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Time-of-day variations and temporal instability of factors affecting injury severities in large-truck crashes

Ali Behnood[a], Fred Mannering[b,*]

[a] Lyles School of Civil Engineering, Purdue University, 550 Stadium Mall, West Lafayette, IN 47907-2051, USA
[b] Department of Civil and Environmental Engineering, University of South Florida, 4202 E Fowler Avenue, ENC 3300, Tampa, FL 33620, USA

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ABSTRACT

Using the data from large-truck crashes in Los Angeles over an eight-year period (January 1, 2010 to December 31, 2017), the variation in the influence of factors affecting injury severities during different time periods of the day (morning and afternoon) and from year to year is studied. To capture potential unobserved heterogeneity, random parameters logit models with heterogeneity in the means and variances of the random parameters were estimated considering three possible crash injury-severity outcomes (no injury, minor injury, and severe injury). Likelihood ratio tests were conducted to assess the transferability of model estimation results from different times of the day and from year to year. Marginal effects of the explanatory variables were also calculated to investigate the stability of individual parameter estimates on injury-severity probabilities across time-of-day/time-period combinations. A wide range of parameters were considered including drivers' characteristics, driver actions, truck's characteristics, weather and environmental conditions, and roadway attributes. The results show instability in the effect of factors that influence injury severities in large-truck vehicle crashes across daily time periods and from year to year. However, there were several variables that exhibited relatively stable effects on injury-severity probabilities including driver ethnicity, crashes occurring while backing, sideswipe crashes, hit-object crashes, parked-vehicle crashes, fixed-object crashes, and truck-driver at fault crashes. The findings of this study should be useful for decision makers and trucking companies to better regulate truck operations by time of day.

1. Introduction

Freight transportation systems play a significant role in the economic vitality of countries. The U.S. freight transportation system moves about 55 million tons of goods daily (U.S. Department of Transportation, 2017). As a dominant freight-carrier mode, trucks carry about 64% of the U.S. freight tonnage (U.S. Department of Transportation, 2017). However, due to the specific features of the large trucks[1], they impose significant safety issues on roadways. The large size and heavy weight of large trucks, while being advantageous in transporting freight efficiently, make them difficult to control, maneuver, and stop. Compared to crashes of other types of vehicles, truck crashes are associated with higher economic losses and traffic-flow disruptions. In addition, the size and weight of large trucks increase the likelihood of severe-injury crashes (Ahmed et al., 2018).

* Corresponding author.
E-mail addresses: abehnood@purdue.edu (A. Behnood), flm@usf.edu (F. Mannering).

[1] The National Highway Traffic Safety Administration (NHTSA) defines a large truck as any medium or heavy truck, excluding buses and motor homes, with a gross vehicle weight rating (GVWR) greater than 10,000 lb (National Highway Traffic Safety Administration, 2018). According to the Federal Highway Administration (FHWA), large trucks mainly include vehicles classified as class 5 to class 13.

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According to the National Highway Traffic Safety Administration (NHTSA), in truck-involved crashes from 2007 to 2016, 72% of the fatalities were the occupants of other vehicles and 11% of the fatalities were not vehicle occupants (pedestrians, pedal cyclists, etc.) (National Highway Traffic Safety Administration, 2018). This clearly shows that large trucks significantly affect the safety of other road users. However, a review of the literature shows that, although the severity of crashes involving large trucks has been the focus of many previous studies, comparatively few studies have investigated the temporal stability of the factors influencing the injury severities of truck-involved crashes (by time of day and by year). The intent of the current paper is to develop statistical models that consider the possibility that the effect of variables that determine resulting injury severities in large-truck crashes may vary by time-of-day and from year to year.

There are at least two reasons to suspect that the factors affecting injury severity change over the day. First, it is possible that human behavior varies by time of day (due to possible fatigue, bio-rhythms, etc.). In fact, there is a considerable body of literature that suggests this. For example, Leone et al. (2017) found people to be more cautious in decision making in the morning, Hasler et al. (2014) found temporal differences in people's neural responses to monetary awards, and Fabbri et al. (2008) found that people had higher subjective alertness in mid-day relative to mornings. And second, unobserved factors related to visibility, lighting, and so on, may vary, particularly throughout the day. Both suggest that time-of-day variations may be playing a significant role in resulting injury severities, and that this role may go beyond the simple use of indicator variables (indicating various time of day intervals) in statistical models. This paper considers the possibility that the effect of all factors that determine injury severities may vary by time of day as opposed to a simple shift in probabilities that results with the use of indicator variables.

