(s_{i,1} = 1, s_{i,2} = 1\right) = P\left(\mathbf{X}_{i,1} < \mathrm{x}_{i,1}, \mathbf{X}_{i,2} < \mathrm{x}_{i,2}\right) &= \int_{-\infty}^{\mathrm{x}_{i,1}} \int_{-\infty}^{\mathrm{x}_{i,2}} \Phi\left(\mathrm{z}_{i,1}, \mathrm{z}_{i,1}; \rho\right) \mathrm{dz}_{i,1} \mathrm{dz}_{i,2} \\ &= F\left(\beta_{i,1}\mathbf{X}_{i,1}, \beta_{i,2}\mathbf{X}_{i,2}; \rho\right) \# \end{aligned} \tag{4}$$

Then, the log-likelihood function based on the maximum likelihood method could be given by (Bhat, 2018),

$$LL = \sum_{i=1}^{N} \left[\begin{array}{c} S_{i,1}S_{i,2} ln\Phi\left(\beta_{i,1}\mathbf{X}_{i,1}, \beta_{i,2}\mathbf{X}_{i,2}, \rho\right) + \left(1 - s_{i,1}\right) s_{i,2} ln\Phi\left(-\beta_{i,1}\mathbf{X}_{i,1}, \beta_{i,2}\mathbf{X}_{i,2}, -\rho\right) \\ +\left(1 - s_{2,1}\right) s_{i,1} ln\Phi\left(\beta_{i,1}\mathbf{X}_{i,1}, -\beta_{i,2}\mathbf{X}_{i,2}, -\rho\right) \\ +\left(1 - s_{i,1}\right)\left(1 - s_{i,2}\right) ln\Phi\left(-\beta_{i,1}\mathbf{X}_{i,1}, -\beta_{i,2}\mathbf{X}_{i,2}, \rho\right) \end{array}\right] \tag{5}$$

Moreover, the multilayer unobserved heterogeneity is considered by incorporating β_i, which is defined as (Mannering et al., 2016),

$$\beta_i = \boldsymbol{b} + \lambda S_i + \Gamma\delta_i \tag{6}$$

Where $\boldsymbol{b}$ denotes the mean estimable parameter across the crashes. The explanatory variables S_i affects the mean of the parameter β_i and the vector λ comprises estimable parameters. Γ is a Cholesky matrix to define the covariances matric for the random parameters, while δ_i is a disturbance term with a mean of 0 and a variance of σ^2.

Considering the standard deviation of the correlated random parameters, this can be specified as follows (Ahmed et al., 2021; Fountas et al., 2018a):

$$\sigma_r = \sqrt{\sigma_{l,l}{}^2 + \sigma_{l,l-1}{}^2 + \sigma_{l,l-2}{}^2 + \cdots + \sigma_{l,1}{}^2} \tag{7}$$

where σ_m denotes the standard deviation of the random parameter $\boldsymbol{r}$, $\sigma_{l,l}$ represents the diagonal element of the Γ matrix, and $\sigma_{l,l-1}$, $\sigma_{l,l-2}$, …, $\sigma_{l,1}$ are the off-diagonal elements of the lower triangular matrix associated with the random parameter $\boldsymbol{r}$.

The mean standard error and the corresponding t-statistic of σ_r are derived as (Fountas et al., 2018a):

$$SE_{\sigma_r} = \frac{S_{\sigma_m}}{\sqrt{N}} \tag{8}$$

$$t_{\sigma_r} = \frac{\sigma_r}{SE_{\sigma_r}} \tag{9}$$

where, S_{σ_m} is the standard deviation of σ_m, while N represents the number of observations. Then, the covariance of two random parameters can be estimated through (Fountas et al., 2021):

$$Cor\left(\chi_{m1,n}, \chi_{m2,n}\right) = \frac{cov\left(\chi_{m1,n}, \chi_{m2,n}\right)}{\sigma_{m1,n}\sigma_{m2,n}} \tag{10}$$

where, $m1$ and $m2$ are the correlated random parameters while $\sigma_{m1,n}$ and $\sigma_{m2,n}$ denote their standard deviations.

A simulated maximum likelihood approach with 1000 Halton draws was used to estimate the models by considering the trade-off between estimation performance and computation time (McFadden and Train, 2000). The normal distribution has been proven to obtain the most suitable statistical fit when exploring the distribution of random parameters (Milton et al., 2008; Behnood and Al-

Bdairi, 2020).

Moreover, the marginal effects could be calculated to measure the expected change in probability of the dependent variable being 1 for a one-unit change in one of the independent variables, holding other variables constant. For the proposed joint random parameters bivariate probit model, the marginal effects E on $j-th$ rear-end crash injury could be expressed as follows (Christofides et al., 1997; Greene, 2012),

$$E_{S_{i,1}} = P_j\left(\bar{s_{i,1}}, s_{i,2}\right)\left[given\mathbf{X}_{i,1} = 1\right] - P_j\left(\bar{s_{i,1}}, s_{i,2}\right)\left[given\mathbf{X}_{i,1} = 0\right], E_{S_{i,2}} = P_j\left(\bar{s_{i,1}}, s_{i,2}\right)\left[given\mathbf{X}_{i,2} = 1\right] - P_j\left(\bar{s_{i,1}}, s_{i,2}\right)\left[given\mathbf{X}_{i,2} = 0\right]\# \tag{11}$$

5. Transferability tests and out-of-sample prediction

The transferability tests are utilized to explore the temporal instability across the three periods and non-transferability of the three ranges of $\Delta\nu$ concerning the rear-end crash model, followed by the out-of-sample prediction.

5.1. Transferability tests

To examine the temporal variation of the estimated model across the three periods, two series of likelihood ratio tests are implemented. The first one is a pairwise test to compare the models corresponding to the two periods and evaluate whether the estimated parameters remain transferable across the three periods (before, during and after COVID-19) (Behnood and Mannering, 2015):

$$\chi^2_{t_1} = -2\left[LL\left(\beta_{t_1t_2}\right) - LL\left(\beta_{t_1}\right)\right] \tag{12}$$

where $LL\left(\beta_{t_1t_2}\right)$ represents the log-likelihood at convergence of the model containing parameters from t_2 while using data from sub-group t_1 (before, during and after COVID-19), and $LL\left(\beta_{t_1}\right)$ denotes the log-likelihood at convergence of the model using data subgroup t_1. The degree of freedom is equivalent to the number of estimated parameters in model $\beta_{t_1t_2}$ (Behnood and Mannering, 2015). To obtain two test results for each model comparison, this test is also estimated by reversing subgroups t_1 and t_2. Table 3 results of the pairwise test between different periods for the rear-end crash models caused by different ranges of $\Delta\nu$ of whether the null hypothesis that the parameters remain stable between two-year periods can be rejected. Overall, the models spanning a two-year period consistently demonstrate disparities, allowing us to reject the null hypothesis with over 99 % confidence. This indicates a high level of certainty that the estimated parameters fluctuate across the designated periods (before, during and after COVID-19).

Another series of likelihood ratio tests was proposed to estimate the temporal stability between the combined model and each separate model (Alnawmasi and Mannering, 2019; Islam and Mannering, 2020):

$$\chi^2_{t_2} = -2\left[LL\left(\beta_{alltime,s}\right) - LL\left(\beta_{t1,s}\right) - LL\left(\beta_{t2,s}\right) - LLL\left(\beta_{t3,s}\right)\right] \tag{13}$$

where $LL\left(\beta_{alltime,s}\right)$ represents the log-likelihood at the convergence of the model for crash group s ($\Delta\nu < 5$ mph, 5 mph $\leq \Delta\nu \leq$ 10 mph, and $\Delta\nu >$ 10 mph) across the three periods (before, during and after COVID-19), and $LL\left(\beta_{ti,s}\right)$ denotes the log-likelihood at the convergence of the models for crash sub-group s in period t (before, during and after COVID-19) data. The degrees of freedom correspond to the sum of the statistically significant parameters from each model, subtracting the count of statistically significant parameters found in the aggregate model. (Washington et al., 2020). The test's model estimation produces χ^2 values of 173.732, 232.440 and 186.473 with 61, 74 and 66 degrees of freedom for rear-end crashes caused by $\Delta\nu < 5$ mph, 5 mph $\leq \Delta\nu \leq$ 10 mph, and $\Delta\nu$ > 10 mph, respectively. This result allows us to reject the null hypothesis, which posits the stability of statistically significant parameters in separate models for rear-end crashes caused by different ranges of $\Delta\nu$, with a confidence level exceeding 99.99 %.

Furthermore, transferability tests for rear-end crashes caused by three distinct $\Delta\nu$ ranges can be executed as outlined by (Behnood and Al-Bdairi, 2020; Islam and Mannering, 2020; Islam and Mannering, 2021):

Table 3
Likelihood ratio test results of rear-end crash models caused by different ranges of $\Delta\nu$ between different periods.

Subgroup	t_1	t_2		
		Before COVID-19 (2019)	During COVID-19 (2020)	After COVID-19 (2021)
$\Delta\nu < 5$ mph	Before COVID-19 (2019)	–	184.165 (33) [> 99.99 %]	358.629 (34) [> 99.99 %]
	During COVID-19 (2020)	268.152 (25) [> 99.99 %]	–	268.238 (34) [> 99.99 %]
	After COVID-19 (2021)	185.534 (25) [> 99.99 %]	126.419 (33) [> 99.99 %]	–
5 mph $\leq \Delta\nu \leq$ 10 mph	Before COVID-19 (2019)	–	126.928 (38) [> 99.99 %]	135.284 (38) [> 99.99 %]
	During COVID-19 (2020)	163.928 (34) [> 99.99 %]	–	228.182 (38) [> 99.99 %]
	After COVID-19 (2021)	198.682 (34) [> 99.99 %]	268.504 (38) [> 99.99 %]	–
$\Delta\nu >$ 10 mph	Before COVID-19 (2019)	–	129.928 (35) [> 99.99 %]	138.126 (32) [> 99.99 %]
	During COVID-19 (2020)	102.628 (32) [> 99.99 %]	–	218.324 (32) [> 99.99 %]
	After COVID-19 (2021)	92.628 (32) [> 99.99 %]	121.316 (35) [> 99.99 %]	–

Note: Degrees of freedom and confidence level are respectively shown in parenthesis and brackets.

$$\chi_s^2 = -2\left[LL\left(\beta_{All\Delta\nu,t}\right) - LL\left(\beta_{s1,t}\right) - LL\left(\beta_{s2,t}\right) - LLL\left(\beta_{s3,t}\right)\right] \tag{14}$$

where $LL(\beta_{All\Delta\nu,t})$ represents the log-likelihood at convergence of the model with rear-end crashes caused by all distinct $\Delta\nu$ ranges in one period t (before, during, and after COVID-19), and $LL(\beta_{s1,t})$ $LL(\beta_{s2,t})$ and $LL(\beta_{s3,t})$ denote the log-likelihoods at convergence for the $\Delta\nu < 5$ mph, 5 mph $\leq \Delta\nu \leq 10$ mph, and $\Delta\nu > 10$ mph models for period t, respectively.

From this, three test outcomes are derived to assess the transferability of the estimated models across the three $\Delta\nu$ ranges for rear-end crash models. Concurrently, the degrees of freedom amount to the total of statistically significant parameters in each separate model minus the count in the combined model, as noted by Washington et al. (2020). The χ^2 test outcomes for the periods before, during, and after COVID-19 are 116.078, 172.856, and 164.012 with 58, 69, and 68 degrees of freedom, respectively. These results indicate that the null hypothesis asserting the equivalency of rear-end crashes caused by three distinct $\Delta\nu$ ranges can be confidently rejected with a certainty greater than 99.99 %.

5.2. Out-of-sample prediction

Besides the transferability tests, out-of-sample predictions are a viable method to assess temporal instability by predicting injury severity outcomes from different period (Alnawmasi and Mannering, 2022; Hou et al., 2022; Wang et al., 2022c). Furthermore, to address the issue of non-transferability, the aggregate severity differences across the rear-end crash models caused by three distinct $\Delta\nu$ ranges could also be examined through out-of-sample prediction. To explore the aggregate effects of temporal variation, one-period's rear-end crash model will be proposed to predict injury severity outcomes using the data from another period, both within the same $\Delta\nu$ range.

Additionally, the estimated parameters derived from a rear-end crash model for a specific $\Delta\nu$ range will be utilized to forecast the outcomes of rear-end crashes within a different $\Delta\nu$ range. This approach serves to elucidate the aggregate discrepancies in rear-end crashes that are attributable to varying $\Delta\nu$ ranges. To conduct the out-of-sample prediction simulation, the estimated parameters from the base model will be applied within the simulation process using 1,000 Halton draws, consistent with those used in the base model estimation.

Regarding temporal instability, Table 4 enumerates the mean differences between the observed model probabilities and the predicted probabilities of injury severity outcomes derived from applying the parameters of a specific period's rear-end crash model to subsequent period data. It is apparent that utilizing the model parameters from before COVID-19 (2019) model to predict rear-end crashes during COVID-19 (2020) for $\Delta\nu < 5$ mph results in a probability decrease for Injury/Fatality outcomes by 0.0029 and 0.0011 for following and leading vehicles, respectively. Adopting the parameters estimated from the before COVID-19 (2019) model to predict rear-end crashes during COVID-19 (2020) for 5 mph $\leq \Delta\nu \leq 10$ mph resulted in a reduction in the probabilities of Injury/Fatality by 0.0045 and 0.0018 for following and leading vehicles, respectively. Furthermore, employing the during COVID-19 (2020) model parameters to forecast injuries from rear-end crashes after COVID-19 (2021) caused by $\Delta\nu > 10$ mph yields overestimated Injury/Fatality probabilities by 0.0062 and 0.0021 for following and leading vehicles, respectively. Given this, the substantial discrepancies in the table suggest a notable temporal instability through the out-of-sample prediction.

It should be noted that utilizing estimated parameters from before COVID-19 (2019) model to predicting rear-end crashes during COVID-19 (2020) produced a consistent decrease in Injury/Fatality probabilities for the following and leading vehicles across three distinct $\Delta\nu$ ranges. Conversely, employing the during COVID-19 (2020) model to predict rear-end crashes after COVID-19 (2019) led to an overestimation of Injury/Fatality probabilities for $\Delta\nu < 5$ mph, while underestimated them for $\Delta\nu$ ranges of 5 mph $\leq \Delta\nu \leq 10$ mph and $\Delta\nu > 10$ mph. Alternatively, employing the before COVID-19 (2019) models to predict rear-end crashes during COVID-19 (2020) led to a continuous increase in the absolute values with an increasing $\Delta\nu$ range. Similarly, using the during COVID-19 (2020) models to predict rear-end crashes after COVID-19 (2021) resulted in a sustained increase in Injury/Fatality outcomes with a rising $\Delta\nu$ range. These patterns correspond with the injury severity distribution trend depicted in Fig. 2, highlighting the aggravating injury severity levels of rear-end crashes during the COVID-19 pandemic and its escalation with an increasing $\Delta\nu$ range. This insight is crucial for highway safety as it underscores the importance of effectively managing speed variations of vehicles to mitigate the severity of rear-end crashes. Speed limits should be thoroughly assessed and tailored to fit road conditions and traffic patterns. This is especially

Table 4
Means of difference in probabilities for Injury/Fatality concerning temporal instability for rear-end crashes.

Sub-group	Predict period	Base period			
		Before COVID-19 (2019)		During COVID-19 (2020)	
		Following vehicle	Leading vehicle	Following vehicle	Leading vehicle
$\Delta\nu < 5$ mph	During COVID-19 (2020)	−0.0029	−0.0011	–	–
	After COVID-19 (2021)	−0.0086	−0.0029	−0.0025	−0.0039
5 mph $\leq \Delta\nu \leq 10$ mph	During COVID-19 (2020)	−0.0045	−0.0018	–	–
	After COVID-19 (2021)	−0.0018	0.0012	0.0029	0.0013
$\Delta\nu > 10$ mph	During COVID-19 (2020)	−0.0136	−0.0086	–	–
	After COVID-19 (2021)	−0.0026	−0.0026	0.0062	0.0021

Note: The presented values displayed reflect the difference in the probabilities for Injury/Fatality outcomes. Correspondingly, the values for NI (no injury) outcomes represent the inverse relationship.

pertinent as increased speed limits have been observed to elevate injury crash rates and resulted injury outcomes (Ahmed et al., 2022; Alnawmasi and Mannering, 2022). In additon, variable speed limit systems, which adapt speed limits in real-time based on traffic, weather, and road conditions, could be particularly effective in controlling $\Delta\nu$ ranges (Ali et al., 2023). By dynamically modulating speed limits, such systems can aid in reducing speed variations among vehicles, potentially diminishing crash severity. Furthermore, enforcement strategies, including the use of speed cameras or heightened patrol presence, play a vital role in ensuring adherence to established speed limits, thus curtailing speed differentials and, consequently, the severity outcomes of crashes (Yasmin et al., 2022).

Table 5 presents the mean differences in probabilities when using the parameters from one rear-end crash model to predict outcomes for a different data. Notably, the probabilities of Injury/Fatality outcomes for both following and leading vehicles are overestimated or underestimated during the COVID-19 period when one $\Delta\nu$ model's parameters are applied to predict outcomes for crashes within other $\Delta\nu$ ranges. Although the differences are minimal (all being lower than 0.01), the findings listed in the table indicate the non-transferability among rear-end crashes across varying $\Delta\nu$ ranges. These results align with the research of Yan et al. (2022), which also reported minor effects due to temporal and crash-type variations. The underlying cause could be the subtle discrepancies in crash distribution, as illustrated in Figs.1 and 2.

Notably, adopting model for 5 mph $\leq \Delta\nu \leq$ 10 mph to predict rear-end crashes with $\Delta\nu <$ 5 mph and $\Delta\nu >$ 10 mph during COVID-19 (2020) resulted in increased probabilities and decreased probabilities, respectively. This finding is corroborated by models established by Nilsson (1981) and Garder and Gadiraju (1989). Nilsson (1981) stated that the rate of injury/fatal crashes decreases with the reduction of speed limits. Furthermore, a larger variance in traffic speed is associated with a higher crash rate, as indicated by Garder and Gadiraju (1989). Kloeden et al. (1997) stated that indicated that the risk of involvement in a casualty crash increases at a rate greater than exponential with the increase in free travel speed above the average speed of passenger vehicles on the road. Moreover, several exceptions were observed in the results listed in Table 5, showing trends that deviate from the above-mentioned patterns. This might be attributed to the complex interactions involved when considering the joint injury outcomes of drivers in rear-end crashes.

In summary, the outcomes derived from out-of-sample predictions substantiate the observed temporal instability and non-transferability issues.

6. Results and discussion

Four modeling methodologies are employed: the joint fixed parameters bivariate probit model, joint random parameters bivariate probit model, joint random parameters bivariate probit model with heterogeneity in means, and the correlated joint random parameters bivariate probit model with heterogeneity in means, all of which are estimated using the rear-end crash data set. Table 6 outlines the results of the goodness-of-fit comparisons, evaluated based on the corrected ρ^2 and the corrected Akaike Information Criterion (AIC). The correlated joint random parameters bivariate probit model with heterogeneity in means demonstrates superior performance, evidenced by its higher ρ^2 value and lower corrected AIC value, in comparison to the other three models across each subgroup. Additionally, χ^2 tests are conducted, leading to the rejection of the null hypothesis that the correlated joint random parameters bivariate probit model with heterogeneity in means is equivalent to the other three models. The findings presented in Table 6 underscore the superior performance of the correlated joint random parameters bivariate probit model with heterogeneity in means, which will be the focus of the subsequent discussion.

Tables 7, 8 and 9 delineate the estimation results for rear-end crashes caused by various $\Delta\nu$ ranges of $\Delta\nu <$ 5 mph, 5 mph $\leq \Delta\nu \leq$ 10 mph, and $\Delta\nu >$ 10 mph utilizing the correlated joint random parameters bivariate probit model with heterogeneity in means. For rear-end crashes caused by $\Delta\nu <$ 5 mph, the models before, during, and following the COVID-19 pandemic exhibit ρ^2 values of 0.317, 0.353, and 0.324, respectively. Otherwise, the models for 5 mph $\leq \Delta\nu \leq$ 10 mph and $\Delta\nu >$ 10 mph consistently demonstrate ρ^2 values exceeding 0.280. In addition, all nine models also report cross-equation correlation coefficients (ρ) greater than 0.55, which span from 0.562 to 0.926 at a confidence level of over 99.99 %. These coefficients substantiate the positive correlation between the injury severity outcomes for the following and leading vehicles, highlighting unobserved factors that jointly influence the injury severity outcomes of both vehicles involved in a rear-end crash.

Specifically, Alnawmasi and Mannering (2023) introduced a partially constrained approach to tackle temporal instability, enabling

Table 5
Means of difference in probabilities for Injury/Fatality by adopting one rear-end crash model to predict another data.