With regard to the possibility that the effects of injury-severity determinants change over time (from year to year), there is a growing body of empirical evidence that supports this possibility. For example, using a Markov switching approach, research by Malyshkina and Mannering (2009) and Xiong and Mannering (2013) found the influence of factors determining injury severity shifted over time. In other work, using data from Chicago, Behnood and Mannering (2015) found that the effect of factors that determined driver injury severities in single-vehicle automobile/truck crashes significantly varied from year to year, and Behnood and Mannering (2016) also found that the effect of factors influencing pedestrian-injury severities resulting from crashes with automobiles and trucks varied significantly from year to year. Mannering (2018) points out that such year to year changes are likely to result from several factors including changes in driver decision making, information processing, risk assessment, and safety attitudes that are driven by changes in vehicle, communication, and information technologies.

The remainder of the paper is organized as follows. We begin with summarizing the findings of the current literature regarding the factors affecting the crash/driver injury severities in crashes involving large trucks. This is followed by a detailed literature review summarizing the methodological approaches used to study injury severities in large-truck crashes. The methodological approach and data used in the current study are then presented. Finally, a discussion on the model estimation findings is provided along with a summary and conclusions.

2. Review of factors affecting the injury-severity of crashes involving large trucks

A wide range of factors have been found to affect injury-severity outcomes in previous large-truck injury-severity studies. Table 1 presents a summary of past research findings with factors found to influence injury severity grouped by driver characteristics, driver actions, crash characteristics, truck characteristics, roadway attributes, environmental conditions, and other variables. Driver characteristics include the driver-related and physiological characteristics of large-truck drivers that significantly affect injury-severity outcomes. Examples of these variables include driver age, gender, and apparent physical condition (alcohol/drug-impaired, fatigued, asleep/fainted). Drivers' actions include variables such as speeding and failing to grant right of way. Crash characteristics include variables such as the type of crash (rollover, rear-end, etc.), movements prior to crash (turning, etc.), and number of vehicles involved in the crash. Truck characteristics include specific features of the truck involved in the crash such as size and weight of the truck, cargo type, and type of the carried goods (hazardous materials, etc.). Roadway attributes include the presence of various types of traffic-control signs and roadway geometry conditions. Environmental conditions include various weather conditions (fog, rain, snow, etc.), roadway surface conditions (dry or wet), and visibility and lightening. Other crash-related factors (other than the above-mentioned factors) are classified as "other variables" include variables such as the time of the crash (day of the week and time of the day), and characteristics of the other vehicles involved in the crash.

Note from the presentation of past findings in Table 1 that some variables were found to have similar effects on crash-injury severities in terms of the direction of the effect, and others have been found to have opposite effects from study to study. This observed disparity of findings could be due to several reasons such as[2]; temporal instability of the data, spatial instability of the data, insufficient number of observations, incompleteness of the data[3], variations in methodological approaches used in past research, and unobserved heterogeneity in the data.

[2] Detailed discussion regarding the variation in the direction of explanatory variables is given in previous studies (see Alnawmasi and Mannering, 2019; Behnood and Mannering, 2016; Behnood and Mannering, 2015; Mannering et al., 2016).

[3] There are also parameters that might be reported as statistically significant factors in some studies while some other studies do not report them as significant factors. This could be the result of missing variables or multicollinearity in the data which may make it difficult to find two highly correlated explanatory variables both statistically significant.

Table 1
Significantly affecting variables on the injury severity of truck-involved crashes: A summary of findings in previous studies.