Base model	Predict data	Before COVID-19 (2019)		During COVID-19 (2020)		After COVID-19 (2021)	
		Following vehicle	Leading vehicle	Following vehicle	Leading vehicle	Following vehicle	Leading vehicle
$\Delta\nu <$ 5 mph	5 mph $\leq \Delta\nu \leq$ 10 mph	0.0031	−0.0011	0.0018	0.0027	0.0057	−0.0032
	$\Delta\nu >$ 10 mph	−0.0048	−0.0028	−0.0006	0.0028	−0.0065	−0.0042
5 mph $\leq \Delta\nu \leq$ 10 mph	$\Delta\nu <$ 5 mph	−0.0026	0.0043	0.0047	0.0008	−0.0026	0.0012
	$\Delta\nu >$ 10 mph	0.0043	0.0015	−0.0015	−0.0012	−0.0032	−0.0024
$\Delta\nu >$ 10 mph	$\Delta\nu <$ 5 mph	0.0035	0.0019	0.0047	0.0008	0.0028	0.0011
	5 mph $\leq \Delta\nu \leq$ 10 mph	−0.0028	−0.0008	−0.0039	0.0006	0.0033	0.0018

Note: The presented values pertain to the difference in the probabilities for Injury/Fatality outcomes, and the values for NI (no injury) outcomes are the inverse.

Table 6
Comparisons of goodness-of-fit measures among four types of joint bivariate probit models.

	Joint fixed parameters bivariate probit model (JFPBP)			Joint random parameters bivariate probit model (JRPBP)			Joint random parameters bivariate probit model with heterogeneity in means (JRPBPHM)			Correlated joint random parameters bivariate probit model with heterogeneity in means (CJRPBPHM)		
	$\Delta\nu < 5$ mph	**5 mph $\leq \Delta\nu \leq$ 10 mph**	**$\Delta\nu > 10$ mph**	**$\Delta\nu < 5$ mph**	**5 mph $\leq \Delta\nu \leq$ 10 mph**	**$\Delta\nu > 10$ mph**	**$\Delta\nu < 5$ mph**	**5 mph $\leq \Delta\nu \leq$ 10 mph**	**$\Delta\nu > 10$ mph**	**$\Delta\nu < 5$ mph**	**5 mph $\leq \Delta\nu \leq$ 10 mph**	**$\Delta\nu > 10$ mph**
Before COVID-19 (2019)												
Number of parameters (K)	19	29	25	22	32	28	24	33	31	31	40	38
Number of observations (N)	1736	2316	3008	1736	2316	3008	1736	2316	3008	1736	2316	3008
Log-likelihood at zero ($LL(0)$)	−1763.776	−2498.339	−3545.620	−1763.776	−2498.339	−3545.620	−1763.776	−2498.339	−3545.620	−1763.776	−2498.339	−3545.620
Log-likelihood at convergence ($LL(\beta)$)	−1266.894	−1691.124	−2509.507	−1238.269	−1652.166	−2457.810	−1216.115	−1635.238	−2425.541	−1203.789	−1616.609	−2396.621
$\rho^2 = 1 - LL(\beta)/LL(0)$	0.282	0.323	0.292	0.298	0.339	0.307	0.311	0.345	0.316	0.317	0.353	0.324
Corrected ρ^2	0.274	0.315	0.286	0.289	0.329	0.300	0.301	0.336	0.309	0.305	0.342	0.315
Corrected AIC	2572.231	3441.009	5069.450	2521.129	3369.257	4972.165	2480.931	3337.459	4913.749	2470.742	3314.660	4870.240
	JFPBP vs JRPBP			**JRPBP vs JRPBPHM**			**JRPBPHM vs CJRPBPHM**					
χ^2 test	57.250 (3) [> 99.99 %]	77.916 (3) [> 99.99 %]	103.394 (3) [> 99.99 %]	44.308 (2) [> 99.99 %]	33.856 (1) [> 99.99 %]	64.538 (3) [> 99.99 %]	24.652 (7) [99.81 %]	37.258 (7) [> 99.99 %]	57.840 (7) [> 99.99 %]			
During COVID-19 (2020)												
Number of parameters (K)	23	31	28	26	34	32	32	37	34	48	44	45
Number of observations (N)	1504	1577	2064	1504	1577	2064	1504	1577	2064	1504	1577	2064
Log-likelihood at zero ($LL(0)$)	−1456.970	−1685.387	−2618.659	−1456.970	−1685.387	−2618.659	−1456.970	−1685.387	−2618.659	−1456.970	−1685.387	−2618.659
Log-likelihood at convergence ((β))	−1096.586	−1224.751	−1899.707	−1034.490	−1198.689	−1870.081	−1007.562	−1173.225	−1851.452	−988.938	−1160.601	−1832.858
$\rho^2 = 1 - LL(\beta)/LL(0)$	0.247	0.273	0.275	0.290	0.289	0.286	0.308	0.304	0.293	0.321	0.311	0.300
Corrected ρ^2	0.236	0.259	0.265	0.277	0.273	0.275	0.293	0.287	0.281	0.299	0.292	0.284
Corrected AIC	2239.918	2512.786	3856.212	2121.931	2466.921	3805.202	2080.560	2422.277	3772.077	2077.109	2411.787	3757.768
	JFPBP vs JRPBP			**JRPBP vs JRPBPHM**			**JRPBPHM vs CJRPBPHM**					
χ^2 test	124.192 (3) [> 99.99 %]	52.124 (3) [> 99.99 %]	59.252 (4) [> 99.99 %]	53.856 (6) [> 99.99 %]	50.928 (3) [> 99.99 %]	37.258 (2) [> 99.99 %]	37.248 (16) [> 99.99 %]	25.248 (7) [99.85 %]	37.188 (11) [> 99.99 %]			
After COVID-19 (2021)												
Number of parameters (K)	25	30	27	30	33	30	33	37	31	49	44	42
Number of observations (N)	1938	2232	3092	1938	2232	3092	1938	2232	3092	1938	2232	3092
Log-likelihood at zero ($LL(0)$)	−2148.719	−2407.725	−3706.473	−2148.719	−2407.725	−3706.473	−2148.719	−2407.725	−3706.473	−2148.719	−2407.725	−3706.473
Log-likelihood at convergence ((β))	−1461.165	−1731.888	−2714.368	−1421.647	−1689.704	−2688.008	−1396.752	−1643.446	−2675.279	−1382.554	−1614.294	−2659.605
$\rho^2 = 1 - LL(\beta)/LL(0)$	0.320	0.281	0.268	0.338	0.298	0.275	0.350	0.317	0.278	0.357	0.330	0.282
Corrected ρ^2	0.311	0.271	0.261	0.328	0.288	0.268	0.339	0.306	0.271	0.340	0.316	0.273
Corrected AIC	2973.010	3524.621	5483.229	2904.269	3446.429	5436.624	2860.683	3362.174	5413.206	2865.703	3318.399	5404.395
	JFPBP vs JRPBP			**JRPBP vs JRPBPHM**			**JRPBPHM vs CJRPBPHM**					
χ^2 test	79.036 (5) [> 99.99 %]	84.368 (3) [> 99.99 %]	52.770 (3) [> 99.99 %]	49.790 (3) [> 99.99 %]	92.516 (4) [> 99.99 %]	25.458 (1) [99.91 %]	28.396 (16) [> 99.99 %]	58.304 (7) [> 99.99 %]	31.348 (11) [> 99.99 %]			

Table 7
Model results of injury severity of freeway two-vehicle rear-end crashes caused by $\Delta v < 5$ mph before, during and after COVID-19 pandemic (t-statistics in parentheses) based on CJRPBPHM.

Variable	$\Delta v < 5$ mph					
	Before COVID-19 (2019)		**During COVID-19 (2020)**		**After COVID-19 (2021)**	
	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers
Constant	−0.726 (−7.95)	−1.410 (−13.23)	−1.346 (−12.60)	−1.647 (−10.51)	−1.068 (−7.28)	−0.726 (−5.18)
Driver Characteristics						
Male V1′s driver (1 if male, 0 otherwise)					−0.194 (−2.29)	
Male V2′s driver (1 if male, 0 otherwise)		−0.269 (−3.18)				
V1′s Below 18 years indicator (1 if age below 18 years, 0 otherwise)					0.395 (3.18)	
V1′s 30–45 years indicator (1 if age between 30 and 45 years, 0 otherwise)			0.162 (2.64)			
V2′s 18–30 years indicator (1 if age between 18 and 30 years, 0 otherwise)		−0.210 (−2.23)				−0.145 (−2.24)
V2′s 30–45 years indicator (1 if age between 30 and 45 years, 0 otherwise)		−0.232 (−2.37)				
Vehicle Characteristics						
V1 Passenger car indicator (1 if passenger car, 0 otherwise)				0.153 (2.50)	0.206 (2.71)	
V1 Heavy truck indicator (1 if heavy truck, 0 otherwise)	−0.590 (−2.95)		−0.707 (−3.10)		−0.751 (−3.23)	
V1 Old indicator (1 if auto age more than 10 years, 0 otherwise)			0.156 (2.14)			
V2 Passenger car indicator (1 if passenger car, 0 otherwise)	−0.398 (4.08)	−0.420 (−4.27)			−0.431 (−4.88)	
V2 SUV indicator (1 if sport utility vehicle (SUV), 0 otherwise)				0.161 (2.36)	−0.225 (−2.38)	
V2 Van indicator (1 if van, 0 otherwise)		0.356 (2.85)				
V2 Heavy truck indicator (1 if heavy truck, 0 otherwise)	0.296 (2.05)		0.451 (2.13)			−0.921 (−5.04)
V2 Other indicator (1 if other types of vehicles, 0 otherwise)			0.315 (2.64)			
V2 Old indicator (1 if auto age more than 10 years, 0 otherwise)				0.424 (4.17)	0.137 (2.78)	
Roadway Characteristics						
Rural areas indicator (1 if roadway is rural, 0 otherwise)			0.188 (2.22)			0.291 (3.37)
Environmental Characteristics						
Sunny indicator (1 if sunny, 0 otherwise)					−0.277 (−3.25)	−0.306 (−3.48)
Cloudy indicator (1 if cloudy, 0 otherwise)			0.160 (2.52)			
Daylight indicator (1 if daylight, 0 otherwise)						−0.543 (−6.61)
Lighted under dark indicator (1 if the roadway is lighted during nighttime, 0 otherwise)	0.297 (2.87)	0.383 (3.76)	0.269 (2.48)			
Non-lighted under dark indicator (1 if the roadway is not lighted during nighttime, 0 otherwise)	0.493 (3.68)	0.475 (3.55)		0.305 (2.94)		
Crash Characteristics						

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Table 7 (*continued*)

Variable	$\Delta\nu$ < 5 mph					
	Before COVID-19 (2019)		During COVID-19 (2020)		After COVID-19 (2021)	
	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers
Driving too close indicator (1 if crash occurred due to driving too close of V1′s driver, 0 otherwise)	−0.368 (−2.10)				−0.427 (−2.09)	
Carelessness indicator (1 if crash occurred due to carelessness of V1′s driver, 0 otherwise)					0.202 (2.30)	
V1′s over speeding indicator (1 if exceeding the speed limit, 0 otherwise)				1.176 (2.23)		
V1 front center indicator (1 if V1′s most damage area is front center, 0 otherwise)				0.574 (5.63)		0.625 (2.81)
V2 rear center indicator (1 if V2′s most damage area is rear center, 0 otherwise)	−0.194 (−2.18)				−0.202 (−2.39)	
Temporal Characteristics						
Weekend indicator (1 if crash occurred on weekend, 0 otherwise)					0.185 (2.25)	
Random parameters						
Male V1′s driver (1 if male, 0 otherwise) [V1]	−0.249 (−2.65)		−0.348 (−2.34)			
Standard deviation	***0.130 (5.43)***		***1.369 (24.50)***			
Male V1′s driver (1 if male, 0 otherwise) [V2]						−0.314 (−3.06)
Standard deviation						***1.012 (2.94)***
Male V2′s driver (1 if male, 0 otherwise) [V2]				−0.664 (−2.98)		−0.102 (−2.06)
Standard deviation				***1.254 (3.65)***		***1.048 (10.47)***
V2 SUV indicator (1 if sport utility vehicle (SUV), 0 otherwise) [V1]	−0.663 (−4.38)					
Standard deviation	***0.337 (3.16)***					
V2 Other indicator (1 if other types of vehicles, 0 otherwise) [V2]				0.574 (2.76)		
Standard deviation				***1.971 (11.84)***		
V1 front center indicator (1 if V1′s most damage area is front center, 0 otherwise) [V2]		0.209 (2.35)				
Standard deviation		***0.313 (2.91)***				
Rural areas indicator (1 if roadway is rural, 0 otherwise) [V1]					0.349 (3.68)	
Standard deviation					***0.618 (11.95)***	
Sunny indicator (1 if sunny, 0 otherwise) [V2]				−1.202 (−5.38)		
Standard deviation				***0.573 (2.74)***		
Lighted under dark indicator (1 if the roadway is lighted during nighttime, 0 otherwise) [V1]					0.335 (3.08)	
Standard deviation					***0.654 (2.14)***	
Lighted under dark indicator (1 if the roadway is lighted during nighttime, 0 otherwise) [V2]				0.643 (2.05)		
Standard deviation				***0.311 (2.50)***		
Carelessness indicator (1 if crash occurred due to carelessness of V1′s driver, 0 otherwise) [V2]						0.230 (2.31)

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Table 7 (*continued*)

Variable	Δv < 5 mph					
	Before COVID-19 (2019)		During COVID-19 (2020)		After COVID-19 (2021)	
	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers
Standard deviation						***0.655 (3.64)***
Heterogeneity in the means of random parameters						
Male V1′s driver (1 if male, 0 otherwise) [V1]: V2′s over speeding indicator (1 if exceeding the speed limit, 0 otherwise)	0.483 (2.36)					
Male V1′s driver (1 if male, 0 otherwise) [V1]: Left curve indicator (1 if left-curved alignment, 0 otherwise)			0.792 (2.03)			
Male V1′s driver (1 if male, 0 otherwise) [V1]: Distraction indicator (1 if crash occurred due to distraction of V1′s driver, 0 otherwise)						0.284 (2.69)
Male V2′s driver (1 if male, 0 otherwise) [V2]: V2 Heavy truck indicator (1 if heavy truck, 0 otherwise)				−1.405 (−2.38)		
Male V2′s driver (1 if male, 0 otherwise) [V2]: Left curve indicator (1 if left-curved alignment, 0 otherwise)				1.149 (2.15)		
Male V2′s driver (1 if male, 0 otherwise) [V2]: V2 rear left indicator (1 if V2′s most damage area is rear left bumper, 0 otherwise)						0.453 (2.27)
V2 SUV indicator (1 if sport utility vehicle (SUV), 0 otherwise) [V1]: Urban areas indicator (1 if roadway is urban, 0 otherwise)	0.373 (2.17)					
V2 Other indicator (1 if other types of vehicles, 0 otherwise) [V2]: V1′s 18–30 years indicator (1 if age between 18 and 30 years, 0 otherwise)				−0.498 (−2.83)		
V2 Other indicator (1 if other types of vehicles, 0 otherwise) [V2]: V2′s over speeding indicator (1 if exceeding the speed limit, 0 otherwise)				2.923 (2.68)		
Rural areas indicator (1 if roadway is rural, 0 otherwise) [V1]: V1 front left indicator (1 if V1′s most damage area is front left bumper, 0 otherwise)					−0.566 (−2.85)	
Sunny indicator (1 if sunny, 0 otherwise) [V2]: Weekend indicator (1 if crash occurred on weekend, 0 otherwise)				−0.109 (−2.66)		
ρ	0.562 (10.23)		0.926 (32.25)		0.829 (26.96)	
Number of parameters (K)	31		48		49	
Number of observations (N)	1736		1504		1938	

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Table 7 (*continued*)

Variable	$\Delta\nu$ < 5 mph					
	Before COVID-19 (2019)		During COVID-19 (2020)		After COVID-19 (2021)	
	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers
Log-likelihood at zero	−1763.776		−1456.970		−2148.719	
Log-likelihood at convergence	−1203.789		−988.938		−1382.554	
$\rho^2 = 1 - LL(\beta)/LL(0)$	0.317		0.321		0.357	
Corrected ρ^2	0.305		0.299		0.340	
Corrected AIC	2470.742		2077.109		2865.703	

Note: V1 and V2 denotes the following vehicle and leading vehicle, respectively. And "Male V1's driver (1 if male, 0 otherwise) [V1]" means that this variable is identified as a random parameter specific to V1 (following vehicle). Moreover, the t-statistics values of over 1.96 and 2.58 denote that this variable is significant corresponding to p-values of less than 0.05 and 0.01, respectively. Specifically, Male V2's driver (1 male, 0 otherwise) presenting a parameter (t-statistics) of −0.269 (−3.18) in before COVID-19 model indicates significantly decreased likelihood of injury/fatality outcomes at 99% level of confidence.

the statistical determination of whether multiple or all parameters exhibit significant variation over time. Importantly, this method allows for the identification of temporally stable parameters using likelihood ratio tests that compare temporally unconstrained and constrained parameters for each variable. Thus, the partially temporal constrained uncorrelated joint random parameters bivariate probit models with heterogeneity in means are also estimated, with the results shown in Appendix C. As shown in Appendix C, several indicators like V1 Heavy truck, V1 Passenger car, V2 Passenger car are found to produce the same parameter value across all periods, while several indicators are also constrained to produce consistent parameter in two of the all years. Such approach proves useful in pinpointing temporally stable parameters, thereby offering effective strategies for safety promotion from a policy perspective.

To further assess temporal instability related to COVID-19 pandemic, issues of non-transferability, and the impact of joint determinants, the marginal effects of significant factors are calculated, with the outcomes presented in Table 10. Appendix B also present the elements of the Cholesky matrix and correlation coefficients for the correlated random parameters corresponding to the nine subgroup models. To show specific interaction between critical factors and pandemic and speed differences, following discussion will be presented based on the results from the correlated joint random parameters bivariate probit model with heterogeneity in means.

6.1. Random parameters and heterogeneity in means

In the models, 13, 9, 11 random parameters are identified in $\Delta\nu < 5$ mph, 5 mph $\leq \Delta\nu \leq 10$ mph, and $\Delta\nu > 10$ mph rear-end crash models, respectively. The male indicator consistently appears as a common variable and is identified as a statistically significant random parameter following a normal distribution in individual models. Specifically, for the following vehicle, the male indicator yields a random parameter with a mean (standard deviation) of −0.249 (0.130), suggesting that approximately 97.2 % of male drivers in the following vehicle are less likely to experience injuries or fatalities in $\Delta\nu < 5$ mph before COVID-19 model. This finding aligns with recent studies (Behnood and Mannering, 2019; Yu et al., 2021), where the gender indicator is also identified as a random parameter. Significant variation among drivers (Mannering et al., 2016), such as differences in weight, height, driving skills, speed selection and physical strength, leads to the observed variability in the effects of gender indicators (Islam and Mannering, 2021; Yan et al., 2021), which are frequently identified as random parameters in the analysis.

Furthermore, the sunny indicator is identified as a random parameter specific to the leading vehicle in $\Delta\nu < 5$ mph and 5 mph $\leq \Delta\nu \leq 10$ mph models. The corresponding normal distributions indicate that 98.2 % and 69.4 % of rear-end crashes under sunny conditions during the COVID-19 models are associated with a lower likelihood of injury or fatality for $\Delta\nu < 5$ mph and 5 mph $\leq \Delta\nu \leq 10$ mph cases, respectively. Likewise, other environmental indictors such as lighting conditions are also identified as random parameters in several models. Similarly, Yan et al. (2022) noted that this indicator, observed as a random parameter, is associated with a lower likelihood of severe injuries in crashes involving collisions with fixed objects. However, Fountas et al., (2021) also identified fine weather as a random parameter, with the marginal effects indicating a higher likelihood of serious and fatal injuries in bicycle-motor crashes. The variations in the effects of environmental characteristics might be explained by the heterogeneity in driving (riding) behaviors and safety attitude induced by favorable weather and lighting conditions (Fountas et al., 2020; Mannering et al., 2016).

Regarding heterogeneity in the means, several variables either increase or decrease the mean values of the random parameters, indicating potential interactions between these variables and the random parameters. For instance, the weekend indicator increases the mean of the male V1′s driver by 0.250 for $\Delta\nu > 10$ mph during COVID rear-end crash model. This male indicator being random with a mean (standard deviation) of −0.268 (0.264), implies that 84.5 % of male drivers in the following vehicle experience a reduced likelihood of injury or fatality. This finding in understandable as the male drivers are more likely to involve alcohol during weekend, and this interaction makes the injury risk of rear-end crashes more serious (Li et al., 2021; Yan et al., 2021).

Consequently, it can be estimated that during weekends, the proportion of male drivers experiencing fewer injury outcomes decreases by 10.4 % (94.9 % minus 84.5 %) in rear-end crashes caused by $\Delta\nu > 10$ mph during COVID-19. This aligns with the observed positive effects of the weekend indicator shown in Table 10. The increase or decrease in means of random parameters capturing the interaction among random parameters and other variables also address the issues of unobserved heterogeneity (Mannering et al., 2016).

Table 8
Model results of injury severity of freeway two-vehicle rear-end crashes caused by 5 mph ≤ $\Delta\nu$ ≤ 10 mph before, during and after COVID-19 pandemic (t-statistics in parentheses) based on CJRPBPHM.