Variables	Findings
Driver characteristics	
Age	Inconsistent trends have been reported regarding the effects of age on injury-severity of crashes involving large trucks. For example, Chang and Mannering (1999) reported that young drivers increase the likelihood of property damage only in truck crashes. Young drivers have also been reported to decrease the likelihood of no-injury in truck crashes (Pahukula et al., 2015), and increase the likelihood of fatalities (Zheng et al., 2018). Chen and Chen (2011) reported that old drivers (older than 50 years old) increased the likelihood of incapacitating injury/fatality in single-vehicle crashes while they had opposite effects in multivehicle crashes. The contradicting observations regarding the age might be due to the unobserved heterogeneity associated with "age" (physical and health condition of the driver). In addition, in previous research, age has been mainly treated as a categorical factor, where researchers have defined their own age categories
Gender	Like age, gender has also been found to have complicated effects on the injury severity of large-truck crashes. However, a fair number of studies have reported that female drivers increase the likelihood of severe and fatal injuries (Chang and Mannering, 1999; Khorashadi et al., 2005; Pahukula et al., 2015). Chen and Chen (2011) reported that in crashes involving large trucks, female drivers increased the likelihood of incapacitating injury/fatality in single-vehicle crashes while they had opposite effects in multi-vehicle crashes. It should be noted that the number of female drivers operating large trucks are much lower than that of male drivers. This significantly affects the number of observations associated with the female drivers in large-truck crashes. Therefore, some crash-related studies may suffer from insufficient observations for female drivers
Fatigued – asleep/fainted	Fatigued drivers increase the probability of severe injuries during peak hours (Hao et al., 2016). Fatigued drivers increase the likelihood of incapacitating injury/fatality in multi-vehicle crashes and have the opposite effects in single-vehicle crashes (Chen and Chen, 2011). Asleep/fainted drivers increase the likelihood of more severe injuries (Chen and Chen, 2011)
Alcohol-impaired	Alcohol consumption does not significantly affect the injury severity of truck crashes (Zhu and Srinivasan, 2011).
Seat-belt and air bag	In single-vehicle and multi-vehicle crashes involving large trucks, the use of seat-belts and the availability of airbags are associated with less severe injuries (Chang and Mannering, 1999; Chen and Chen, 2011; Zhu and Srinivasan, 2011)
Driver actions	
Speeding	Speeding increases the likelihood of severe and fatal injuries in truck crashes (Ahmed et al., 2018; Chang and Mannering, 1999). Speeding has also been reported to have random effects on driver-injury severities involving large trucks in both single-vehicle and multi-vehicle crashes (Chen and Chen, 2011)
Failing to grant right of way	"Failing to grant right of way" decreases the likelihood of possible injuries and increases the likelihood of property damage only and severe injuries (Chang and Mannering, 1999)
Improper passing	Improper passing as the primary collision factor decreases the likelihood of more severe injuries in both rural and urban areas (Khorashadi et al., 2005)
Crash characteristics	
Entering/leaving driveway	Crashes when trucks enter/leave the driveway are associated with higher likelihood of possible injuries (Chang and Mannering, 1999)
Right/left turn	The likelihood of severe injuries in truck crashes increases when a vehicle makes a right/left turn (Chang and Mannering, 1999). In rural/urban areas, a right/left turn is associated with decreased likelihood of more severe injuries (Khorashadi et al., 2005)
Rear end	Rear end crashes are associated with a higher probability of having a severe injury in truck-involved crashes (Chang and Mannering, 1999). In rural areas, rear end crashes increase the likelihood of complaint of pain and visible injury outcomes and decrease the likelihood of no injury and severe-fatal injury outcomes while in urban areas they only decrease the likelihood of complaint of pain outcome and increase the likelihood of other injury-severity outcomes (Khorashadi et al., 2005)
Collision with opposite direction	Collisions with opposite directions increases the likelihood of more severe injuries (Zheng et al., 2018)
Ran off the roadway	Ran off the roadway increase the likelihood of minor and severe injuries in single-vehicle and multi-vehicle truck-involved crashes (Chen and Chen, 2011)
Number of vehicles	Truck crash severity increases with an increase in the number of vehicles in the crash (Zheng et al., 2018)
Truck characteristics	
Vehicle weight	Heavy gross vehicle weight (over 20,000 lb) increase the likelihood of more severe injuries (Zheng et al., 2018)
Cargo body	Cargo tank, flatbed, and grain trucks, or trucks towing another vehicle are associated with higher injury severities (Zheng et al., 2018)
	Single unit truck in single-vehicle and multi-vehicle crashes, respectively, decreases and increases the likelihood of incapacitating injury/fatal (Chen and Chen, 2011). Carrying hazardous materials is associated with increased likelihood of more severe injuries (Chen and Chen, 2011)
Roadway attributes	
Speed control	Speed control for truck drivers significantly reduces the truck driver's injury severity (Hao et al., 2016)
Posted speed limit	Higher speed limits increase injury severity in truck crashes (Chang and Mannering, 1999)
Stop sign/flasher	A fair number of studies has reported that stop sign/flasher decreases the likelihood of more severe injuries (Chen and Chen, 2011). In single-vehicle crashes involving large truck, stop sign/flasher decreases the likelihood of both possible injury/non-incapacitating injury and incapacitating injury/fatal outcomes
Highway-railroad crossing	Highway-railroad crossing increases the likelihood of more severe injuries (Hao et al., 2016)
Concrete median barrier	Concrete median barrier increases the likelihood of severe/fatal injuries (Khorashadi et al., 2005)