Variable	5 mph ≤ $\Delta\nu$ ≤ 10 mph					
	Before COVID-19 (2019)		During COVID-19 (2020)		After COVID-19 (2021)	
	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers
Constant	−0.796 (−6.59)	−0.771 (−5.10)	−1.124 (−11.55)	−1.321 (−7.95)	−0.287 (−2.35)	−1.006 (−7.29)
Driver Characteristics						
Male V1′s driver (1 if male, 0 otherwise)	−0.245 (−3.40)			0.282 (3.05)		
Male V2′s driver (1 if male, 0 otherwise)				−0.293 (−3.39)		−0.242 (−3.54)
V1′s Below 18 years indicator (1 if age below 18 years, 0 otherwise)			−0.446 (−2.40)	−0.355 (−2.15)		
V1′s 30–45 years indicator (1 if age between 30 and 45 years, 0 otherwise)						0.124 (2.73)
V1′s Above 45 years indicator (1 if age above 45 years, 0 otherwise)				0.246 (2.54)		
V2′s 18–30 years indicator (1 if age between 18 and 30 years, 0 otherwise)		−0.128 (−2.71)		−0.393 (−3.67)		
V2′s 30–45 years indicator (1 if age between 30 and 45 years, 0 otherwise)				−0.276 (−2.85)		
Vehicle Characteristics						
V1 Passenger car indicator (1 if passenger car, 0 otherwise)				0.289 (3.03)		
V1 Heavy truck indicator (1 if heavy truck, 0 otherwise)	−0.679 (−2.67)	0.462 (3.04)	−0.566 (−2.78)		−0.891 (−3.62)	0.429 (2.94)
V2 Passenger car indicator (1 if passenger car, 0 otherwise)	−0.194 (−2.19)	−0.065 (−2.93)	−0.185 (−2.05)	−0.289 (−3.03)	−0.362 (−3.50)	−0.088 (−2.23)
V2 SUV indicator (1 if sport utility vehicle (SUV), 0 otherwise)					−0.310 (−3.01)	
V2 Van indicator (1 if van, 0 otherwise)			−0.269 (−2.33)		−0.314 (−2.78)	
V2 Heavy truck indicator (1 if heavy truck, 0 otherwise)	0.587 (4.60)	−0.608 (−3.44)		−0.688 (−3.88)		
V2 Old indicator (1 if auto age more than 10 years, 0 otherwise)	0.105 (2.38)	0.243 (3.49)	0.333 (3.78)			
Roadway Characteristics						
Level indicator (1 if level grade, 0 otherwise)		−0.147 (−2.36)			−0.267 (2.19)	
Left curve indicator (1 if left-curved alignment, 0 otherwise)			0.215 (2.68)			
Rural areas indicator (1 if roadway is rural, 0 otherwise)			0.154 (2.69)	0.273 (2.76)	0.243 (3.07)	
Environmental Characteristics						
Sunny indicator (1 if sunny, 0 otherwise)		−0.069 (−2.86)			−0.144 (−2.47)	
Cloudy indicator (1 if cloudy, 0 otherwise)	0.392 (3.04)					0.273 (3.10)
Rainy indicator (1 if rainy, 0 otherwise)					−0.265 (−2.89)	
Other weather indicator (1 if other weather conditions, 0 otherwise)			1.229 (2.27)			
Lighted under dark indicator (1 if the roadway is lighted during nighttime, 0 otherwise)			0.463 (4.56)	0.555 (5.38)	0.262 (2.02)	0.331 (2.65)
Non-lighted under dark indicator (1 if the roadway is not		0.159 (2.56)		0.493 (3.74)	0.465 (3.18)	0.299 (2.13)

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Table 8 (*continued*)

Variable	5 mph ≤ Δν ≤ 10 mph					
	Before COVID-19 (2019)		During COVID-19 (2020)		After COVID-19 (2021)	
	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers
lighted during nighttime, 0 otherwise)						
Crash Characteristics						
Driving too close indicator (1 if crash occurred due to driving too close of V1′s driver, 0 otherwise)			−0.587 (−2.15)			
Distraction indicator (1 if crash occurred due to distraction of V1′s driver, 0 otherwise)		0.122 (2.64)		0.282 (3.17)		
V1′s over speeding indicator (1 if exceeding the speed limit, 0 otherwise)	0.471 (5.12)	0.270 (2.91)				0.140 (2.28)
V1 front center indicator (1 if V1′s most damage area is front center, 0 otherwise)		0.197 (2.84)		0.225 (2.54)		0.092 (2.09)
V1 front left indicator (1 if V1′s most damage area is front left bumper, 0 otherwise)					−0.447 (−2.26)	
V1 front right indicator (1 if V1′s most damage area is front right bumper, 0 otherwise)	−0.579 (−4.86)				−0.151 (−2.37)	
V2 rear center indicator (1 if V2′s most damage area is rear center, 0 otherwise)	−0.296 (−3.56)		−0.179 (−2.11)		−0.282 (−3.57)	
V2 rear right indicator (1 if V2′s most damage area is rear right, 0 otherwise)						−0.274 (−2.10)
Temporal Characteristics						
Weekend indicator (1 if crash occurred on weekend, 0 otherwise)	0.200 (2.63)					
Day indicator (1 if crash occurred during daytime, 0 otherwise)		−0.376 (−4.85)			−0.176 (−2.43)	
Random parameters						
Male V1′s driver (1 if male, 0 otherwise) [V1]					−0.199 (−2.29)	
Standard deviation					***0.192 (2.01)***	
Male V2′s driver (1 if male, 0 otherwise) [V2]		−0.249 (−2.22)				
Standard deviation		***0.519 (5.43)***				
V2′s 30–45 years indicator (1 if age between 30 and 45 years, 0 otherwise) [V2]					−0.404 (−3.69)	
Standard deviation					***0.105 (2.51)***	
V1 front right indicator (1 if V1′s most damage area is front right bumper, 0 otherwise) [V1]			−1.313 (−5.05)			
Standard deviation			***0.403 (2.15)***			
V1 front left indicator (1 if V1′s most damage area is front left bumper, 0 otherwise) [V1]	−0.980 (−2.41)					
Standard deviation	***0.878 (2.27)***					
Sunny indicator (1 if sunny, 0 otherwise) [V2]				−0.494 (−5.02)		
Standard deviation				***0.972 (15.30)***		
Lighted under dark indicator (1 if the roadway is lighted during nighttime, 0 otherwise) [V1]			0.444 (2.68)			
Standard deviation			***0.614 (4.72)***			
Day indicator (1 if crash occurred during daytime, 0 otherwise) [V1]	−0.239 (−1.96)					
Standard deviation	***0.435 (8.75)***					

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Table 8 (*continued*)

Variable	5 mph ≤ Δν ≤ 10 mph					
	Before COVID-19 (2019)		During COVID-19 (2020)		After COVID-19 (2021)	
	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers
Day indicator (1 if crash occurred during daytime, 0 otherwise) [V2]						−0.515 (−4.00)
Standard deviation						***0.517 (2.51)***
Heterogeneity in the means of random parameters						
Male V1′s driver (1 if male, 0 otherwise) [V1]: V1′s Below 18 years indicator (1 if age below 18 years, 0 otherwise)					−0.678 (−2.89)	
Male V1′s driver (1 if male, 0 otherwise) [V1]: V2 Heavy truck indicator (1 if heavy truck, 0 otherwise)					0.437 (3.07)	
V2′s 30–45 years indicator (1 if age between 30 and 45 years, 0 otherwise) [V2]: V2 Heavy truck indicator (1 if heavy truck, 0 otherwise)					0.395 (2.90)	
Sunny indicator (1 if sunny, 0 otherwise) [V2]: V1′s over speeding indicator (1 if exceeding the speed limit, 0 otherwise)				0.245 (2.20)		
Sunny indicator (1 if sunny, 0 otherwise) [V2]: V2 Van indicator (1 if van, 0 otherwise)				0.483 (2.12)		
V1 front right indicator (1 if V1′s most damage area is front right bumper, 0 otherwise) [V1]: Left curve indicator (1 if left-curved alignment, 0 otherwise)			1.166 (2.79)			
V1 front right indicator (1 if V1′s most damage area is front right bumper, 0 otherwise) [V1]: V1′s over speeding indicator (1 if exceeding the speed limit, 0 otherwise)			0.574 (2.13)			
Day indicator (1 if crash occurred during daytime, 0 otherwise) [V1]: Cloudy indicator (1 if cloudy, 0 otherwise)	−0.409 (−2.39)					
Day indicator (1 if crash occurred during daytime, 0 otherwise) [V1]: Carelessness indicator (1 if crash occurred due to carelessness of V1′s driver, 0 otherwise)	−0.114 (−2.06)					
Day indicator (1 if crash occurred during daytime, 0 otherwise) [V2]: V2 Heavy truck indicator (1 if heavy truck, 0 otherwise)						−0.388 (−2.82)
Day indicator (1 if crash occurred during daytime, 0 otherwise) [V2]: V1′s over speeding indicator (1 if exceeding the speed limit, 0 otherwise)						0.339 (2.05)
ρ	0.749 (24.22)		0.697 (16.86)		0.671 (18.23)	
Number of parameters (K)	40		44		44	
Number of observations (N)	2316		1577		2232	
Log-likelihood at zero	−2498.339		−1685.387		−2407.725	
Log-likelihood at convergence	−1616.609		−1160.601		−1614.294	

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Table 8 (*continued*)

Variable	$5\text{ mph} \le \Delta\nu \le 10\text{ mph}$					
	Before COVID-19 (2019)		During COVID-19 (2020)		After COVID-19 (2021)	
	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers
$\rho^2 = 1 - LL(\beta)/LL(0)$	0.353		0.311		0.330	
Corrected ρ^2	0.342		0.292		0.316	
Corrected AIC	3314.660		2411.787		3318.399	

As indicated in Appendix B, a notable negative correlation of −0.739 is observed between the V1 front center and the V2 SUV indicators. This suggests a negative impact on the injury severity level, characterized by the unobserved heterogeneity interaction between these two random parameters for $\Delta\nu < 5$ mph before COVID-19. In other words, rear-end crashes in which an SUV is struck by another vehicle, resulting in the most significant damage to the front center of the striking vehicle, are likely to have a lower likelihood of injury or fatality. SUVs usually have a stronger and higher rear structure than many other vehicles (Wenzel and Ross, 2005). When a smaller vehicle hits an SUV, its front crumple zones activate effectively, lessening the impacts on injury severity for both vehicles' drivers (Havarsad, 2018). Additionally, the front center of modern vehicle, is designed with efficient crumple zones. Impacts to this area generally pose a lower risk of intruding into the passenger cabin, reducing the chances of direct injury to the drivers (Diaz and Costas, 2020). However, the front center indicator is observed to increase the injury severity outcomes of following vehicle's driver in this model. Apparently, the heterogeneity captured by the coefficient of correlation between these two random parameters leads to diminished effects on the injury outcomes of rear-end crashes. This interaction reveals counterbalancing effects on injury severity, as captured by the correlation between the variations of vehicle-specific and crash-specific indicators. Moreover, under certain circumstances, some random parameters might not be statistically significant at the 95 % confidence level if the correlation is not considered. For instance, in the uncorrelated parameters model with $5\text{ mph} \le \Delta\nu \le 10$ mph after COVID-19, the V1 male indicator shows a t-statistics value of only 1.57 for the standard deviation when tested as a random parameter.

Additionally, rear-end crashes involving two male drivers are found to result in fewer injuries and fatalities in scenarios with $\Delta\nu < 5$ mph and $\Delta\nu > 10$ mph during COVID-19, with the values of −0.625 and −0.515 as detailed in Appendix B,respectively. This correlation, revealed through the correlated random parameters approach, offers new insights and facilitates further exploration into the interactive unobserved heterogeneity concerning the injury severity outcomes for both drivers involved in a two-vehicle rear-end crash. Such unobserved heterogeneity captured by the correlation might be overlooked in the fixed parameters and uncorrelated random parameters bivariate probit models.

6.2. Driver characteristics

Regarding gender-related indicators, the presence of a male driver in either the following or leading vehicle significantly influences the injury outcomes. Specifically, a male driver in the following vehicle is negatively associated with injury/fatality outcomes in rear-end crashes with $\Delta\nu < 5$ mph before COVID-19. The marginal effects detailed in Table 10 show that this factor reduces the likelihood of injury/fatality outcomes for following vehicles in eight models, as depicted in Fig. 3 (a). Additionally, this factor is significant for the leading vehicle in two sub-groups, exhibiting variable impacts on injury/fatality outcomes. As demonstrated in Fig. 3 (a), for rear-end crashes with $\Delta\nu < 5$ mph before COVID-19, this indicator lessens the probability of injury/fatality outcomes, but it increases for $5\text{ mph} \le \Delta\nu \le 10$ mph crashes during COVID-19. This can be attributed to the fact that a $\Delta\nu$ typically results in a higher amount of kinetic energy being involved, which in turn can lead to more severe consequences for the leading vehicles. Conversely, it consistently appears that male drivers of leading vehicles generally reduce the likelihood of injury/fatality outcomes in all rear-end crash scenarios, as indicated in Fig. 3 (b). For the following vehicle, the male driver of leading vehicle reduces the probability of injury/fatality by 0.0442 for $\Delta\nu > 10$ mph during COVID-19, specifying potential issues of non-transferability and temporal instability.

The tendency of male drivers to have greater muscle mass and bone density potentially enhances their physical resilience in rear-end crashes, whether they are striking or being struck by another vehicle (Nieves et al., 2009). Additionally, male drivers often prefer larger or heavier vehicles, like SUVs, compared to female drivers, offering more protection when hit by another car (McCartt and Northrup, 2004). Nevertheless, male drivers who typically drive larger vehicles are more likely to inflict severe injury outcomes on another vehicle when involved in a rear-end crash (Wang et al., 2022a).

Furthermore, during COVID-19, marginal effects indicated a greater decrease in the involvement of male drivers in the leading vehicle for rear-end crashes with $\Delta\nu < 5$ mph and $5\text{ mph} \le \Delta\nu \le 10$ mph, compared to other periods. A similar trend was observed for following vehicle's drivers in rear-end crashes caused by $\Delta\nu < 5$ mph during the pandemic. Although mobility significantly decreased for both male and female drivers during COVID-19 (Lee et al., 2023; Muhammad et al., 2020), the movement patterns between genders diverged, with women tending to restrict their movements more than men (Reish, 2021). However, in subgroups with $\Delta\nu > 10$ mph, this trend was not observed, showing a continuous reduction in the corresponding effects for drivers of both following and leading vehicles over the three periods. Despite the interactions between COVID-19 and driving behaviors, their impact on rear-end crashes caused by $\Delta\nu > 10$ mph was not significant. This suggests potential facts that greater speed difference may lead to increased injury risks in rear-end crashes (Doecke et al., 2020).

Regarding the age of drivers, the drivers of distinct age ranges are found to significantly affect the injury outcomes for the following

Table 9
Model results of injury severity of freeway two-vehicle rear-end crashes caused by $\Delta\nu > 10$ mph before, during and after COVID-19 pandemic (t-statistics in parentheses) based on CJRPBPHM.

Variable	$\Delta\nu > 10$ mph					
	Before COVID-19 (2019)		During COVID-19 (2020)		After COVID-19 (2021)	
	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers
Constant	−0.451 (−4.44)	−0.643 (−6.94)	−0.558 (−4.59)	−0.694 (−9.27)	−0.538 (−4.10)	−0.746 (−7.52)
Driver Characteristics						
Male V2′s driver (1 if male, 0 otherwise)			−0.149 (−2.18)			−0.224 (−4.08)
V1′s Below 18 years indicator (1 if age below 18 years, 0 otherwise)	−0.152 (−2.44)				−0.288 (−2.33)	
V1′s 18–30 years indicator (1 if age between 18 and 30 years, 0 otherwise)					−0.091 (−2.54)	
V1′s 30–45 years indicator (1 if age between 30 and 45 years, 0 otherwise)		0.118 (1.97)		0.176 (2.49)		
V1′s Above 45 years indicator (1 if age above 45 years, 0 otherwise)			0.139 (2.58)			
V2′s Below 18 years indicator (1 if age below 18 years, 0 otherwise)		−0.747 (−3.02)				
V2′s 18–30 years indicator (1 if age between 18 and 30 years, 0 otherwise)		−0.122 (−2.02)				
V2′s Above 45 years indicator (1 if age above 45 years, 0 otherwise)					0.201 (3.40)	
Vehicle Characteristics						
V1 Passenger car indicator (1 if passenger car, 0 otherwise)		−0.184 (−2.49)		−0.167 (−2.63)	0.150 (2.49)	−0.270 (−3.94)
V1 SUV indicator (1 if sport utility vehicle (SUV), 0 otherwise)						0.291 (3.60)
V1 Van indicator (1 if van, 0 otherwise)						0.209 (2.65)
V1 Heavy truck indicator (1 if heavy truck, 0 otherwise)		0.392 (3.00)	−0.511 (−3.12)			
V2 Passenger car indicator (1 if passenger car, 0 otherwise)	−0.273 (−3.41)	0.160 (2.03)	−0.245 (−3.61)			0.182 (3.24)
V2 SUV indicator (1 if sport utility vehicle (SUV), 0 otherwise)	−0.148 (−2.73)				−0.279 (−3.76)	
V2 Van indicator (1 if van, 0 otherwise)	−0.124 (−2.98)				−0.568 (−4.13)	
V2 Heavy truck indicator (1 if heavy truck, 0 otherwise)			0.659 (5.36)			
V2 Old indicator (1 if auto age more than 10 years, 0 otherwise)			0.204 (2.86)	0.149 (2.10)		
Roadway Characteristics						
Right curve indicator (1 if right-curved alignment, 0 otherwise)		0.417 (2.71)				
Rural areas indicator (1 if roadway is rural, 0 otherwise)			0.110 (2.65)			0.133 (2.43)
Environmental Characteristics						
Sunny indicator (1 if sunny, 0 otherwise)					0.164 (2.71)	
Cloudy indicator (1 if cloudy, 0 otherwise)		0.134 (2.03)			0.460 (4.10)	0.132 (2.84)
Daylight indicator (1 if daylight, 0 otherwise)						−0.159 (−2.42)
Lighted under dark indicator (1 if the roadway is lighted			0.213 (2.00)	0.170 (2.05)		

(continued on next page)

Table 9 (*continued*)

Variable	Δv > 10 mph					
	Before COVID-19 (2019)		**During COVID-19 (2020)**		**After COVID-19 (2021)**	
	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers
during nighttime, 0 otherwise)						
Non-lighted under dark indicator (1 if the roadway is not lighted during nighttime, 0 otherwise)	0.136 (2.20)	0.440 (3.92)	0.472 (3.47)	0.293 (2.17)		0.197 (2.92)
Crash Characteristics						
Driving too close indicator (1 if crash occurred due to driving too close of V1′s driver, 0 otherwise)			−0.496 (−2.71)			
Carelessness indicator (1 if crash occurred due to carelessness of V1′s driver, 0 otherwise)			−0.173 (−2.11)			
Distraction indicator (1 if crash occurred due to distraction of V1′s driver, 0 otherwise)			0.184 (2.37)	0.146 (2.14)		
V1′s over speeding indicator (1 if exceeding the speed limit, 0 otherwise)	0.744 (9.07)	0.685 (7.92)		0.555 (5.95)	0.599 (7.47)	0.497 (6.25)
V1 front left indicator (1 if V1′s most damage area is front left bumper, 0 otherwise)			−0.376 (−2.88)			
V1 front right indicator (1 if V1′s most damage area is front right bumper, 0 otherwise)			−0.382 (−3.12)			
V2 rear center indicator (1 if V2′s most damage area is rear center, 0 otherwise)	−0.267 (−4.16)		−0.240 (−3.07)		−0.195 (−3.41)	
V2 rear left indicator (1 if V2′s most damage area is rear left bumper, 0 otherwise)	−0.272 (−2.75)					
Temporal Characteristics						
Day indicator (1 if crash occurred during daytime, 0 otherwise)		−0.272 (−3.87)				
Random parameters						
Male V1′s driver (1 if male, 0 otherwise) [V1]	−0.296 (−4.56)		−0.268 (−2.58)		−0.261 (−4.24)	
Standard deviation	***0.609 (4.76)***		***0.264 (5.36)***		***0.312 (6.66)***	
Male V2′s driver (1 if male, 0 otherwise) [V2]		−0.417 (−6.73)		−0.469 (−4.18)		
Standard deviation		***0.797 (17.97)***		***0.916 (10.14)***		
V2′s Above 45 years indicator (1 if age above 45 years, 0 otherwise) [V2]						−0.108 (−2.64)
Standard deviation						***0.879 (2.84)***
V2 Passenger car indicator (1 if passenger car, 0 otherwise) [V1]					−0.618 (−7.94)	
Standard deviation					***0.580 (2.09)***	
V2 Heavy truck indicator (1 if heavy truck, 0 otherwise) [V2]				−0.805 (−2.37)		
Standard deviation				***2.748 (10.15)***		
V1′s over speeding indicator (1 if exceeding the speed limit, 0 otherwise) [V1]			0.494 (3.11)			
Standard deviation			***1.002 (10.99)***			
Day indicator (1 if crash occurred during daytime, 0 otherwise) [V1]	−0.417 (−6.73)				−0.417 (−6.38)	
Standard deviation	***0.797 (17.97)***				***0.997 (24.66)***	
Heterogeneity in the means of random parameters						

(*continued on next page*)

Table 9 (*continued*)

Variable	$\Delta\nu > 10$ mph					
	Before COVID-19 (2019)		**During COVID-19 (2020)**		**After COVID-19 (2021)**	
	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers
Male V1′s driver (1 if male, 0 otherwise) [V1]: Weekend indicator (1 if crash occurred on weekend, 0 otherwise)	0.411 (4.06)		0.250 (2.41)			
Male V1′s driver (1 if male, 0 otherwise) [V1]: V2 Heavy truck indicator (1 if heavy truck, 0 otherwise)	0.531 (3.35)					
Male V2′s driver (1 if male, 0 otherwise) [V2]: V2 Heavy truck indicator (1 if heavy truck, 0 otherwise)		−0.985 (−5.64)				
Male V2′s driver (1 if male, 0 otherwise) [V2]: Day indicator (1 if crash occurred during daytime, 0 otherwise)				−0.313 (−2.67)		
V2′s Above 45 years indicator (1 if age above 45 years, 0 otherwise) [V2]: Weekend indicator (1 if crash occurred on weekend, 0 otherwise)					0.138 (2.63)	
V2 Heavy truck indicator (1 if heavy truck, 0 otherwise) [V2]: V2′s 30–45 years indicator (1 if age between 30 and 45 years, 0 otherwise)				−0.626 (−2.74)		
Day indicator (1 if crash occurred during daytime, 0 otherwise) [V1]: V1 front left indicator (1 if V1′s most damage area is front left bumper, 0 otherwise)	−0.329 (−2.19)					
ρ	0.663 (23.64)		0.721 (22.96)		0.574 (18.40)	
Number of parameters (K)	38		45		42	
Number of observations (N)	3008		2064		3092	
Log-likelihood at zero	−3545.620		−2618.659		−3706.473	
Log-likelihood at convergence	−2396.621		−1832.858		−2659.605	
$\rho^2 = 1 - LL(\beta)/LL(0)$	0.324		0.300		0.282	
Corrected ρ^2	0.315		0.284		0.273	
Corrected AIC	4870.240		3757.768		5404.395	

and leading vehicle. The driver of following vehicle of below 18 years old reduces the injury outcomes of both following and leading vehicle in one rear-end crash for 5 mph $\leq \Delta\nu \leq$ 10 mph during COVID-19. However, this indicator increases the injury or fatality likelihood of the following vehicle by 0.1545 for $\Delta\nu <$ 5 mph after COVID-19, addressing the issue of non-transferability. Young drivers are frequently characterized by tendencies towards impatient and aggressive driving behaviors (Lambert, 2012). These drivers often maintain shorter distances between their vehicle and the one ahead, increasing their likelihood of injury or fatality in rear-end collisions, especially in situations requiring emergency braking by the leading vehicle. Drivers in the following vehicle, aged 30–45 years old, are linked to higher likelihood of injuries or fatalities with $\Delta\nu <$ 5 mph after COVID-19. Moreover, these drivers tend to contribute to a higher injury/fatality likelihood for drivers of the leading vehicle in rear-end crashes with 5 mph $\leq \Delta\nu \leq$ 10 mph after COVID-19, and $\Delta\nu >$ 10 mph before and during COVID-19. This age group may experience increased stress and distraction due to the multitude of responsibilities related to work and family life, potentially impacting their driving abilities and behavior (Vegega et al., 2013).

Furthermore, drivers in the following vehicle aged above 45 years are more likely to suffer injury or fatality in rear-end crashes with $\Delta\nu >$ 10 mph occurring during COVID-19. Notably, for individual models the drivers aged above 45 years also cause higher injury/fatality likelihood of other drivers in the rear-end crashes. These drivers also increase the injury/fatality likelihood of leading vehicle's drivers by 0.0545 in rear-end crashes with 5 mph $\leq \Delta\nu \leq$ 10 mph after COVID-19. Specifically, drivers in the leading vehicle aged over 45 years also contribute to an increased probability of injury or fatality, by 0.0816 and 0.0545, for drivers of following and leading vehicle, respectively in rear-end crashes with $\Delta\nu >$ 10 mph, after COVID-19. Additionally, in individual models, drivers aged above 45

Table 10

The marginal effects of determinants in freeway two-vehicle rear-end crashes (the values of V1|V2 mean the marginal effects for following vehicle| leading vehicle).

<table>
<tr><th>Variable</th><th colspan="3">Δν < 5 mph</th><th colspan="3">5 mph ≤ Δν ≤ 10 mph</th><th colspan="3">Δν > 10 mph</th></tr>
<tr><th></th><th>Before COVID-19 (2019) V1|V2</th><th>During COVID-19 (2020) V1|V2</th><th>After COVID-19 (2021) V1|V2</th><th>Before COVID-19 (2019) V1|V2</th><th>During COVID-19 (2020) V1|V2</th><th>After COVID-19 (2021) V1|V2</th><th>Before COVID-19 (2019) V1|V2</th><th>During COVID-19 (2020) V1|V2</th><th>After COVID-19 (2021) V1|V2</th></tr>
<tr><td>Driver Characteristics</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Male V1′s driver (1 if male, 0 otherwise)</td><td>−0.0835| –</td><td>−0.1167| –</td><td>−0.0788| −0.0384</td><td>−0.1205| –</td><td>–| 0.0557</td><td>−0.0461| –</td><td>−0.1285| –</td><td>−0.0991| –</td><td>−0.0897| –</td></tr>
<tr><td>Male V2′s driver (1 if male, 0 otherwise)</td><td>–| −0.0435</td><td>–| −0.0709</td><td>–| −0.0301</td><td>–| −0.0417</td><td>–| −0.0628</td><td>–| −0.0492</td><td>–| −0.0731</td><td>−0.0442| −0.0671</td><td>–| −0.0367</td></tr>
<tr><td>V1′s Below 18 years indicator (1 if age below 18 years, 0 otherwise)</td><td></td><td></td><td>0.1545| –</td><td></td><td>−0.2067| −0.1257</td><td></td><td>−0.0756| –</td><td></td><td>−0.1163| –</td></tr>
<tr><td>V1′s 18–30 years indicator (1 if age between 18 and 30 years, 0 otherwise)</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>−0.0422| –</td></tr>
<tr><td>V1′s 30–45 years indicator (1 if age between 30 and 45 years, 0 otherwise)</td><td></td><td>0.0643| –</td><td></td><td></td><td></td><td>–| 0.0254</td><td>–| 0.0242</td><td>–| 0.0289</td><td></td></tr>
<tr><td>V1′s Above 45 years indicator (1 if age above 45 years, 0 otherwise)</td><td></td><td></td><td></td><td></td><td>–| 0.0545</td><td></td><td></td><td>0.0465| –</td><td></td></tr>
<tr><td>V2′s Below 18 years indicator (1 if age below 18 years, 0 otherwise)</td><td></td><td></td><td></td><td>–| −0.0296</td><td></td><td></td><td>–| −0.1558</td><td></td><td></td></tr>
<tr><td>V2′s 18–30 years indicator (1 if age between 18 and 30 years, 0 otherwise)</td><td>–| −0.0345</td><td></td><td>–| −0.0216</td><td>–| −0.0334</td><td>–| −0.0914</td><td></td><td>–| −0.0252</td><td></td><td></td></tr>
<tr><td>V2′s 30–45 years indicator (1 if</td><td>–| −0.0382</td><td></td><td></td><td></td><td>–| −0.0583</td><td>−0.0634|–|</td><td></td><td></td><td></td></tr>
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Table 10 (*continued*)

Variable	Δν < 5 mph Before COVID-19 (2019) **V1|V2**	 During COVID-19 (2020) **V1|V2**	 After COVID-19 (2021) **V1|V2**	5 mph ≤ Δν ≤ 10 mph Before COVID-19 (2019) **V1|V2**	 During COVID-19 (2020) **V1|V2**	 After COVID-19 (2021) **V1|V2**	Δν > 10 mph Before COVID-19 (2019) **V1|V2**	 During COVID-19 (2020) **V1|V2**	 After COVID-19 (2021) **V1|V2**
age between 30 and 45 years, 0 otherwise)									
V2's Above 45 years indicator (1 if age above 45 years, 0 otherwise)									0.0816| 0.0545
Vehicle Characteristics									
V1 Passenger car indicator (1 if passenger car, 0 otherwise)		–| 0.0243	0.0732| –		–| 0.0459		–| −0.0152	–| −0.0308	0.0599| −0.0436
V1 SUV indicator (1 if sport utility vehicle (SUV), 0 otherwise)									–| 0.0477
V1 Van indicator (1 if van, 0 otherwise)									–| 0.0323
V1 Heavy truck indicator (1 if heavy truck, 0 otherwise)	−0.2495| –	−0.3390| –	−0.2562| –	−0.2888| 0.1671	−0.2896| –	−0.3606| 0.0778	–| 0.0523	−0.1911| –	
V1 Old indicator (1 if auto age more than 10 years, 0 otherwise)		0.0002| –							
V2 Passenger car indicator (1 if passenger car, 0 otherwise)	−0.1313| −0.0375		−0.1584| –	−0.0602| −0.0153	−0.0854| −0.0607	−0.2262| −0.0869	−0.1904| 0.0258	−0.0842| –	−0.1704| 0.0312
V2 SUV indicator (1 if sport utility vehicle (SUV), 0 otherwise)	−0.1175| –	–| 0.0243	−0.1179| –			−0.2053| –	−0.1434| –		−0.1205| –
V2 Van indicator (1 if van, 0 otherwise)	–| 0.0579				−0.1893| –	−0.1915| –	−0.1287| –		−0.2320| –
V2 Heavy truck indicator (1 if	0.0886| –	0.1680| –	–| −0.1708	0.2037| −0.1021	–| −0.1727			0.2198| −0.0952	

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Table 10 (*continued*)

Variable	Δν < 5 mph			5 mph ≤ Δν ≤ 10 mph			Δν > 10 mph		
	Before COVID-19 (2019) **V1|V2**	During COVID-19 (2020) **V1|V2**	After COVID-19 (2021) **V1|V2**	Before COVID-19 (2019) **V1|V2**	During COVID-19 (2020) **V1|V2**	After COVID-19 (2021) **V1|V2**	Before COVID-19 (2019) **V1|V2**	During COVID-19 (2020) **V1|V2**	After COVID-19 (2021) **V1|V2**
heavy truck, 0 otherwise)									
V2 Other indicator (1 if other types of vehicles, 0 otherwise)		0.1259| 0.0532							
V2 Old indicator (1 if auto age more than 10 years, 0 otherwise)		–| 0.0005	0.0058| –	0.0087| 0.1507	−0.0008| –			0.0686| 0.0387	
Roadway Characteristics									
Level indicator (1 if level grade, 0 otherwise)				–| −0.0372		−0.1032| –			
Left curve indicator (1 if left-curved alignment, 0 otherwise)					0.0008| –				
Right curve indicator (1 if right-curved alignment, 0 otherwise)							–| 0.0784		
Rural areas indicator (1 if roadway is rural, 0 otherwise)		0.0906| –	0.1559| 0.1032		0.0829| 0.0162			0.0493| –	–| 0.0229
Environmental Characteristics									
Sunny indicator (1 if sunny, 0 otherwise)		–| −0.0392	−0.1011| −0.0563	–| −0.0285	–| −0.0566	−0.0664| –			0.0619| –
Cloudy indicator (1 if cloudy, 0 otherwise)		0.0786| –		0.0689| –		–| 0.0499	0.0647		0.1746| 0.1524
Rainy indicator (1 if rainy, 0 otherwise)						−0.1209| –			
Other weather indicator (1 1 if other weather conditions, 0 otherwise)					0.0757| –				

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Table 10 (*continued*)

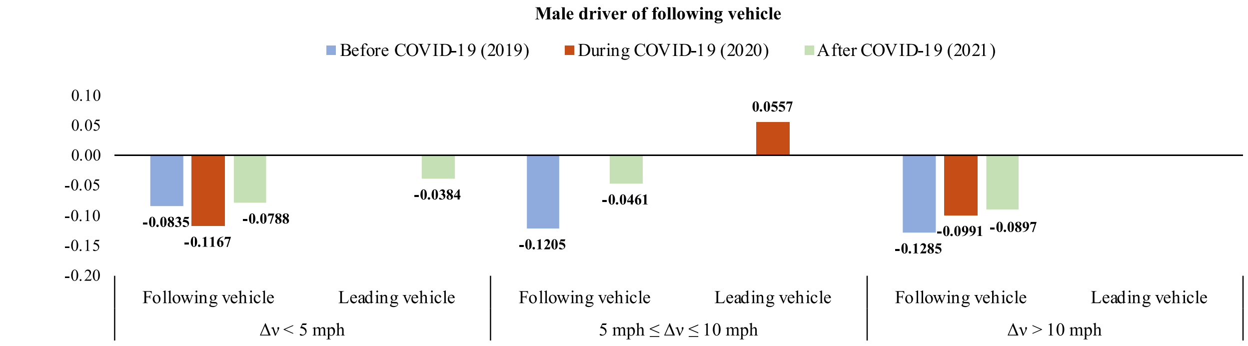
Variable	**Δν < 5 mph**			**5 mph ≤ Δν ≤ 10 mph**			**Δν > 10 mph**		
	Before COVID-19 (2019) **V1|V2**	During COVID-19 (2020) **V1|V2**	After COVID-19 (2021) **V1|V2**	Before COVID-19 (2019) **V1|V2**	During COVID-19 (2020) **V1|V2**	After COVID-19 (2021) **V1|V2**	Before COVID-19 (2019) **V1|V2**	During COVID-19 (2020) **V1|V2**	After COVID-19 (2021) **V1|V2**
Daylight indicator (1 if daylight, 0 otherwise)			–| −0.0909						–| −0.0283
Lighted under dark indicator (1 if the roadway is lighted during nighttime, 0 otherwise)	0.0478| 0.0638	0.0929| 0.0704	0.1291| –		0.1063| 0.0562	0.1038| 0.0650		0.2231| 0.0945	
Non-lighted under dark indicator (1 if the roadway is not lighted during nighttime, 0 otherwise)	0.0686| 0.0772	–| 0.0761		–| 0.0481	0.1859| 0.1144	0.1655| 0.0963	0.1243| 0.0792	0.2641| 0.1371	–| 0.1036
Crash Characteristics									
Driving too close indicator (1 if crash occurred due to driving too close of V1′s driver, 0 otherwise)	−0.1421| –		−0.1602| –		−0.2723| –			−0.1794| –	
Carelessness indicator (1 if crash occurred due to carelessness of V1′s driver, 0 otherwise)			0.0785| 0.0378					−0.0583| –	
Distraction indicator (1 if crash occurred due to distraction of V1′s driver, 0 otherwise)				–| 0.0302	–| 0.0687	–| 0.0228		0.0556| 0.0334	
V1′s over speeding indicator (1 if exceeding the speed limit, 0 otherwise)		–| 0.0981		0.2441| 0.1739		–| 0.0522	0.2842| 0.1589	0.1840| 0.1037	0.2459| 0.1632
V1 front center indicator (1 if V1′s most	–| 0.0425	–| 0.0538	–| 0.0096	–| 0.0353	–| 0.0472	–| 0.0160			

(*continued on next page*)

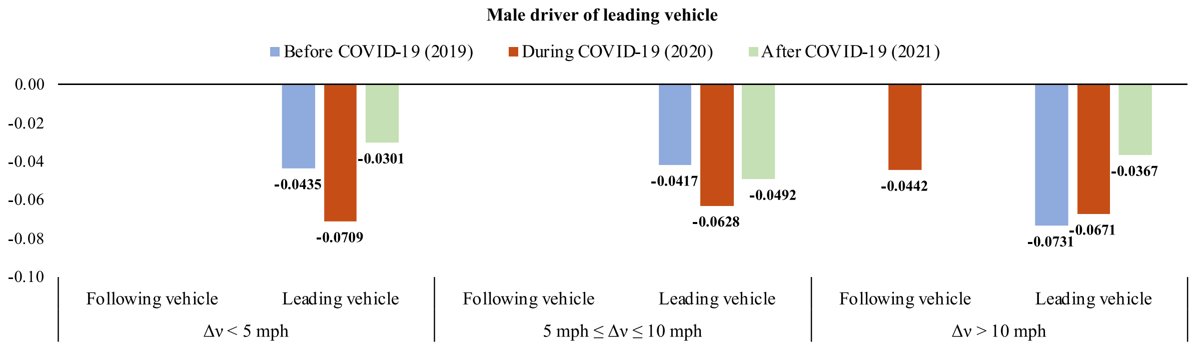
Table 10 (*continued*)

Variable	Δv < 5 mph			5 mph ≤ Δv ≤ 10 mph			Δv > 10 mph		
	Before COVID-19 (2019) **V1|V2**	During COVID-19 (2020) **V1|V2**	After COVID-19 (2021) **V1|V2**	Before COVID-19 (2019) **V1|V2**	During COVID-19 (2020) **V1|V2**	After COVID-19 (2021) **V1|V2**	Before COVID-19 (2019) **V1|V2**	During COVID-19 (2020) **V1|V2**	After COVID-19 (2021) **V1|V2**
damage area is front center, 0 otherwise)									
V1 front left indicator (1 if V1′s most damage area is front left bumper, 0 otherwise)				−0.1516| –		−0.2055| –		−0.1213| –	
V1 front right indicator (1 if V1′s most damage area is front right bumper, 0 otherwise)				−0.1871| –	−0.2655| –	−0.0791| –		−0.1186| –	
V2 rear center indicator (1 if V2′s most damage area is rear center, 0 otherwise)	−0.0633| –		−0.0433| –	−0.0866| –	−0.0802| –	−0.1518| –	−0.1175| –	−0.0809| –	−0.0774| –
V2 rear left indicator (1 if V2′s most damage area is rear left bumper, 0 otherwise)							−0.1143| –		
V2 rear right indicator (1 if V2′s most damage area is rear right bumper, 0 otherwise)						–| −0.0517			
Temporal Characteristics									
Weekend indicator (1 if crash occurred on weekend, 0 otherwise)			0.0618| –	0.0988| –					
Day indicator (1 if crash occurred during daytime, 0 otherwise)				−0.1764| −0.0834		−0.0857| −0.0341	−0.0993| −0.0486		−0.0677| –

Note: V1 and V2 denotes the following vehicle and leading vehicle, respectively.



(a) The male driver of following vehicle



(b) The male driver of leading vehicle

Fig. 3. The marginal effects of gender indicator corresponding to the injury/fatality outcomes.

years are also associated with a higher likelihood of causing injury or fatality to other drivers involved in rear-end crashes. Consistent with the research conducted by Lombardi et al. (2017), this finding can potentially be attributed to the diminished perception and reaction capabilities, as well as the reduced physiological robustness, of older drivers (Marmeleira et al., 2009).

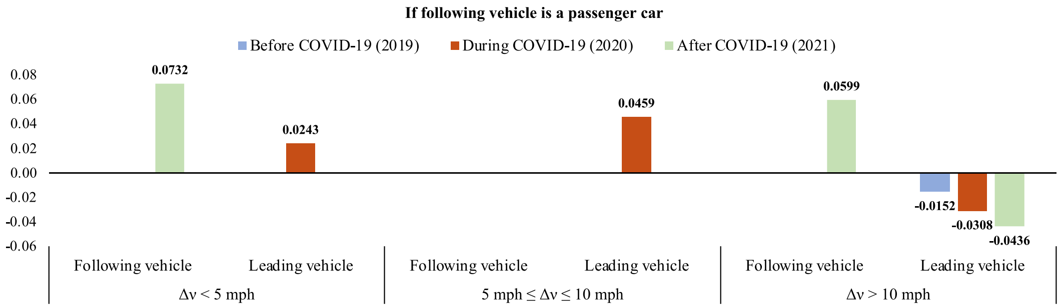
Notably, during COVID-19, drivers aged 30–45 years old were more frequently found to influence injury severity outcomes in models. This age group typically carries significant work and family responsibilities (Singh et al., 2022). The pandemic circumstances likely necessitated their continued travel for essential work or family-related duties, leading to higher road traffic exposure compared to other age groups who had the opportunity to remain at home (Delbosc and McCarthy, 2021; Shaer and Haghshenas, 2021).

6.3. Vehicle characteristics

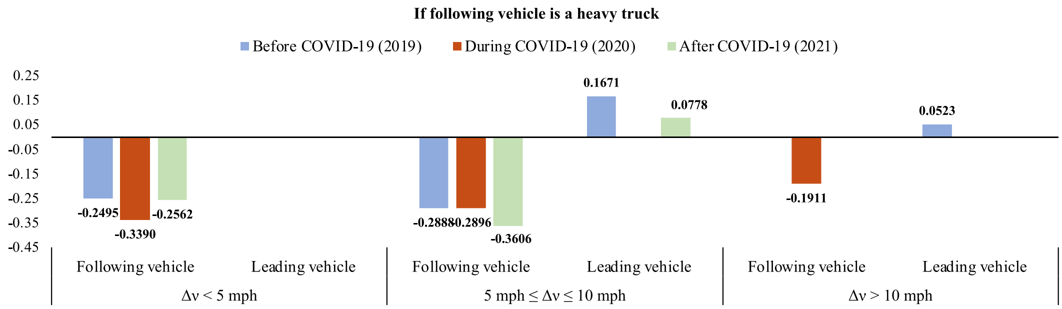
Regarding vehicle-specific attributes, passenger cars, SUVs, vans, trucks and other types significantly influence injury severity outcomes in the rear-end crashes.