(*continued on next page*)

Table 1 (*continued*)

Variables	Findings
Environmental conditions	
Visibility	Poor visibility tends to increase the likelihood of severe injuries in large truck crashes (Hao et al., 2016)
Weather condition	Bad weather such as sleet, snow, fog, rain, and cloudiness increase the likelihood of more severe injuries (Ahmed et al., 2018; Hao et al., 2016; Zheng et al., 2018). In urban areas, rain decreases the likelihood of more severe injuries (Khorashadi et al., 2005). Strong crosswind increases the likelihood of more severe injuries (Zheng et al., 2018). Good weather increases the likelihood of fatal crashes (Zheng et al., 2018)
Roadway surface condition	Dry road surface condition tends to increase the likelihood of severe injury and fatal injury in truck crashes (Chang and Mannering, 1999). Wet road surface condition tends to increase the likelihood of more severe injuries (Zheng et al., 2018). Snow/slush road surface has random effects on driver-injury severity in single-vehicle and multi-vehicle truck-involved accidents (Chen and Chen, 2011). In multi-vehicle accidents, snow/slush road surface increase the likelihood of possible injury/non-incapacitating injury severities and decrease the likelihood of incapacitating injury/fatal severities. In single-vehicle accidents, snow/slush road surface decreases both possible injury/non-incapacitating injuries and incapacitating injury/fatal injuries. Ice road surface increases the likelihood of no-injury crashes (Chen and Chen, 2011)
Darkness	Dark condition including dawn and dusk is associate with an increase in the probability of severe more severe injuries (Pahukula et al., 2015)
Other variables	
Time of crash	Peak-hours crashes increase the probability of driver's injury severity in truck-involved crashes (Chang and Mannering, 1999; Hao et al., 2016; Zhu and Srinivasan, 2011). Truck crashes on weekends are associated with increased likelihood of property damage only in truck crashes (Chang and Mannering, 1999)
Other party type	Truck accidents with passenger cars, small trucks, and large trucks are associated with higher likelihood of property damage only crashes (Chang and Mannering, 1999; Khorashadi et al., 2005)

3. Methodological approaches used in large-truck injury-severity

Previous research has used a wide variety of methodological approaches to study the injury-severity of crashes involving large trucks (Table 2 presents a summary). Many of the previous studies on the injury-severity of large-truck crashes have used a discrete-outcome modeling because available data on traffic-related crashes typically report discrete outcomes for injury-levels. Therefore, logit, probit, and their extension statistical models have been used in most prior studies.[4] In an early work, Chang and Mannering (1999) used a nested logit model to study the injury-severities of the most severely injured vehicle occupant in truck-involved and non-truck-involved accidents using data from the State of Washington during 1994. To investigate the difference between rural and urban driver-injury severities in large-truck crashes in California from 1997 to 2000, Khorashadi et al. (2005) used a standard multinomial logit model. In other work, Hao et al. (2016) used ten-years of accident data starting from 2002 to develop an ordered probit model for the driver injury-severities in truck-involved accidents at highway-rail grade crossing in the United States.