The following vehicle being passenger cars are positively related to the injury/fatality likelihood of following vehicle for $\Delta\nu < 5$ mph and $\Delta\nu > 10$ mph after COVID-19 rear-end crashes. The passenger cars are smaller and lighter, offering less protection could be severely damaged while striking another vehicle. Furthermore, when passenger cars collide with taller vehicles, the impact point becomes critical, often bypassing key safety features and resulting in more severe injuries. As depicted in Fig. 4 (a), the likelihood of injury or fatality for following vehicles, which are passenger cars, is positively correlated with the driver of the leading vehicles in rear-end crashes involving $\Delta\nu < 5$ mph during COVID-19. Otherwise, this indicator tends decrease the injury/fatality likelihood for rear-end crashes caused by $\Delta\nu > 10$ mph before, during and after COVID-19. This observed variation, suggesting non-transferability, could be attributed to differing mechanisms in rear-end crashes involving passenger cars, influenced by the distinct effects of varying $\Delta\nu$ values.

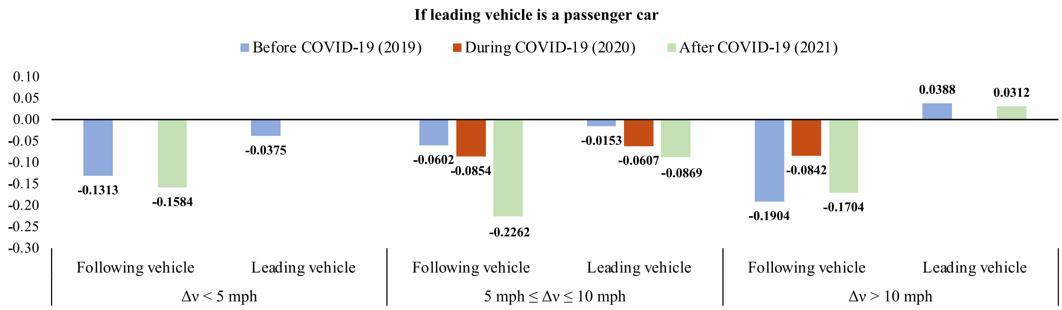
Conversely, when a heavy truck strikes another vehicle, the driver of the struck vehicle is more likely to suffer injuries or fatalities, while the truck driver generally experiences less severe outcomes. The marginal effects, detailed in Fig. 4 (b), demonstrate consistent results for the following vehicle's driver across rear-end crashes with $\Delta\nu < 5$ mph and 5 mph $\leq \Delta\nu \leq$ 10 mph for all periods. However, this variable only reduces the likelihood of injury or fatality by 0.1911 during the COVID-19 period, suggesting potential temporal instability in rear-end crashes with $\Delta\nu > 10$ mph.



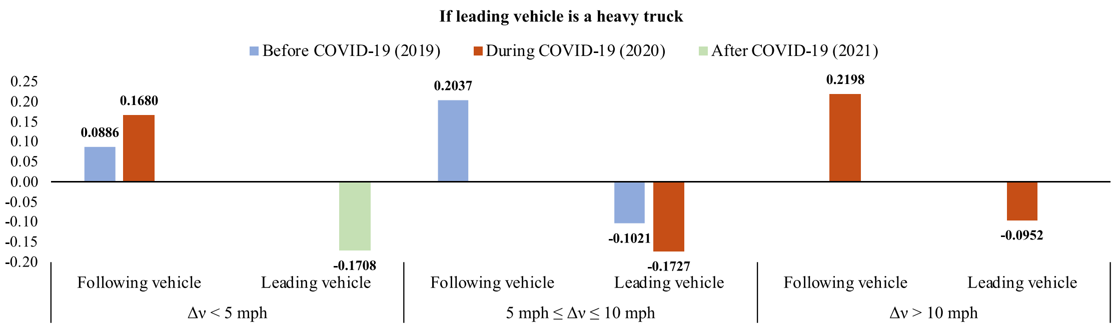
(a) If following vehicle is a passenger car



(b) If following vehicle is a heavy truck



(c) If leading vehicle is a passenger car



(d) If leading vehicle is a heavy truck

Fig. 4. The marginal effects of vehicle type indicator corresponding to the injury/fatality outcomes.

For rear-end crashes occurring after COVID-19 with $\Delta\nu > 10$ mph, the likelihood of injury outcomes for drivers of the leading vehicle is expected to increase by 0.0477 and 0.0323 if struck by an SUV or a van, respectively. Additionally, drivers of following vehicles over 10 years old are more susceptible to injury or fatality in rear-end crashes caused by $\Delta\nu < 5$ mph during the COVID-19 period.

When the leading vehicle is a passenger car, there is generally a reduced likelihood of injury or fatality for the drivers of the following vehicle across all models, with the exception of the $\Delta\nu < 5$ mph during COVID-19 model. Moreover, the variable decreases the likelihood of injuries or fatalities for rear-end crashes with $\Delta\nu < 5$ mph before COVID-19, and 5 mph $\leq \Delta\nu \leq$ 10 mph before, during and after COVID-19. As depicted in Fig. 4 (c), in rear-end crash models with $\Delta\nu > 10$ mph, occurring both before and after COVID-19. this factor leads to an increased likelihood of injury or fatality by 0.0258 and 0.0312 for drivers of leading vehicles, respectively. This observed trend could be attributed to the fact that a greater $\Delta\nu$ is typically associated with more severe outcomes (Huang et al., 2008; Wang et al., 2022a).

Striking an SUV or van similarly decreases the likelihood of injury or fatality, though this indicator is not consistently significant across all models, indicating potential issues of non-transferability and temporal instability. However, the driver of an SUV as the leading vehicle experiences an increased likelihood of injury or fatality by 0.0243 and 0.1066 for $\Delta\nu < 5$ mph during COVID-19 and $\Delta\nu > 10$ mph before COVID-19 models, respectively. In scenarios where a van is the leading vehicle, the likelihood of injury or fatality increases by 0.0827 for the $\Delta\nu < 5$ mph before COVID-19 model when struck by another vehicle. A contributing factor might be the higher center of gravity in these vehicles, increasing the risk of rollovers upon impact. Additionally, the lack of certain safety features in SUVs and vans may not offer adequate protection for drivers compared with passenger cars.

As depicted in Fig. 4 (d), when a heavy truck is struck in a collision, the driver of the following (striking) vehicle faces an increased likelihood of injury or fatality, which escalates with a higher $\Delta\nu$ range. Meanwhile, truck drivers being struck exhibit an increased likelihood of injury or fatality by 0.1708, 0.1021, 0.1727, and 0.0952 for $\Delta\nu < 5$ mph after COVID-19, 5 mph $\leq \Delta\nu \leq$ 10 mph before and during COVID-19, and $\Delta\nu > 10$ mph during COVID-19 models, respectively. Interestingly, it was observed that if either the following or leading vehicle is a heavy truck, there is a decrease in injury severity outcomes for their drivers during COVID-19 across all $\Delta\nu$ ranges. This significant reduction might be attributed to the reduced interactions of heavy trucks with other vehicle types, particularly passenger cars or vans, thereby decreasing the crash risk (Zhu and Srinivasan, 2011). The usage of these lighter vehicles likely decreased due to lockdowns, increased remote work, and reduced social activities (Parr et al., 2020; Shah et al., 2020).

In cases where the leading vehicle is other types (such as light trucks, pick-ups and trailers), the likelihood of injury for the corresponding driver increases by 0.0532 for the $\Delta\nu < 5$ during COVID-19 models. Furthermore, this factor raises the likelihood of injury outcomes for the following vehicle by 0.1259 in the $\Delta\nu < 5$ mph during COVID-19 model. This finding is reasonable given that during COVID-19, there was a notable surge in the deployment of special vehicles, encompassing those designated for rescue, disinfection, command, and vaccine delivery (Grimm, 2021).

A vehicle aged over 10 years tends to increase the driver's injury and fatality likelihood when struck by another vehicle in individual models. Particularly, this variable increases the injury/fatality likelihood by 0.0686 and 0.0387, respectively during COVID-19 with $\Delta\nu$ over 10 mph. Although the drivers involved might have extensive driving experience, the risk of injury in rear-end crashes, particularly when striking another vehicle, can be increased due to the inadequate protection offered by older vehicles (Heisler, 2002), and poor mechanical properties and low stability (Ren and Xu, 2023). This heightened risk often stems from vehicle defects and the absence of regular vehicle inspections. Moreover, Ren and Xu (2023) also identified this indicator as a random parameter in their studies, emphasizing the existing heterogeneity in how the interaction between older vehicles and their experienced drivers influences injury severity.

Drivers of vehicles aged over 10 years are more likely to experience increased injury and fatality risks when struck by another vehicle in individual models. Specifically, this factor increases the injury/fatality likelihood by 0.0686 and 0.0387 for following and leading vehicle, respectively, during COVID-19 for rear-end crashes with $\Delta\nu$ exceeding 10 mph. However, this variable increases the injury/fatality likelihood of following vehicle's drivers for $\Delta\nu < 5$ mph after COVID-19, 5 mph $\leq \Delta\nu \leq$ 10 mph before COVID-19, and $\Delta\nu > 10$ mph during COVID-19 models. While it is negatively related to the injury/fatality likelihood for 5 mph $\leq \Delta\nu \leq$ 10 mph during COVID-19 model, indicating temporal instable and non-transferable.

6.4. Roadway characteristics

Level grade is found to decease the injury/fatal likelihood of leading vehicle before COVID-19 and following vehicle after COVID-19 by 0.0372 and 0.1032, respectively with 5 mph $\leq \Delta\nu \leq$ 10 mph. In addition, both the drivers of the following and leading vehicle experience decreased injury and fatality risks for $\Delta\nu > 10$ mph after COVID-19 while operating within level-grade segments.

Moreover, left curved segments are found to increase the injury outcomes of following vehicle's drivers by 0.0008 for rear-end crashes with 5 mph $\leq \Delta\nu \leq$ 10 mph during COVID-19. And the right segments tend to increase that of leading vehicles' drivers by 0.0784 for $\Delta\nu > 10$ mph before COVID-19 model. The curved segments can diminish a driver's visibility and increase their driving workload while navigating (Wang et al., 2020). This may make it more challenging for drivers to anticipate and react to the sudden stopping or slowing down of leading vehicles, potentially leading to more severe injuries. Additionally, vehicles on curved segments are likely to be subjected to centrifugal forces that can affect their stability, potentially exacerbating the impacts when they are struck by other vehicles. Moreover, during COVID-19, drivers were potentially more prone to inattentiveness and careless driving when approaching curved road segments (Islam et al., 2023).

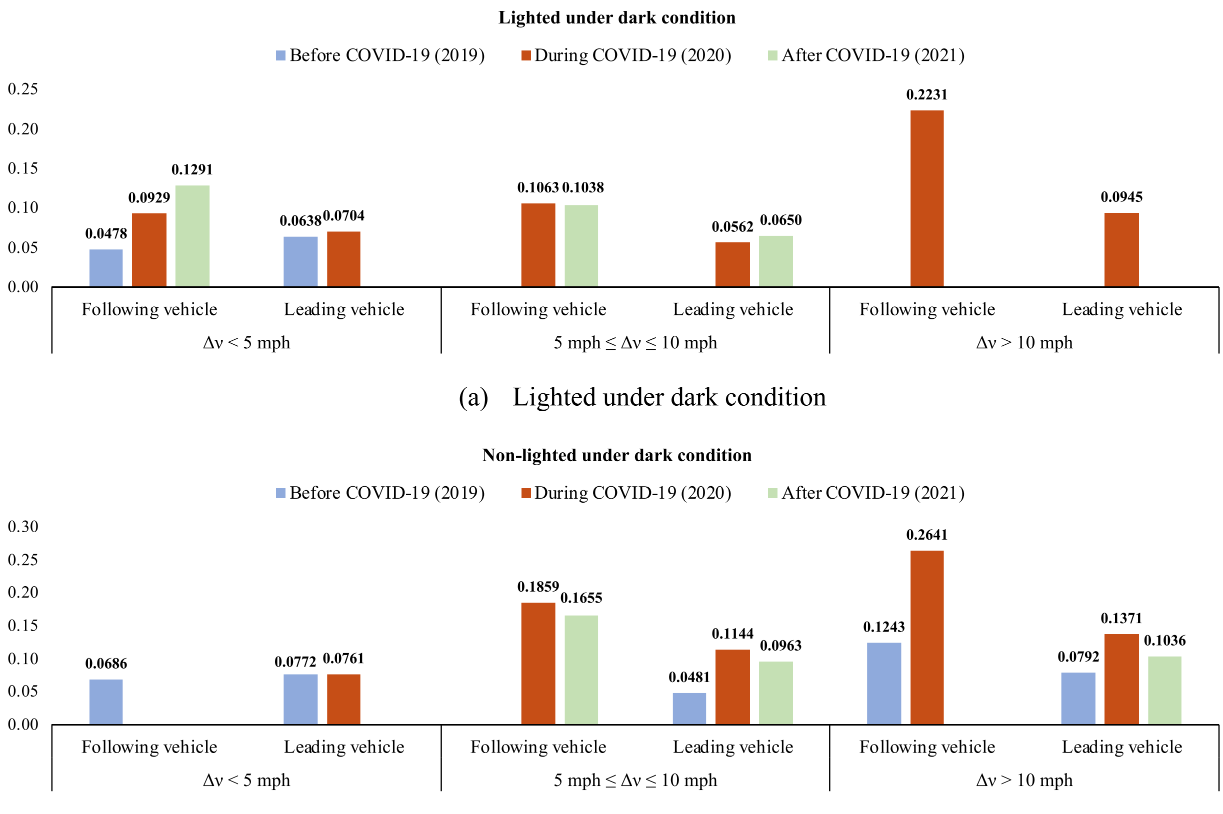
Furthermore, rural areas are associated with an increase in the severity of injury outcomes for both following and leading vehicles in individual models. Specifically, after COVID-19 with $\Delta\nu < 5$ mph, drivers of following and leading vehicles face a 0.1559 and 0.1032 higher likelihood of injury or fatality, respectively. This trend might be attributed to higher operating speeds, often prevalent in rural areas due to less traffic, which can lead to more serious outcomes (Chen et al., 2016; Huang et al., 2008; Zeng et al., 2019). Notably, this indicator consistently heightened injury severity outcomes across all $\Delta\nu$ ranges during COVID-19. This finding is corroborated by Gupta et al. (2023), who reported that the pandemic led to increased travel speeds and heightened injury severity in traffic crashes on rural freeways. Interestingly, the marginal effects suggest a decreasing trend in the likelihood of increased injury severity with higher $\Delta\nu$ ranges during COVID-19. A possible explanation is that driving at higher speeds in rural areas makes drivers more cautious compared to those at lower speeds. Despite the higher potential for injuries or fatalities, these drivers may engage in actions that mitigate the extent of damage and injuries (Quimby et al., 1999). Alternatively, drivers with advanced driving skills and perceived ability are more likely to exceed speed limits (Peterson and Gaugler, 2021), particularly in free-flowing traffic conditions within rural areas during COVID-19 (Lee et al., 2023).

6.5. Environmental characteristics

Sunny weather conditions are typically associated with a decreased likelihood of injury or fatality in individual models, except for drivers in the following vehicle after COVID-19 involved in collisions with $\Delta\nu > 10$ mph. This trend is logical, as the enhanced visibility during sunny conditions affords drivers more time to react to upcoming rear-end crashes, potentially reducing the severity of injuries (Das et al., 2018). However, the noted exception may be due to the substantial impact of $\Delta\nu$ exceeding 10 mph, which can result in more severe injuries.

Conversely, cloudy conditions tend to increase the likelihood of injury or fatality in individual models, suggesting possible issues of non-transferability and temporal instability. Notably, after COVID-19, drivers of both following and leading vehicles in rear-end crashes with $\Delta\nu > 10$ mph exhibit an increased injury/fatality likelihood by 0.1746 and 0.1524, respectively. This observation aligns with findings from recent studies (Chen et al., 2016; Wang et al., 2022a), although it contrasts with other research (Yu et al., 2015). The diminished visibility in cloudy weather conditions may contribute to more severe outcomes in rear-end crashes.

Furthermore, dark conditions during nighttime, regardless of lighting, heighten the risk of injury for drivers of both following and



(a) Lighted under dark condition

(a) Non-lighted under dark condition

Fig. 5. The marginal effects of lighted indicator corresponding to the injury/fatality outcomes.

leading vehicles, whereas daylight has the opposite effect. This highlights the increased risk of rear-end crashes during nighttime, characterized by low visibility, which can impair driving performance and exacerbate injury severities (Zamani et al., 2021). Furthermore, the marginal effects of the two indicators are depicted in Fig. 5.

It is noteworthy that rear-end crashes occurring during nighttime in unlighted conditions are typically linked to a greater likelihood of injury or fatality compared to those occurring in lighting environments. For both following and leading vehicles, the impact on the likelihood of injury/fatality escalates with increasing $\Delta\nu$ ranges under both lighting conditions. Furthermore, under unlit conditions at night, the likelihood of injury or fatality during the COVID-19 period exhibits a more significant increase compared to other time periods. Specifically, for rear-end crashes caused by $\Delta\nu > 10$ mph, the non-lighted under dark indicator leads to an increase in injury severity for the drivers of both the following and leading vehicles, by 0.2641 and 0.1371, respectively. This is consistent with the evidence confirmed by recent studies, which verified the link between the pandemic and risky driving behaviors (Tucker and Marsh, 2021). Drivers tends to suffer more risky behaviors such as speeding, inattentive driving, drink-driving during pandemic (Lee et al., 2023), which significantly increase the injury risk.

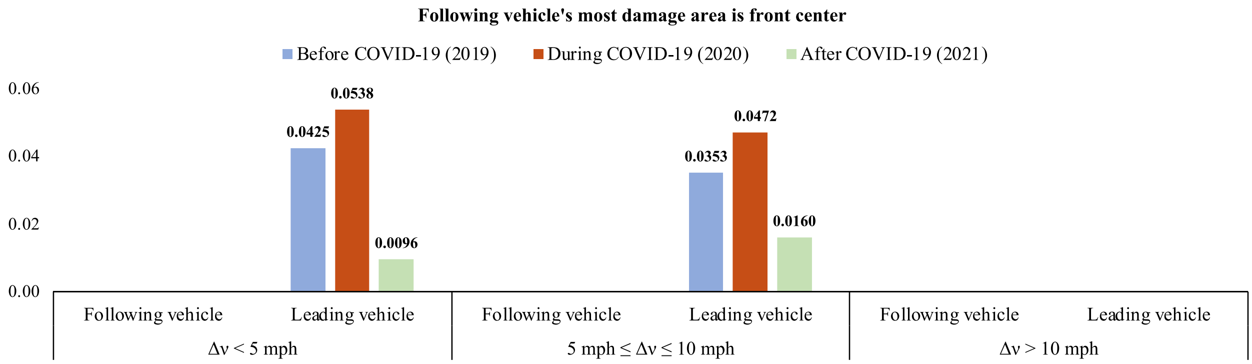
6.6. Crash characteristics

Regarding crash-related attributes, the distraction behaviors of drivers in the following vehicles are positively correlated with the likelihood of injury or fatality in individual models. Careless behaviors of drivers in following vehicles are likely to increase the injury/fatality risk for both drivers in crashes with $\Delta\nu < 5$ mph after COVID-19, while decreasing the risk for drivers of following vehicles in incidents with $\Delta\nu > 10$ mph during COVID-19. This non-transferability highlights the diverse impacts of careless behavior in rear-end crashes involving different $\Delta\nu$ values.

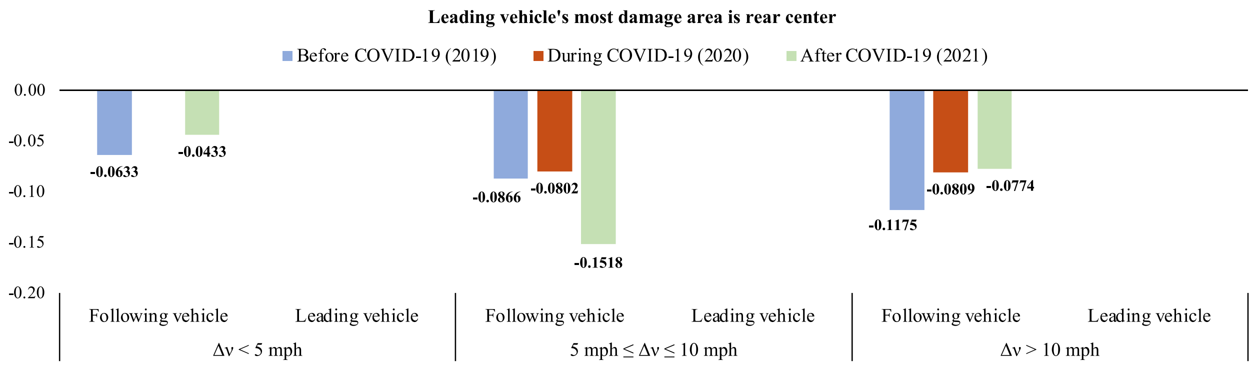
Additionally, over speeding by following vehicles heightens the risk of injuries or fatalities for drivers involved in rear-end crashes, also indicating potential instability and non-transferability. It is observed that when the following vehicle exceeds the speed limit, the risk of injury outcomes intensifies with greater $\Delta\nu$.

When drivers of following vehicles maintain a very close distance, their injury severity outcomes tend to decrease in individual cases. This could potentially be explained by their more cautious driving behavior when the distance narrows significantly, diminishing the injury outcomes.

Conversely, the V1 front center indicator increases the likelihood of injury or fatality for drivers of the leading vehicles in all



(a) If following vehicle's most damage area is front center



(b) If leading vehicle's most damage area is rear center

Fig. 6. The marginal effects of most damage area corresponding to the injury/fatality outcomes.

models, except for rear-end crashes with $\Delta\nu > 10$ mph occurring during and after COVID-19. Meanwhile, V1 front left and right indicators reduce this risk for drivers of the following vehicles in individual models. Additionally, the V2 rear center indicator lowers the likelihood of injury or fatality for drivers of the following vehicle in all models, with the exception of rear-end crashes with $\Delta\nu < 5$ mph during COVID-19. These findings align with the evidence presented by Bedard et al. (2002), who observed that, compared to front-impact crashes, collisions involving the right side and rear of vehicles were associated with lower odds of fatal injuries. The marginal effects for the V1 front center and V2 rear center indicators are shown in Fig. 6. In essence, if the following vehicle strikes the leading vehicle from a direct, straight-on position, it tends to decrease the injury risk for the driver of the following vehicle but increases it for the leading vehicle's driver.

Modern vehicle models feature crumple zones in the left and right front areas, designed to deform during a crash, effectively absorbing and dispersing energy away from the passenger cabin to reduce injury risk (Havarsad, 2018). In collisions impacting these areas, forces are directed outward, away from the driver, unlike front center impacts where forces may directly affect the driver. Additionally, damage to these front areas typically does not severely penetrate the cabin, preserving its integrity which is crucial for protecting occupants from serious injuries (Diaz and Costas, 2020).

Regarding rear center impacts, the collision force spreads across the vehicle's structure instead of concentrating in one area, and this spread lessens the force felt by occupants. The trunk or rear compartment adds extra space and structure to absorb and spread out the crash energy, acting as a buffer to protect the cabin (Davies, 2012; Heisler, 2002). Additionally, modern vehicle seats and headrests are designed to shield occupants from whiplash and spinal injuries common in rear-end crashes (Viano, 2023).

6.7. *Temporal characteristics*

Weekend is found to increase the injury/fatality likelihood of following vehicle in $\Delta\nu < 5$ mph after COVID-19 and 5 mph $\leq \Delta\nu \leq 10$ mph before COVID-19 model by 0.0618 and 0.0988, respectively. This is consistent with the findings of (Adanu et al., 2018), which might be caused by leisurely driving and reckless driving during weekends. Moreover, the frequent alcohol involvement on weekends might be another possible reason, which ultimately increases the possibility of severe outcomes (Li et al., 2021). The younger drivers, who are statistically more prone to collisions, might be more prevalent on the roads during weekends. Otherwise, this indicator is not statistically significant in during COVID-19 models. This finding can be attributed to the COVID-19 pandemic, which resulted in lockdowns, increased remote work, and diminished social activities (Benke et al., 2020; Semple et al., 2021; Shah et al., 2020). Due to these changes, the typical recreational and social travel during weekends substantially declined (Parr et al., 2020), leading to a reduced distinction in driving behaviors and crash risks between weekdays and weekends (Saladie et al., 2020).

The daytime indicator is associated with a reduced likelihood of injury outcomes for drivers involved in rear-end crashes within the 5 mph $\leq \Delta\nu \leq 10$ mph and $\Delta\nu > 10$ mph models, both before and after the COVID-19 period. This outcome is anticipated, as better visibility during the daytime enables drivers to react more effectively to mitigate the impact of impending rear-end collisions, a finding supported by (Zeng et al., 2019). It is noteworthy that the marginal effects of this indicator show a lesser decrease for the $\Delta\nu > 10$ mph compared to the 5 mph $\leq \Delta\nu \leq 10$ mph model, suggesting non-transferability across different $\Delta\nu$ ranges. During COVID-19 pandemic, daytime was not a significant factor in models, likely due to the pandemic's impact on traffic patterns and behaviors. Lockdowns, remote working, and travel restrictions led to a decrease in usual peak traffic periods (De Vos, 2020), reducing the variance in crash risks between day and night (Lee et al., 2023). Travel, predominantly for essential activities, became more uniform across different times (Beck and Hensher, 2020), resulting in a consistent crash risk throughout the day. Furthermore, increased stress and fatigue due to the pandemic may have similarly affected drivers during both day and night (Yasin, et al., 2021), contributing to a uniform level of risk at all times.

Additionally, the hurricane season, spanning from June to November, does not demonstrate significant influence in these models.

7. Conclusions

To investigate the temporal instability and non-transferability of factors influencing rear-end crashes across different $\Delta\nu$ ranges, three groups of correlated joint random parameters bivariate probit models have been developed. These models are based on two-vehicle rear-end crashes that occurred on interstate freeways in Florida from 2019 to 2021, divided by before, during and after the COVID-19 pandemic. The models consider two possible injury severity outcomes of no injury and injury/fatality for both drivers involved in these crashes. A variety of explanatory variables are examined, including driver, vehicle, roadway, environmental, crash, and temporal attributes.

The superior performance of the correlated joint random parameters bivariate probit model with heterogeneity in means is indicated by higher ρ^2 value and lower corrected AIC values. Robust results from likelihood ratio tests and out-of-sample predictions confirm the issues of temporal instability and non-transferability.

Moreover, the calculation of marginal effects sheds light on these issues, revealing that certain determinants, especially those with greater $\Delta\nu$ or occurring during the COVID-19 period, are associated with a higher likelihood of injury or fatality. This finding provides evidence of increased risk outcomes due to greater $\Delta\nu$ and the COVID-19 pandemic, from which several effective measures could be derived. Significant effects on the injury severity outcomes of drivers for both following and leading vehicles are observed from several explanatory variables. Additionally, three or more random parameters are identified in all nine models, and other variables produce significant heterogeneity in the means of random parameters, further substantiating the presence of unobserved heterogeneity. The significant correlation among the random parameters offers new insights into the interactive unobserved heterogeneity relating to the injury severity outcomes of both drivers in a two-vehicle rear-end crash.

Instead of focusing solely on one party, the employment of these developed approaches reveals the potential interactions among numerous variables affecting the injury severity outcomes of both drivers. Such heterogeneity, overlooked in the fixed parameters and uncorrelated random parameters model counterparts, provides valuable insights for safety promotion.

Nevertheless, there are some limitations in the current study. For instance, duration, ranges and restriction limits of the lockdown measures differed among various regions in Florida. This variation presents a significant challenge in classifying crash incidents into distinct phases, such as pre-lockdown, during lockdown, and post-lockdown. Future research could benefit from a more detailed differentiation of crash data, leading to more accurate and precise findings. Future research could also focus on incorporating deep learning and economic modeling approaches to capture the interaction and unobserved heterogeneity more effectively in crash analysis. Additionally, a joint analysis of the rate and injury severity of rear-end crashes at the same aggregate level might aid in the development of more effective countermeasures. Regarding the issue of transferability, future research would be directed towards exploring more advanced partially constrained approaches (Alnawmasi and Mannering, 2023) in terms of spatial shifts or other perspectives. This will involve combining data from multiple years or distinct sub-group to yield new insights.

Based on the findings, it is advisable that older drivers participate in educational programs. For future pandemic-like situations, more restriction program should be developed for drivers aged 30–45 years old who travel for essential work or family-related duties, to ensure driving safety. More education programs should be created for the special drivers who experience increased instances of speeding and fatigue driving due to official duties during the pandemic. Additionally, vehicles with a longer service life (over 10 years) should undergo comprehensive performance and safety checks, with a focus on rear (end) bumpers, airbags and seat belts. Increased prominence of curved signs and lane lines, particularly for left-curved roadway segments, is recommended to improve driver awareness and safety. The implementation of additional facilities and measures including speed cameras or heightened patrol presence, is advised to enforce speed limits, especially for the rural areas. Moreover, variable speed limit systems could help in reducing speed variation based on the traffic flow and driving conditions, enhancing overall road safety.

CRediT authorship contribution statement

Chenzhu Wang: Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mohamed Abdel-Aty:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Funding acquisition. **Lei Han:** Validation, Supervision, Data curation, Conceptualization.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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Appendix A

Table A1

Descriptive statistics (Std. Dev. in parenthesis) of significant variables for injury severity models of rear-end crashes by different ranges of $\Delta\nu$ before, during and after COVID-19 pandemic.

Variable	$\Delta\nu$ < 5 mph			5 mph ≤ $\Delta\nu$ ≤ 10 mph			$\Delta\nu$ > 10 mph		
	Before COVID-19 (2019)	**During COVID-19 (2020)**	**After COVID-19 (2021)**	**Before COVID-19 (2019)**	**During COVID-19 (2020)**	**After COVID-19 (2021)**	**Before COVID-19 (2019)**	**During COVID-19 (2020)**	**After COVID-19 (2021)**
The proportion of Injury/Fatality for following vehicle (V1)	0.126	0.141	0.144	0.122	0.148	0.137	0.163	0.230	0.176
The proportion of Injury/Fatality for leading vehicle (V2)	0.130	0.136	0.149	0.163	0.164	0.159	0.185	0.231	0.195
Driver Characteristics									
Male V1′s driver (1 if male, 0 otherwise)	0.661 (0.484)	0.676 (0.468)	0.685 (0.465)	0.658 (0.474)	0.686 (0.464)	0.681 (0.466)	0.655 (0.472)	0.693 (0.461)	0.682 (0.466)
Male V2′s driver (1 if male, 0 otherwise)	0.626 (0.484)	0.674 (0.469)	0.650 (0.477)	0.605 (0.489)	0.654 (0.476)	0.640 (0.480)	0.614 (0.487)	0.621 (0.485)	0.628 (0.485)
V1′s Below 18 years indicator (1 if age below 18 years, 0 otherwise)	0.082 (0.274)	0.088 (0.283)	0.090 (0.287)	0.066 (0.249)	0.075 (0.264)	0.078 (0.269)	0.059 (0.236)	0.072 (0.258)	0.064 (0.245)
V1′s 18–30 years indicator (1 if age between 18 and 30 years, 0 otherwise)	0.354 (0.478)	0.371 (0.483)	0.375 (0.484)	0.412 (0.492)	0.430 (0.495)	0.409 (0.492)	0.416 (0.493)	0.404 (0.491)	0.416 (0.493)
V1′s 30–45 years indicator (1 if age between 30 and 45 years, 0 otherwise)	0.280 (0.449)	0.270 (0.444)	0.272 (0.445)	0.270 (0.444)	0.286 (0.452)	0.283 (0.450)	0.275 (0.447)	0.284 (0.451)	0.281 (0.450)
V1′s Above 45 years indicator (1 if age above 45 years, 0 otherwise)	0.284 (0.451)	0.271 (0.445)	0.263 (0.440)	0.251 (0.434)	0.209 (0.406)	0.229 (0.421)	0.249 (0.433)	0.240 (0.427)	0.238 (0.426)
V2′s Below 18 years indicator (1 if age below 18 years, 0 otherwise)	0.023 (0.150)	0.023 (0.149)	0.017 (0.127)	0.016 (0.125)	0.023 (0.149)	0.020 (0.141)	0.023 (0.149)	0.024 (0.154)	0.032 (0.175)
V2′s 18–30 years indicator (1 if age between 18 and 30 years, 0 otherwise)	0.257 (0.437)	0.238 (0.426)	0.261 (0.439)	0.236 (0.425)	0.230 (0.421)	0.242 (0.429)	0.245 (0.430)	0.266 (0.442)	0.268 (0.443)
V2′s 30–45 years indicator (1 if age between 30 and 45 years, 0 otherwise)	0.319 (0.466)	0.340 (0.474)	0.360 (0.469)	0.328 (0.470)	0.322 (0.467)	0.333 (0.471)	0.314 (0.464)	0.310 (0.462)	0.317 (0.465)
V2′s Above 45 years indicator (1 if age above 45 years, 0 otherwise)	0.401 (0.490)	0.399 (0.490)	0.397 (0.489)	0.420 (0.494)	0.425 (0.495)	0.405 (0.491)	0.418 (0.493)	0.400 (0.490)	0.383 (0.486)
Vehicle Characteristics									
V1 Passenger car indicator (1 if passenger car, 0 otherwise)	0.550 (0.498)	0.519 (0.500)	0.507 (0.500)	0.558 (0.497)	0.550 (0.498)	0.518 (0.500)	0.573 (0.495)	0.541 (0.498)	0.549 (0.498)
V1 SUV indicator (1 if sport utility vehicle (SUV), 0 otherwise)	0.154 (0.361)	0.173 (0.378)	0.177 (0.382)	0.190 (0.392)	0.178 (0.382)	0.216 (0.412)	0.188 (0.390)	0.187 (0.390)	0.201 (0.401)
V1 Van indicator (1 if van, 0 otherwise)	0.046 (0.208)	0.043 (0.203)	0.053 (0.223)	0.063 (0.243)	0.044 (0.205)	0.051 (0.219)	0.049 (0.216)	0.048 (0.215)	0.057 (0.231)
V1 Bus indicator (1 if bus, 0 otherwise)	0.002 (0.042)	0.001 (0.026)	0.001 (0.023)	0.001 (0.029)	0.001 (0.025)	0.000 (0.000)	0.001 (0.032)	0.000 (0.022)	0.002 (0.048)
V1 Heavy truck indicator (1 if heavy truck, 0 otherwise)	0.080 (0.271)	0.077 (0.267)	0.076 (0.265)	0.047 (0.213)	0.055 (0.227)	0.051 (0.220)	0.045 (0.206)	0.060 (0.238)	0.049 (0.215)
V1 Other indicator (1 if other types of vehicles, 0 otherwise)	0.169 (0.375)	0.187 (0.390)	0.187 (0.390)	0.141 (0.348)	0.174 (0.379)	0.164 (0.370)	0.145 (0.352)	0.163 (0.369)	0.142 (0.349)
V2 Passenger car indicator (1 if passenger car, 0 otherwise)	0.484 (0.500)	0.448 (0.497)	0.430 (0.495)	0.468 (0.499)	0.431 (0.495)	0.421 (0.494)	0.475 (0.499)	0.453 (0.498)	0.446 (0.497)

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Table A1 (*continued*)

Variable	$\Delta\nu$ < 5 mph			5 mph ≤ $\Delta\nu$ ≤ 10 mph			$\Delta\nu$ > 10 mph		
	Before COVID-19 (2019)	During COVID-19 (2020)	After COVID-19 (2021)	Before COVID-19 (2019)	During COVID-19 (2020)	After COVID-19 (2021)	Before COVID-19 (2019)	During COVID-19 (2020)	After COVID-19 (2021)
V2 SUV indicator (1 if sport utility vehicle (SUV), 0 otherwise)	0.237 (0.425)	0.225 (0.418)	0.274 (0.446)	0.264 (0.441)	0.235 (0.424)	0.292 (0.455)	0.258 (0.437)	0.256 (0.437)	0.289 (0.453)
V2 Van indicator (1 if van, 0 otherwise)	0.053 (0.224)	0.062 (0.241)	0.057 (0.231)	0.057 (0.232)	0.056 (0.231)	0.060 (0.238)	0.060 (0.237)	0.058 (0.234)	0.047 (0.211)
V2 Bus indicator (1 if bus, 0 otherwise)	0.002 (0.042)	0.000 (0.000)	0.000 (0.000)	0.001 (0.021)	0.001 (0.025)	0.001 (0.030)	0.001 (0.026)	0.000 (0.000)	0.002 (0.040)
V2 Heavy truck indicator (1 if heavy truck, 0 otherwise)	0.090 (0.287)	0.117 (0.322)	0.099 (0.298)	0.076 (0.265)	0.131 (0.337)	0.090 (0.286)	0.058 (0.233)	0.083 (0.276)	0.069 (0.254)
V2 Other indicator (1 if other types of vehicles, 0 otherwise)	0.135 (0.342)	0.148 (0.355)	0.140 (0.347)	0.135 (0.341)	0.146 (0.353)	0.137 (0.344)	0.194 (0.356)	0.150 (0.357)	0.148 (0.355)
V1 Old indicator (1 if auto age more than 10 years, 0 otherwise)	0.530 (0.499)	0.471 (0.499)	0.433 (0.496)	0.513 (0.500)	0.485 (0.500)	0.404 (0.491)	0.518 (0.500)	0.499 (0.500)	0.417 (0.493)
V2 Old indicator (1 if auto age more than 10 years, 0 otherwise)	0.367 (0.482)	0.342 (0.475)	0.283 (0.451)	0.358 (0.479)	0.342 (0.474)	0.269 (0.444)	0.377 (0.485)	0.363 (0.481)	0.286 (0.452)
Roadway Characteristics									
Level indicator (1 if level grade, 0 otherwise)	0.935 (0.246)	0.938 (0.242)	0.957 (0.204)	0.929 (0.257)	0.934 (0.248)	0.945 (0.227)	0.924 (0.265)	0.906 (0.291)	0.923 (0.266)
Left curve indicator (1 if left-curved alignment, 0 otherwise)	0.012 (0.107)	0.019 (0.138)	0.011 (0.106)	0.009 (0.093)	0.021 (0.143)	0.016 (0.124)	0.013 (0.112)	0.016 (0.25)	0.009 (0.093)
Right curve indicator (1 if right-curved alignment, 0 otherwise)	0.008 (0.089)	0.010 (0.099)	0.008 (0.088)	0.014 (0.117)	0.013 (0.112)	0.009 (0.094)	0.013 (0.116)	0.016 (0.124)	0.011 (0.104)
Straight indicator (1 if straight alignment, 0 otherwise)	0.980 (0.141)	0.971 (0.169)	0.980 (0.139)	0.978 (0.148)	0.966 (0.180)	0.975 (0.155)	0.974 (0.160)	0.969 (0.175)	0.980 (0.139)
Lane_2 indicator (1 if crash occurred on two lanes on each side of road, 0 otherwise)	0.017 (0.130)	0.017 (0.128)	0.018 (0.133)	0.011 (0.103)	0.008 (0.090)	0.010 (0.099)	0.011 (0.104)	0.012 (0.107)	0.009 (0.095)
Lane_3 indicator (1 if crash occurred on three or more lanes on each side of road, 0 otherwise)	0.982 (0.135)	0.983 (0.128)	0.979 (0.144)	0.987 (0.115)	0.992 (0.090)	0.988 (0.109)	0.987 (0.115)	0.988 (0.107)	0.990 (0.101)
Rural areas indicator (1 if roadway is rural, 0 otherwise)	0.630 (0.483)	0.629 (0.483)	0.634 (0.482)	0.604 (0.489)	0.632 (0.483)	0.624 (0.485)	0.563 (0.496)	0.556 (0.497)	0.576 (0.494)
Urban areas indicator (1 if roadway is urban, 0 otherwise)	0.370 (0.483)	0.371 (0.483)	0.366 (0.482)	0.396 (0.489)	0.368 (0.483)	0.376 (0.485)	0.437 (0.496)	0.444 (0.497)	0.424 (0.494)
Dry surface indicator (1 if roadway surface is dry, 0 otherwise)	0.794 (0.405)	0.778 (0.416)	0.819 (0.385)	0.809 (0.393)	0.784 (0.411)	0.810 (0.392)	0.797 (0.403)	0.786 (0.410)	0.835 (0.371)
Environmental Characteristics									
Sunny indicator (1 if sunny, 0 otherwise)	0.693 (0.461)	0.689 (0.463)	0.707 (0.455)	0.674 (0.469)	0.681 (0.466)	0.702 (0.457)	0.674 (0.469)	0.680 (0.467)	0.719 (0.450)
Cloudy indicator (1 if cloudy, 0 otherwise)	0.173 (0.379)	0.156 (0.363)	0.170 (0.376)	0.200 (0.400)	0.173 (0.378)	0.169 (0.375)	0.201 (0.401)	0.183 (0.386)	0.168 (0.374)
Rainy indicator (1 if rainy, 0 otherwise)	0.131 (0.337)	0.154 (0.361)	0.116 (0.320)	0.120 (0.325)	0.143 (0.350)	0.122 (0.327)	0.125 (0.330)	0.133 (0.339)	0.109 (0.311)
Other weather indicator (1 1 if other weather conditions, 0 otherwise)	0.003 (0.054)	0.002 (0.045)	0.007 (0.082)	0.006 (0.075)	0.003 (0.056)	0.007 (0.082)	0.001 (0.026)	0.005 (0.069)	0.004 (0.065)
Daylight indicator (1 if daylight, 0 otherwise)	0.182 (0.386)	0.195 (0.396)	0.183 (0.387)	0.191 (0.393)	0.202 (0.402)	0.171 (0.376)	0.168 (0.374)	0.205 (0.404)	0.168 (0.374)
Lighted under dark indicator (1 if the roadway is lighted during nighttime, 0 otherwise)	0.085 (0.278)	0.089 (0.285)	0.103 (0.304)	0.098 (0.297)	0.112 (0.316)	0.109 (0.312)	0.070 (0.255)	0.082 (0.274)	0.078 (0.268)

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Table A1 (*continued*)