Most recent studies have recognized the importance of unobserved heterogeneity in model estimation. In crash-related data, unobserved heterogeneity may arise from various sources such as unobserved driver characteristics, vehicle characteristics, roadway attributes, and environmental factors (Mannering et al., 2016). In general, previous research has shown that, depending on the nature of the data, models accounting for unobserved heterogeneity can be statistically superior. These heterogeneity models can account for observation-specific variations in the effects of explanatory variables (Behnood et al., 2014; Anastasopoulos et al., 2016; Behnood and Mannering, 2016; Sarwar and Anastasopoulos, 2017). Specifically, regarding the study of injury-severity of large-truck crashes, Chen and Chen (2011), Islam and Hernandez (2013b), and Pahukula et al., (2015) estimated random parameters multinomial logit models, and Islam and Hernandez (2013a) and Uddin and Huynh (2018) estimated random-parameters ordered probit models.

However, in the study of large-truck[5] injury severities, the authors are not aware of any research to date that has extended random parameters models to account for possible heterogeneity in the means and variance of random parameters. Such an extension allows a more generalized approach to capture unobserved heterogeneity (Mannering et al., 2016) and this has been

[4] For injury severity analysis in general (including studies not restricted to large-truck involvement), a wide variety of ordered and unordered discrete outcome methodological approaches have been used to study the crash-injury severities including ordered logit/probit models, multinomial logit models, latent class models, Markov-switching logit models, random parameters logit models with heterogeneity in means and/or variances, and others (Savolainen et al., 2011; Mannering and Bhat, 2014; Mannering et al., 2016). While modeling approaches have become more sophisticated over time, it is important to note that the choice of one modeling approach over another is often data-dependent and thus a universal statement of the methodological superiority of one method over another cannot be made.

[5] The injury-severity analysis could benefit from estimating separate models for different truck classes (truck class 5 to truck class 13) and/or service types (long haul vs. short haul, less-than-truckload vs. truckload, etc.). Identifying different classes of data that share common features to estimate separate models for different sub-groups of data has been the approach used by several researchers (Morgan and Mannering, 2011; Behnood et al., 2014; Anderson and Hernandez, 2017; Fountas et al., 2019). As an example, Behnood and Mannering (2016) studied the effects of occupants on drive-injury severities in single-vehicle crashes by using three different injury-severity sub-groups that were defined based on the number of occupants in the vehicles. However, careful consideration needs to be given to having a sufficient number of observations for model estimation when dealing with sub-group estimations. In the current study, to account for the unobserved heterogeneity in the data, a random parameters logit model with heterogeneity in the means and variances of the random parameters was used. The unobserved heterogeneity found with such an estimation could be capturing the effect of truck-class effects as well as other sources of unobserved heterogeneity.

Table 2
Summary of methodological approaches previously used in the study of large-truck crashes injury severities.

Methodological Approach	Previous Research
Multinomial logit model	Khorashadi et al. (2005)
Nested Logit model	Chang and Mannering (1999)
Ordered logit/probit model	Hao et al. (2016), Uddin and Huynh (2018)
Random parameters ordered probit model	Islam and Hernandez (2013a), Uddin and Huynh (2018)
Heteroskedastic ordered probit model	Lemp et al. (2011), Zhu and Srinivasan (2011)
Spatial generalized ordered probit model	Zou et al. (2017)
Random parameters (mixed) logit model	Chen and Chen (2011), Islam and Hernandez (2013b), Pahukula et al. (2015)
Gradient boosting data mining model	Zheng et al. (2018)
Bayesian binary logit model	Ahmed et al. (2018)

shown to produce statistically superior models in a number of recent crash-injury-severity studies (Seraneeprakarn et al., 2017; Behnood and Mannering, 2017b; Waseem et al., 2019; Alnawmasi and Mannering, 2019). The current paper will allow for possible heterogeneity in the means and variances of random parameters while studying various temporal aspects of injury severities in large-truck crashes.