Variable	$\Delta\nu$ < 5 mph			5 mph ≤ $\Delta\nu$ ≤ 10 mph			$\Delta\nu$ > 10 mph		
	Before COVID-19 (2019)	**During COVID-19 (2020)**	**After COVID-19 (2021)**	**Before COVID-19 (2019)**	**During COVID-19 (2020)**	**After COVID-19 (2021)**	**Before COVID-19 (2019)**	**During COVID-19 (2020)**	**After COVID-19 (2021)**
Non-lighted under dark indicator (1 if the roadway is not lighted during nighttime, 0 otherwise)	0.679 (0.467)	0.663 (0.473)	0.659 (0.474)	0.646 (0.478)	0.630 (0.483)	0.666 (0.472)	0.704 (0.457)	0.647 (0.478)	0.692 (0.462)
Crash Characteristics									
Driving too close indicator (1 if crash occurred due to driving too close of V1′s driver, 0 otherwise)	0.066 (0.248)	0.045 (0.208)	0.051 (0.220)	0.058 (0.234)	0.041 (0.197)	0.065 (0.247)	0.054 (0.225)	0.045 (0.206)	0.043 (0.202)
Carelessness indicator (1 if crash occurred due to carelessness of V1′s driver, 0 otherwise)	0.552 (0.497)	0.530 (0.499)	0.572 (0.495)	0.785 (0.411)	0.748 (0.434)	0.745 (0.436)	0.784 (0.412)	0.742 (0.438)	0.770 (0.421)
Distraction indicator (1 if crash occurred due to distraction of V1′s driver, 0 otherwise)	0.160 (0.367)	0.187 (0.390)	0.193 (0.395)	0.216 (0.412)	0.241 (0.428)	0.272 (0.445)	0.265 (0.441)	0.260 (0.439)	0.260 (0.439)
V1′s over speeding indicator (1 if exceeding the speed limit, 0 otherwise)	0.030 (0.171)	0.023 (0.151)	0.021 (0.142)	0.142 (0.349)	0.225 (0.418)	0.168 (0.374)	0.105 (0.307)	0.159 (0.366)	0.127 (0.334)
V2′s over speeding indicator (1 if exceeding the speed limit, 0 otherwise)	0.023 (0.150)	0.020 (0.140)	0.018 (0.133)	0.013 (0.115)	0.016 (0.127)	0.018 (0.133)	0.003 (0.055)	0.006 (0.076)	0.004 (0.065)
V1 front center indicator (1 if V1′s most damage area is front center, 0 otherwise)	0.463 (0.499)	0.436 (0.496)	0.480 (0.500)	0.652 (0.476)	0.602 (0.490)	0.642 (0.480)	0.652 (0.476)	0.618 (0.486)	0.655 (0.476)
V1 front left indicator (1 if V1′s most damage area is front left bumper, 0 otherwise)	0.099 (0.299)	0.081 (0.273)	0.093 (0.290)	0.092 (0.289)	0.091 (0.287)	0.089 (0.285)	0.099 (0.299)	0.089 (0.285)	0.086 (0.280)
V1 front right indicator (1 if V1′s most damage area is front right bumper, 0 otherwise)	0.150 (0.358)	0.143 (0.350)	0.146 (0.353)	0.134 (0.341)	0.147 (0.354)	0.124 (0.329)	0.111 (0.314)	0.123 (0.328)	0.101 (0.301)
V2 rear center indicator (1 if V2′s most damage area is rear center, 0 otherwise)	0.408 (0.492)	0.378 (0.485)	0.416 (0.493)	0.615 (0.487)	0.528 (0.499)	0.602 (0.490)	0.611 (0.488)	0.578 (0.494)	0.616 (0.486)
V2 rear left indicator (1 if V2′s most damage area is rear left bumper, 0 otherwise)	0.134 (0.341)	0.146 (0.353)	0.144 (0.352)	0.131 (0.338)	0.131 (0.338)	0.118 (0.322)	0.112 (0.315)	0.119 (0.324)	0.107 (0.309)
V2 rear right indicator (1 if V2′s most damage area is rear right bumper, 0 otherwise)	0.100 (0.300)	0.079 (0.270)	0.085 (0.278)	0.095 (0.293)	0.105 (0.306)	0.089 (0.284)	0.099 (0.299)	0.101 (0.301)	0.094 (0.292)
Temporal Characteristics									
Hurricane indicator (1 if crash occurred in hurricane season (June to November), 0 otherwise)	0.475 (0.500)	0.535 (0.499)	0.531 (0.499)	0.471 (0.499)	0.519 (0.500)	0.526 (0.499)	0.475 (0.499)	0.505 (0.500)	0.525 (0.499)
Weekend indicator (1 if crash occurred on weekend, 0 otherwise)	0.234 (0.424)	0.249 (0.432)	0.245 (0.430)	0.247 (0.431)	0.244 (0.429)	0.258 (0.438)	0.185 (0.389)	0.219 (0.414)	0.231 (0.422)
Day indicator (1 if crash occurred during daytime, 0 otherwise)	0.711 (0.454)	0.686 (0.464)	0.673 (0.469)	0.692 (0.462)	0.645 (0.479)	0.695 (0.461)	0.739 (0.439)	0.688 (0.463)	0.719 (0.450)

Appendix B

Table B1
Elements of the Cholesky matrix (t-stats in parentheses), and correlation coefficients [in brackets] for the correlated random parameters in two-vehicle rear-end crashes caused by $\Delta\nu < 5$ mph Before COVID-19 (2019).

$\Delta\nu$ < 5 mph	**Before COVID-19 (2019)**		
	Male V1′s driver (1 if male, 0 otherwise) [V1]	**V2 SUV indicator (1 if sport utility vehicle (SUV), 0 otherwise) [V1]**	**V1 front center indicator (1 if V1′s most damage area is front center, 0 otherwise) [V2]**
Male V1′s driver (1 if male, 0 otherwise) [V1]	0.073 (5.43) [1.000]	−0.108 (−2.02) [−0.826]	0.183 (3.30) [0.940]
V2 SUV indicator (1 if sport utility vehicle (SUV), 0 otherwise) [V1]	−0.108 (−2.02) [−0.826]	0.337 (3.16) [1.000]	−0.232(−4.03) [−0.739]
V1 front center indicator (1 if V1′s most damage area is front center, 0 otherwise) [V2]	0.183 (3.30) [0.940]	−0.232(−4.03) [−0.739]	0.105 (2.91) [1.000]

Note: V1 and V2 denotes the following vehicle and leading vehicle, respectively. And “Male V1's driver (1 if male, 0 otherwise) [V1]” means that this variable is identified as a random parameter specific to V1 (following vehicle).

Table B2
Elements of the Cholesky matrix (t-stats in parentheses), and correlation coefficients [in brackets] for the correlated random parameters in two-vehicle rear-end crashes caused by $\Delta\nu < 5$ mph during COVID-19 (2020).

$\Delta\nu$ < 5 mph	**During COVID-19 (2020)**				
	Male V1′s driver (1 if male, 0 otherwise) [V1]	**Male V2′s driver (1 if male, 0 otherwise) [V2]**	**V2 Other indicator (1 if other types of vehicles, 0 otherwise) [V2]**	**Sunny indicator (1 if sunny, 0 otherwise) [V2]**	**Lighted under dark indicator (1 if the roadway is lighted during nighttime, 0 otherwise) [V2]**
Male V1′s driver (1 if male, 0 otherwise) [V1]	1.368 (24.50) [1.000]	−0.457 (−3.19) [−0.625]	0.556 (4.16) [0.762]	−0.431 (−2.17) [−0.563]	0.526 (3.97) [0.651]
Male V2′s driver (1 if male, 0 otherwise) [V2]	−0.457 (−3.19) [−0.625]	0.234 (3.65) [1.000]	−0.570 (−7.12) [−0.832]	0.858 (7.94) [0.273]	0.496 (5.29) [0.371]
V2 Other indicator (1 if other types of vehicles, 0 otherwise) [V2]	0.556 (4.16) [0.762]	−0.570 (−7.12) [−0.832]	1.576 (11.84) [1.000]	−0.534 (−3.19) [−0.315]	−0.898 (−6.11) [−0.436]
Sunny indicator (1 if sunny, 0 otherwise) [V2]	−0.431 (−2.17) [−0.563]	0.858 (7.94) [0.273]	−0.534 (−3.19) [−0.315]	0.436 (2.74) [1.000]	−0.372 (−4.49) [−0.649]
Lighted under dark indicator (1 if the roadway is lighted during nighttime, 0 otherwise) [V2]	0.526 (3.97) [0.651]	0.496 (5.29) [0.371]	−0.898 (−6.11) [−0.436]	−0.372 (−4.49) [−0.649]	0.310 (2.50) [1.000]

Table B3
Elements of the Cholesky matrix (t-stats in parentheses), and correlation coefficients [in brackets] for the correlated random parameters in two-vehicle rear-end crashes caused by $\Delta\nu < 5$ mph after COVID-19 (2021).

Δν < 5 mph	**After COVID-19 (2021)**				
	Rural areas indicator (1 if roadway is rural, 0 otherwise) [V1]	**Lighted under dark indicator (1 if the roadway is lighted during nighttime, 0 otherwise) [V1]**	**Male V1′s driver (1 if male, 0 otherwise) [V2]**	**Male V2′s driver (1 if male, 0 otherwise) [V2]**	**Carelessness indicator (1 if crash occurred due to carelessness of V1′s driver, 0 otherwise) [V2]**
Rural areas indicator (1 if roadway is rural, 0 otherwise) [V1]	0.618 (11.95) [1.000]	−0.654 (−7.89) [−0.999]	−0.444 (−6.35) [−0.439]	−0.311 (−4.56) [−0.297]	−0.407 (−6.00) [−0.621]
Lighted under dark indicator (1 if the roadway is lighted during nighttime, 0 otherwise) [V1]	−0.654 (−7.89) [−0.999]	0.011 (2.14) [1.000]	0.661 (9.21) [0.449]	−0.425 (−6.01) [0.290]	−0.146 (−2.24) [0.618]
Male V1′s driver (1 if male, 0 otherwise) [V2]	−0.444 (−6.35) [−0.439]	0.661 (9.21) [0.449]	0.172 (2.94) [1.000]	−0.601 (−7.39) [−0.647]	0.455 (7.23) [0.178]
Male V2′s driver (1 if male, 0 otherwise) [V2]	−0.311 (−4.56) [−0.297]	−0.425 (−6.01) [0.290]	−0.601 (−7.39) [−0.647]	0.906 (10.47) [1.000]	0.185 (2.40) [0.519]
Carelessness indicator (1 if crash occurred due to carelessness of V1′s driver, 0 otherwise) [V2]	−0.407 (−6.00) [−0.621]	−0.146 (−2.24) [0.618]	0.455 (7.23) [0.178]	0.185 (2.40) [0.519]	0.230 (2.31) [1.000]

Table B4
Elements of the Cholesky matrix (t-stats in parentheses), and correlation coefficients [in brackets] for the correlated random parameters in two-vehicle rear-end crashes caused by 5 mph $\leq \Delta\nu \leq$ 10 mph Before COVID-19 (2019).

5 mph ≤ Δν ≤ 10 mph	**Before COVID-19 (2019)**		
	V1 front left indicator (1 if V1′s most damage area is front left bumper, 0 otherwise) [V1]	**Day indicator (1 if crash occurred during daytime, 0 otherwise) [V1]**	**Male V2′s driver (1 the V1′s driver is male, 0 otherwise) [V2]**
V1 front left indicator (1 if V1′s most damage area is front left bumper, 0 otherwise) [V1]	0.345 (2.27) [1.000]	0.345 (2.27) [0.920]	−0.461 (−10.38) [−0.208]
Day indicator (1 if crash occurred during daytime, 0 otherwise) [V1]	0.345 (2.27) [0.920]	0.435 (8.75) [1.000]	0.079 (2.86) [0.153]
Male V2′s driver (1 the V1′s driver is male, 0 otherwise) [V2]	−0.461 (−10.38) [−0.208]	0.079 (2.86) [0.153]	0.224 (5.43) [1.000]

Table B5
Elements of the Cholesky matrix (t-stats in parentheses), and correlation coefficients [in brackets] for the correlated random parameters in two-vehicle rear-end crashes caused by 5 mph $\leq \Delta\nu \leq$ 10 mph during COVID-19 (2020).

5 mph ≤ Δν ≤ 10 mph	During COVID-19 (2020)		
	V1 front center indicator (1 if V1′s most damage area is front center, 0 otherwise) [V1]	Lighted under dark indicator (1 if the roadway is lighted during nighttime, 0 otherwise) [V1]	Sunny indicator (1 if sunny, 0 otherwise) [V2]
V1 front center indicator (1 if V1′s most damage area is front center, 0 otherwise) [V1]	0.402 (2.15) [1.000]	−0.219 (−2.87) [−0.358]	−0.576 (−10.36) [−0.613]
Lighted under dark indicator (1 if the roadway is lighted during nighttime, 0 otherwise) [V1]	−0.219 (−2.87) [−0.358]	0.573 (4.72) [1.000]	−0.191 (−2.07) [0.232]
Sunny indicator (1 if sunny, 0 otherwise) [V2]	−0.576 (−10.36) [−0.613]	0.191 (−2.07) [0.232]	0.762 (15.30) [1.000]

Table B6
Elements of the Cholesky matrix (t-stats in parentheses), and correlation coefficients [in brackets] for the correlated random parameters in two-vehicle rear-end crashes caused by 5 mph $\leq \Delta\nu \leq$ 10 mph after COVID-19 (2021).

5 mph ≤ Δν ≤ 10 mph	After COVID-19 (2021)		
	Male V1′s driver (1 if male, 0 otherwise) [V1]	V2′s 30–45 years indicator (1 if age between 30 and 45 years, 0 otherwise) [V2]	Day indicator (1 if crash occurred during daytime, 0 otherwise) [V2]
Male V1′s driver (1 if male, 0 otherwise) [V1]	0.087 (2.01) [1.000]	0.172 (3.58) [0.893]	0.491 (10.23) [0.216]
V2′s 30–45 years indicator (1 if age between 30 and 45 years, 0 otherwise) [V2]:	0.172 (3.58) [0.893]	0.479 (6.00) [1.000]	−0.122 (−2.78) [−0.237]
Day indicator (1 if crash occurred during daytime, 0 otherwise) [V2]	0.491 (10.23) [0.216]	−0.122 (−2.78) [−0.237]	0.105 (2.51) [1.000]

Table B7
Elements of the Cholesky matrix (t-stats in parentheses), and correlation coefficients [in brackets] for the correlated random parameters in two-vehicle rear-end crashes caused by $\Delta\nu >$ 10 mph Before COVID-19 (2019).

Δν > 10 mph	Before COVID-19 (2019)		
	V1 Passenger car indicator (1 if passenger car, 0 otherwise) [V1]	Day indicator (1 if crash occurred during daytime, 0 otherwise) [V1]	V2 Passenger car indicator (1 if passenger car, 0 otherwise) [V2]
V1 Passenger car indicator (1 if passenger car, 0 otherwise) [V1]	0.163 (4.76) [1.000]	−0.587 (−13.10) [−0.964]	−0.284 (−7.52) [0.289]
Day indicator (1 if crash occurred during daytime, 0 otherwise) [V1]	−0.587 (−13.10) [−0.964]	0.390 (9.44) [1.000]	−0.318 (−8.03) [−0.398]
V2 Passenger car indicator (1 if passenger car, 0 otherwise) [V2]	−0.284 (−7.52) [0.289]	−0.318 (−8.03) [−0.398]	0.674 (17.97) [1.000]

Table B8
Elements of the Cholesky matrix (t-stats in parentheses), and correlation coefficients [in brackets] for the correlated random parameters in two-vehicle rear-end crashes caused by $\Delta\nu >$ 10 mph during COVID-19 (2020).

Δν > 10 mph	During COVID-19 (2020)			
	Male V1′s driver (1 if male, 0 otherwise) [V1]	V1′s over speeding indicator (1 if exceeding the speed limit, 0 otherwise) [V1]	Male V2′s driver (1 if male, 0 otherwise) [V2]	V2 Heavy truck indicator (1 if heavy truck, 0 otherwise) [V2]
Male V1′s driver (1 if male,	0.218 (5.36) [1.000]	0.148 (3.39) [0.561]	−0.370 (−7.50) [−0.515]	−0.458 (−2.47) [−0.136]

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Table B8 (*continued*)

$\Delta\nu > 10$ mph	During COVID-19 (2020)			
	Male V1′s driver (1 if male, 0 otherwise) [V1]	V1′s over speeding indicator (1 if exceeding the speed limit, 0 otherwise) [V1]	Male V2′s driver (1 if male, 0 otherwise) [V2]	V2 Heavy truck indicator (1 if heavy truck, 0 otherwise) [V2]
0 otherwise) [V1]				
V1′s over speeding indicator (1 if exceeding the speed limit, 0 otherwise) [V1]	0.148 (3.39) [0.561]	1.002 (10.99) [1.000]	−0.294 (−6.82) [−0.321]	0.499 (3.33) [0.182]
Male V2′s driver (1 if male, 0 otherwise) [V2]	−0.370 (−7.50) [−0.515]	−0.294 (−6.82) [−0.321]	−0.470 (−4.18) [1.000]	−0.632 (−12.07) [−0.660]
V2 Heavy truck indicator (1 if heavy truck, 0 otherwise) [V2]	−0.458 (−2.47) [−0.136]	0.499 (3.33) [0.182]	−0.632 (−12.07) [−0.660]	−0.805 (−2.37) [1.000]

Table B9
Elements of the Cholesky matrix (t-stats in parentheses), and correlation coefficients [in brackets] for the correlated random parameters in two-vehicle rear-end crashes caused by $\Delta\nu > 10$ mph after COVID-19 (2021).

$\Delta\nu > 10$ mph	After COVID-19 (2021)			
	Male V1′s driver (1 if male, 0 otherwise) [V1]	V2 Passenger car indicator (1 if passenger car, 0 otherwise) [V1]	Day indicator (1 if crash occurred during daytime, 0 otherwise) [V1]	V2′s Above 45 years indicator (1 if age above 45 years, 0 otherwise) [V2]
Male V1′s driver (1 if male, 0 otherwise) [V1]	0.312 (6.66) [1.000]	0.518 (8.28) [0.893]	−0.151 (−3.26) [−0.152]	0.804 (12.88) [0.915]
V2 Passenger car indicator (1 if passenger car, 0 otherwise) [V1]	0.518 (8.28) [0.893]	0.109 (2.09) [1.000]	0.237 (4.63) [0.268]	−0.241 (−4.52) [0.880]
Day indicator (1 if crash occurred during daytime, 0 otherwise) [V1]	−0.151 (−3.26) [−0.152]	0.237 (4.63) [0.268]	0.986 (24.66) [1.000]	0.247 (5.36) [0.138]
V2′s Above 45 years indicator (1 if age above 45 years, 0 otherwise) [V2]	0.804 (12.88) [0.915]	−0.241 (−4.52) [0.880]	0.247 (5.36) [0.138]	0.082 (2.84) [1.000]

Appendix C

Table C1
Model results of injury severity of freeway two-vehicle rear-end crashes caused by three $\Delta\nu$ ranges before (2019), during (2020) and after (2021) COVID-19 pandemic (t-statistics in parentheses) based on partially temporal constrained uncorrelated joint random parameters bivariate probit models with heterogeneity in means.

Variable	$\Delta\nu < 5$ mph		5 mph $\leq \Delta\nu \leq$ 10 mph		$\Delta\nu > 10$ mph	
	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers
Constant [2019]	−0.732 (−7.95)	−1.414 (−13.04)	−0.796 (−6.59)	−0.771 (−5.10)	−0.352 (−3.53)	−0.686 (−7.58)
Constant [2020]	−1.336 (−12.67)	−1.280 (−11.21)	−1.115 (−11.52)	−1.252 (−7.37)	−0.569 (−4.67)	−0.676 (−9.17)
Constant [2021]	−1.066 (−7.66)	−0.529 (−4.11)	−1.027 (−3.61)	−1.046 (−7.63)	−0.617 (−4.68)	−0.755 (−7.62)

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Table C1 (*continued*)

Variable	Δv < 5 mph		5 mph ≤ Δv ≤ 10 mph		Δv > 10 mph	
	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers
Variables producing the same parameter value across all periods						
V1 Heavy truck indicator (1 if heavy truck, 0 otherwise) [2019, 2020, 2021]	−0.627 (−2.94)		−0.682 (−2.89)			
V1 Passenger car indicator (1 if passenger car, 0 otherwise) [2019, 2020, 2021]						−0.198 (−2.74)
V2 Passenger car indicator (1 if passenger car, 0 otherwise) [2019, 2020, 2021]			−0.231 (−2.32)	−0.128 (−2.78)	−0.329 (−4.78)	
Non-lighted under dark indicator (1 if the roadway is not lighted during nighttime, 0 otherwise) [2019, 2020, 2021]				0.218 (3.29)		0.318 (2.78)
V1 front center indicator (1 if V1′s most damage area is front center, 0 otherwise) [2019, 2020, 2021]				0.165 (2.36)		
V1′s over speeding indicator (1 if exceeding the speed limit, 0 otherwise) [2019, 2020, 2021]						0.539 (6.47)
V2 rear center indicator (1 if V2′s most damage area is rear center, 0 otherwise) [2019, 2020, 2021]			−0.253 (−2.84)		−0.228 (−3.51)	
Driver Characteristics						
Male V1′s driver (1 if male, 0 otherwise) [2021]	−0.197 (−2.48)					
Male V1′s driver (1 if male, 0 otherwise) [2019, 2021]			−0.217 (−2.75)			
Male V1′s driver (1 if male, 0 otherwise) [2020]				0.236 (2.64)		
Male V2′s driver (1 male, 0 otherwise) [2019, 2021]		−0.274 (−3.08)				
Male V2′s driver (1 if male, 0 otherwise) [2020, 2021]				−0.287 (−3.65)	−0.178 (−3.24)	
V1′s Below 18 years indicator (1 if age below 18 years, 0 otherwise) [2021]	0.398 (2.92)		−0.432 (−2.28)	−0.314 (−2.01)		
V1′s Below 18 years indicator (1 if age below 18 years, 0 otherwise) [2019, 2021]					−0.204 (−2.38)	
V1′s 18–30 years indicator (1 if age between 18 and 30 years, 0 otherwise) [2021]					−0.083 (−2.24)	
V1′s 30–45 years indicator (1 if age between 30 and 45 years, 0 otherwise) [2020]	0.159 (2.22)			0.118 (2.24)		
V1′s 30–45 years indicator (1 if age between 30 and 45 years, 0 otherwise) [2019, 2020]						0.143 (2.18)
V1′s Above 45 years indicator (1 if age above 45 years, 0 otherwise) [2020]				0.217 (2.17)		
V1′s Above 45 years indicator (1 if age above 45 years, 0 otherwise) [2019]					0.147 (2.65)	
V2′s Below 18 years indicator (1 if age below 18 years, 0 otherwise) [2019]						−0.732 (−2.92)
V2′s 18–30 years indicator (1 if age between 18 and 30 years, 0 otherwise) [2019, 2021]		−0.187 (−2.31)				

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Table C1 (*continued*)

Variable	Δv < 5 mph		5 mph ≤ Δv ≤ 10 mph		Δv > 10 mph	
	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers
V2′s 18–30 years indicator (1 if age between 18 and 30 years, 0 otherwise) [2019]						−0.143 (−2.24)
V2′s 18–30 years indicator (1 if age between 18 and 30 years, 0 otherwise) [2019, 2020]				−0.267 (−2.37)		
V2′s 30–45 years indicator (1 if the age between 30 and 45 years, 0 otherwise) [2019]		−0.237 (−2.49)				
V2′s 30–45 years indicator (1 if age between 30 and 45 years, 0 otherwise) [2020]				0.245 (−2.48)		
V2′s Above 45 years indicator (1 if age above 45 years, 0 otherwise) [2021]					0.223 (3.51)	
Vehicle Characteristics						
V1 Passenger car indicator (1 if passenger car, 0 otherwise) [2021]	0.213 (2.82)				0.165 (2.53)	
V1 Passenger car indicator (1 if passenger car, 0 otherwise) [2020]		0.143 (2.25)		0.238 (2.87)		
V1 SUV indicator (1 if sport utility vehicle (SUV), 0 otherwise) [2021]						0.287 (3.54)
V1 Van indicator (1 if van, 0 otherwise) [2021]						0.203 (2.53)
V1 Heavy truck indicator (1 if heavy truck, 0 otherwise) [2020]					−0.502 (−2.87)	
V1 Heavy truck indicator (1 if heavy truck, 0 otherwise) [2019]						0.343 (2.37)
V1 Heavy truck indicator (1 if heavy truck, 0 otherwise) [2019, 2021]				0.443 (2.99)		
V1 Old indicator (1 if V1′ auto age is more than 10 years, 0 otherwise) [2020]	0.147 (1.90)					
V2 Passenger car indicator (1 passenger car, 0 otherwise) [2019, 2021]	−0.428 (4.27)					0.175 (2.46)
V2 Passenger car indicator (1 passenger car, 0 otherwise) [2019]		−0.417 (−4.02)				
V2 Van indicator (1 if van, 0 otherwise) [2020, 2021]			−2.767 (−2.65)			
V2 SUV indicator (1 if support utility vehicle (SUV), 0 otherwise) [2020]		0.198 (2.53)				
V2 SUV indicator (1 if support utility vehicle (SUV), 0 otherwise) [2021]	−0.219 (−2.25)		−0.298 (−2.57)			
V2 SUV indicator (1 if sport utility vehicle (SUV), 0 otherwise) [2019, 2021]					−0.176 (−2.89)	
V2 Van indicator (1 if van, 0 otherwise) [2019]		0.342 (2.19)				
V2 Van indicator (1 if van, 0 otherwise) [2019, 2021]					−0.273 (−3.28)	
V2 Heavy truck indicator (1 if heavy truck, 0 otherwise) [2019]			0.483 (4.38)			
V2 Heavy truck indicator (1 if heavy truck, 0 otherwise) [2019, 2020]	0.392 (2.07)			−0.638 (−3.63)		

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Table C1 (*continued*)

Variable	Δν < 5 mph		5 mph ≤ Δν ≤ 10 mph		Δν > 10 mph	
	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers
V2 Heavy truck indicator (1 if heavy truck, 0 otherwise) [2021]		−0.671 (−3.94)				
V2 Heavy truck indicator (1 if heavy truck, 0 otherwise) [2020]					0.728 (5.43)	
V2 Other indicator (1 if other types of vehicles, 0 otherwise) [2020]	0.302 (2.47)					
V2 Old indicator (1 if auto age more than 10 years, 0 otherwise) [2019, 2020]			0.214 (2.68)			
V2 Old indicator (1 if auto age more than 10 years, 0 otherwise) [2019]				0.328 (3.24)		
V2 Old indicator (1 if V2′ auto age is more than 10 years, 0 otherwise) [2021]	0.160 (2.89)					
V2 Old indicator (1 if V2′ auto age is more than 10 years, 0 otherwise) [2020]		0.369 (4.17)			0.201 (2.72)	0.143 (2.11)
Roadway Characteristics						
Level indicator (1 if level grade, 0 otherwise) [2021]			−0.235 (2.02)			
Level indicator (1 if level grade, 0 otherwise) [2019]				−0.138 (−2.21)		
Left curve indicator (1 if left-curved alignment, 0 otherwise) [2020]			0.225 (2.72)			
Right curve indicator (1 if right-curved alignment, 0 otherwise) [2019]						0.402 (2.43)
Rural areas indicator (1 if roadway is rural, 0 otherwise) [2020, 2021]			0.217 (2.78)			
Rural areas indicator (1 if roadway is rural, 0 otherwise) [2020]	0.204 (2.25)			2.287 (2.18)	0.134 (2.47)	
Rural areas indicator (1 if roadway is rural, 0 otherwise) [2021]		0.232 (3.01)				0.143 (2.51)
Environmental Characteristics						
Sunny indicator (1 if sunny, 0 otherwise) [2019]				−0.127 (−2.94)		
Sunny indicator (1 if sunny, 0 otherwise) [2021]	−0.246 (−3.15)	−0.209 (−2.71)	−0.157 (−2.58)		0.165 (2.75)	
Cloudy indicator (1 if cloudy, 0 otherwise) [2020]	0.181 (2.61)					
Cloudy indicator (1 if cloudy, 0 otherwise) [2019]			0.367 (2.78)			
Cloudy indicator (1 if cloudy, 0 otherwise) [2021]				0.223 (2.76)	0.467 (4.32)	
Cloudy indicator (1 if cloudy, 0 otherwise) [2019, 2021]						0.143 (2.46)
Rainy indicator (1 if rainy, 0 otherwise) [2021]			−0.221 (−2.62)			
Other weather indicator (1 if other weather conditions, 0 otherwise) [2020]			1.018 (2.08)			
Daylight indicator (1 if daylight, 0 otherwise) [2021]		−0.527 (−6.13)				−0.164 (−2.64)
Lighted under dark indicator (1 if the roadway is lighted during nighttime, 0 otherwise) [2019, 2020]	0.256 (2.48)					

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Table C1 (*continued*)

Variable	Δv < 5 mph		5 mph ≤ Δv ≤ 10 mph		Δv > 10 mph	
	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers
Lighted under dark indicator (1 if the roadway is lighted during nighttime, 0 otherwise) [2019]		0.378 (3.33)				
Lighted under dark indicator (1 if the roadway is lighted during nighttime, 0 otherwise) [2020]					0.234 (2.21)	0.183 (2.14)
Non-lighted under dark indicator (1 if the roadway is not lighted during nighttime, 0 otherwise) [2019]	0.475 (3.55)					
Non-lighted under dark indicator (1 if the roadway is not lighted during nighttime, 0 otherwise) [2019, 2020]		0.378 (3.04)			0.342 (3.02)	
Lighted under dark indicator (1 if the roadway is lighted during nighttime, 0 otherwise) [2020, 2021]			0.356 (3.27)	0.468 (4.89)		
Non-lighted under dark indicator (1 if the roadway is not lighted during nighttime, 0 otherwise) [2021]			0.432 (2.87)			
Crash Characteristics						
Driving too close indicator (1 if crash occurred due to driving too close of V1′s driver, 0 otherwise) [2019, 2021]	−0.414 (−2.21)					
Driving too close indicator (1 if crash occurred due to driving too close of V1′s driver, 0 otherwise) [2020]			−0.492 (−2.03)		−0.487 (−2.58)	
Distraction indicator (1 if crash occurred due to distraction of V1′s driver, 0 otherwise) [2019, 2020]				0.217 (2.78)		
Distraction indicator (1 if crash occurred due to distraction of V1′s driver, 0 otherwise) [2020]					0.182 (2.24)	0.133 (2.02)
V1′s over speeding indicator (1 if exceeding the speed limit, 0 otherwise) [2019]			0.446 (4.68)			
V1′s over speeding indicator (1 if exceeding the speed limit, 0 otherwise) [2019, 2021]				0.223 (2.47)		
Carelessness indicator (1 if crash occurred due to carelessness of V1′s driver, 0 otherwise) [2021]	0.223 (2.32)					
Carelessness indicator (1 if crash occurred due to carelessness of V1′s driver, 0 otherwise) [2020]					−0.143 (−2.02)	
V1′s over speeding indicator (1 if exceeding the speed limit, 0 otherwise) [2020]		1.114 (2.13)				
V1′s over speeding indicator (1 if exceeding the speed limit, 0 otherwise) [2019, 2021]					0.639 (8.92)	

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Table C1 (*continued*)

Variable	$\Delta\nu$ < 5 mph		5 mph ≤ $\Delta\nu$ ≤ 10 mph		$\Delta\nu$ > 10 mph	
	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers
V1 front center indicator (1 if V1′s most damage area is front center, 0 otherwise) [2020, 2021]		0.487 (3.34)				
V2 rear center indicator (1 if V2′s most damage area is rear center, 0 otherwise) [2019, 2021]	−0.199 (−2.27)					
V1 front left indicator (1 if V1′s most damage area is front left bumper, 0 otherwise) [2021]			−3.782 (−2.02)			
V1 front left indicator (1 if V1′s most damage area is front left bumper, 0 otherwise) [2020]					−0.343 (−2.76)	
V1 front right indicator (1 if V1′s most damage area is front right bumper, 0 otherwise) [2019, 2021]			−0.327 (−3.20)			
V1 front right indicator (1 if V1′s most damage area is front right bumper, 0 otherwise) [2020]					−0.324 (−2.87)	
V2 rear right indicator (1 if V2′s most damage area is rear right, 0 otherwise) [2021]				−0.265 (−2.25)		
V2 rear left indicator (1 if V2′s most damage area is rear left bumper, 0 otherwise) [2019]					−0.243 (−2.21)	
Temporal Characteristics						
Weekend indicator (1 if crash occurred on weekend, 0 otherwise) [2021]	0.179 (2.01)					
Weekend indicator (1 if crash occurred on weekend, 0 otherwise) [2019]			0.190 (2.41)			
Day indicator (1 if crash occurred during daytime, 0 otherwise) [2021]			−0.169 (−2.31)			
Day indicator (1 if crash occurred during daytime, 0 otherwise) [2019]				−0.334 (−4.39)		−0.223 (−3.27)
Random parameters						
Male V1′s driver (1 if male, 0 otherwise) [V1] [2019]	−0.2359 (−2.27)				−0.265 (−4.45)	
Standard deviation	***0.142 (4.37)***				***0.538 (4.34)***	
Male V1′s driver (1 if male, 0 otherwise) [V1] [2020]	−0.373 (−2.40)				−0.227 (−2.15)	
Standard deviation	***1.324 (21.26)***				***0.232 (4.38)***	
Male V1′s driver (1 if male, 0 otherwise) [V2] [2021]		−0.287 (−2.82)			−0.261 (−3.98)	
Standard deviation		***1.010 (2.76)***			***0.278 (5.18)***	
Male V2′s driver (1 if male, 0 otherwise) [V2] [2019]				−0.234 (−2.19)		−0.389 (−5.82)
Standard deviation				***0.476 (4.62)***		***0.728 (7.78)***
Male V2′s driver (1 if male, 0 otherwise) [V2] [2020]		−0.527 (−2.81)				−0.423 (−3.69)
Standard deviation		***1.182 (3.24)***				***0.739 (8.29)***
V2′s 30–45 years indicator (1 if age between 30 and 45 years, 0 otherwise) [V2] [2021]			−0.376 (−3.43)			
Standard deviation			***0.093 (2.42)***			

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Table C1 (*continued*)

Variable	Δv < 5 mph		5 mph ≤ Δv ≤ 10 mph		Δv > 10 mph	
	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers
V2′s Above 45 years indicator (1 if age above 45 years, 0 otherwise) [V2] [2021]						−0.491 (−2.43)
Standard deviation						***0.812 (2.57)***
V2 Heavy truck indicator (1 if heavy truck, 0 otherwise) [V2] [2020]						−0.928 (−3.78)
Standard deviation						***1.812 (7.28)***
V2 SUV indicator (1 if support utility vehicle (SUV), 0 otherwise) [V1] [2019]	−0.663 (−4.38)					
Standard deviation	***0.337 (3.16)***					
V2 Other indicator (1 if other types of vehicles, 0 otherwise) [V2] [2020]		0.215 (2.07)				
Standard deviation		***1.181 (9.01)***				
V1 front center indicator (1 if V1′s most damage area is front center, 0 otherwise) [V2] [2019]		0.214 (2.21)				
Standard deviation		***0.321 (2.78)***				
V1 front right indicator (1 if V1′s most damage area is front right bumper, 0 otherwise) [V1] [2020]			−1.283 (−4.78)			
Standard deviation			***0.383 (2.08)***			
Rural areas indicator (1 if roadway is rural, 0 otherwise) [V1] [2021]	0.342 (3.157)					
Standard deviation	***0.578 (9.67)***					
Sunny indicator (1 if sunny, 0 otherwise) [V2] [2020]		−0.521 (−3.03)				
Standard deviation		***0.891 (2.41)***				
Lighted under dark indicator (1 if the roadway is lighted during nighttime, 0 otherwise) [V1] [2021]	0.317 (2.67)					
Standard deviation	***0.456 (2.05)***					
V1′s over speeding indicator (1 if exceeding the speed limit, 0 otherwise) [V1] [2020]						0.732 (3.11)
Standard deviation						***0.679 (7.38)***
Carelessness indicator (1 if crash occurred due to carelessness of V1′s driver, 0 otherwise) [V2] [2021]		0.221 (2.16)				
Standard deviation		***0.627 (3.28)***				
V1 front left indicator (1 if V1′s most damage area is front left bumper, 0 otherwise) [V1] [2019]			−0.870 (−2.31)			
Standard deviation			***0.783 (2.01)***			
Sunny indicator (1 if sunny, 0 otherwise) [V2] [2020]				−0.432 (−5.01)		
Standard deviation				***0.845 (12.21)***		
Lighted under dark indicator (1 if the roadway is lighted during nighttime, 0 otherwise) [V1] [2020]			0.424 (2.43)			
Standard deviation			***0.576 (4.34)***			
Day indicator (1 if crash occurred during daytime, 0 otherwise) [V1] [2019]			−0.243 (−1.98)			−0.425 (−3.28)
Standard deviation			***0.412 (6.83)***			***1.328 (9.27)***

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Table C1 (*continued*)

Variable	Δν < 5 mph		5 mph ≤ Δν ≤ 10 mph		Δν > 10 mph	
	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers
Day indicator (1 if crash occurred during daytime, 0 otherwise) [V2] [2021]				−0.521 (−4.42)		−0.542 (−4.58)
Standard deviation				***0.508 (2.28)***		***0.682 (13.23)***
Heterogeneity in the means of random parameters						
Male V1′s driver (1 the V1′s driver is male, 0 otherwise) [V1]: V2′s over speeding indicator (1 if exceeding the speed limit, 0 otherwise) [2019]	0.489 (1.98)					
Male V1′s driver (1 if male, 0 otherwise) [V1]: Left curve indicator (1 if the roadway alignment is left-curved, 0 otherwise) [2020]	0.815 (2.18)					
Male V1′s driver (1 if male, 0 otherwise) [V1]: Distraction indicator (1 if crash occurred due to distraction of V1′s driver, 0 otherwise) [2021]		0.267 (2.647)				
Male V1′s driver (1 if male, 0 otherwise) [V1]: Weekend indicator (1 if crash occurred on weekend, 0 otherwise) [2019]					0.328 (3.29)	
Male V1′s driver (1 if male, 0 otherwise) [V1]: Weekend indicator (1 if crash occurred on weekend, 0 otherwise) [2020]					0.232 (2.34)	
Male V1′s driver (1 if male, 0 otherwise) [V1]: V2 Heavy truck indicator (1 if heavy truck, 0 otherwise) [2019]					0.524 (3.18)	
Male V2′s driver (1 if male, 0 otherwise) [V2]: V2 Heavy truck indicator (1 if V2 is a heavy truck, 0 otherwise) [2020]		−1.237 (−2.21)				−0.826 (−5.27)
Male V2′s driver (1 if male, 0 otherwise) [V2]: Left curve indicator (1 if the roadway alignment is left-curved, 0 otherwise) [2020]		1.121 (2.01)				
Male V2′s driver (1 if male, 0 otherwise) [V2]: Day indicator (1 if crash occurred during daytime, 0 otherwise) [2020]						−0.307 (−2.59)
V2′s 30–45 years indicator (1 if age between 30 and 45 years, 0 otherwise) [V2]: V2 Heavy truck indicator (1 if heavy truck, 0 otherwise) [2021]			0.438 (3.02)			
V2′s Above 45 years indicator (1 if age above 45 years, 0 otherwise) [V2]: Weekend indicator (1 if crash occurred on					0.121 (2.49)	

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Table C1 (*continued*)

Variable	$\Delta\nu < 5$ mph		5 mph $\leq \Delta\nu \leq$ 10 mph		$\Delta\nu > 10$ mph	
	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers
weekend, 0 otherwise) [2021]						
V2 Other indicator (1 if other types of vehicles, 0 otherwise) [V2]: V1′s 18–30 years indicator (1 if age of between 18 and 30 years, 0 otherwise) [2020]		−0.387 (−2.64)				
V2 Other indicator (1 if other types of vehicles, 0 otherwise) [V2]: V2′s over speeding indicator (1 if exceeding the speed limit, 0 otherwise) [2020]		1.464 (2.47)				
V2 Heavy truck indicator (1 if heavy truck, 0 otherwise) [V2]: V2′s 30–45 years indicator (1 if age between 30 and 45 years, 0 otherwise) [2020]						−0.589 (−2.58)
Sunny indicator (1 if sunny, 0 otherwise) [V2]: V1′s over speeding indicator (1 if exceeding the speed limit, 0 otherwise) [2020]				0.243 (2.14)		
Sunny indicator (1 if sunny, 0 otherwise) [V2]: V2 Van indicator (1 if van, 0 otherwise) [2020]				0.432 (2.02)		
V1 front right indicator (1 if V1′s most damage area is front right bumper, 0 otherwise) [V1]: Left curve indicator (1 if left-curved alignment, 0 otherwise) [2020]			1.043 (2.37)			
V1 front right indicator (1 if V1′s most damage area is front right bumper, 0 otherwise) [V1]: V1′s over speeding indicator (1 if exceeding the speed limit, 0 otherwise) [2020]			0.532 (2.15)			
Rural areas indicator (1 if roadway is rural, 0 otherwise) [V1]: V1 front left indicator (1 if V1′s most damage area is front left bumper, 0 otherwise) [2021]	−0.493 (−2.57)					
Sunny indicator (1 if sunny, 0 otherwise) [V2]: Weekend indicator (1 if crash occurred on weekend, 0 otherwise) [2020]		−0.162 (−2.79)				
Day indicator (1 if crash occurred during daytime, 0 otherwise) [V1]: Cloudy indicator (1 if cloudy, 0 otherwise) [2019]			−0.432 (−2.43)			
Day indicator (1 if crash occurred during daytime, 0 otherwise) [V2]: V2 Heavy truck indicator (1 if heavy truck, 0 otherwise) [2021]				−0.343 (−2.43)		

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Table C1 (*continued*)

Variable	Δv < 5 mph		5 mph ≤ Δv ≤ 10 mph		Δv > 10 mph	
	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers	Following vehicle drivers	Leading vehicle drivers
Day indicator (1 if crash occurred during daytime, 0 otherwise) [V1]: V1 front left indicator (1 if V1′s most damage area is front left bumper, 0 otherwise) [2019]					−0.318 (−2.06)	
ρ	0.768 (18.27)		0.702 (21.29)		0.623 (19.27)	
Number of parameters (K)	74		77		78	
Number of observations (N)	5178		6125		8164	
Log-likelihood at zero	−5183.178		−6523.125		−9868.072	
Log-likelihood at convergence	−3458.904		−4397.750		−6923.072	
$\rho^2 = 1 - LL(\beta)/LL(0)$	0.333		0.326		0.298	
Corrected ρ^2	0.323		0.317		0.292	
Corrected AIC	7067.983		8951.486		14003.668	

Note: V1 and V2 denotes the following vehicle and leading vehicle, respectively. And "Male V1's driver (1 the V1's driver is male, 0 otherwise) [V1]" means that this variable is identified as a random parameter specific to V1 (following vehicle).

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