4. Methodological approach

Heterogeneity models include a wide variety of models such as random parameters logit models (Anastasopoulos and Mannering, 2011; Cerwick et al., 2014; Behnood and Mannering, 2015, 2017a,b,c; Seraneeprakarn et al., 2017), latent class models (Xiong and Mannering, 2013; Behnood et al., 2014; Yasmin et al., 2014; Fountas et al. 2018a), random parameters ordered probit model (Fountas and Anastasopoulos, 2017, 2018; Fountas et al. 2018b), bivariate/multivariate models with random parameters (Abay et al., 2013; Russo et al., 2014), and Markov switching models (Malyshkina and Mannering, 2009; Xiong et al., 2014).

In this paper, crash-injury severities (the most severely injured person[6] in a crash involving a large truck) are studied by considering three discrete crash-injury severity levels; no injury (property damage only), minor injury (possible injury and non-incapacitating), and severe injury (incapacitating or fatal). To arrive at a random parameters logit model that allows for heterogeneity in the means and variances of the random parameters, a function that determines the crash injury-severity of the most severely injured person in a crash involving a large truck is defined as;

$$S_{kn} = \boldsymbol{\beta}_k \boldsymbol{X}_{kn} + \varepsilon_{kn} \tag{1}$$

where S_{kn} is an injury-severity function determining the probability of large-truck crash injury-severity category k in crash n, $\mathbf{X}_{kn}$ is a vector of explanatory variable that affect large-truck crash injury-severity level k, $\boldsymbol{\beta}_k$ is a vector of estimable parameters, and ε_{kn} is the error term which is assumed to be generalized extreme value distributed. The outcome probabilities of a random parameters logit model of crash injury severity, which accounts for unobserved heterogeneity in the data, can be derived as (McFadden and Train, 2000; Washington et al., 2011),

$$P_n(k) = \int \frac{EXP(\boldsymbol{\beta}_k \boldsymbol{X}_{kn})}{\sum_{\forall K} EXP(\boldsymbol{\beta}_k \boldsymbol{X}_{kn})} f(\boldsymbol{\beta}|\boldsymbol{\varphi}) d\boldsymbol{\beta} \tag{2}$$

where $P_n(k)$ is the probability of crash n having the crash injury severity k, $f(\boldsymbol{\beta}|\boldsymbol{\varphi})$ is the density function of $\boldsymbol{\beta}$ with $\boldsymbol{\varphi}$ referring to vector of parameters (mean and variance) of that density function, and all other terms are as previously defined. To account for the unobserved heterogeneity in the means and variances of random parameters, $\boldsymbol{\beta}_{kn}$ is treated as a vector of estimable parameters that varies across crashes as (Seraneeprakarn et al., 2017; Behnood and Mannering, 2017b; Waseem et al., 2019; Alnawmasi and Mannering, 2019):

$$\boldsymbol{\beta}_{kn} = \beta_k + \Theta_{kn} \boldsymbol{Z}_{kn} + \sigma_{kn} EXP(\boldsymbol{\omega}_{kn} \boldsymbol{W}_{kn}) v_{kn} \tag{3}$$

where β_k is the mean parameter estimate across all crashes, $\mathbf{Z}_{kn}$ is a vector of explanatory variables that captures heterogeneity in the mean that affect large-truck injury severity level k, $\boldsymbol{\Theta}_{kn}$ is a corresponding vector of estimable parameters, $\mathbf{W}_{kn}$ is a vector of explanatory variables that captures heterogeneity in the standard deviation σ_{kn} with corresponding parameter vector $\boldsymbol{\omega}_{kn}$, and v_{kn} is a disturbance term.

In this study, a wide range of density functions were considered in the empirical analysis including the normal, lognormal, triangular, and uniform distributions. However, the empirical analysis showed that no distribution was statistically superior to the normal distribution. The model estimation was undertaken using simulated likelihood with 1000 Halton draws (McFadden and Train, 2000). Marginal effects, which give the effect that one-unit increase in an explanatory variable

[6] The crash injury-severity of the truck driver was also initially considered. However, it was observed that the "severe injury" outcome did not have a sufficient number of observations to produce reliable results. One reason for this could be due to the large size and heavy weight of trucks, which makes truck drivers less likely to be severely injured. However, crashes involving large trucks significantly affect the injury severity of other road-users. Therefore, in the current study, it was decided to statistically assess the injury-severity of the most injured person as opposed to the injury-severity of the truck driver.

Table 3
Crash injury frequency and percentage distribution by different time periods.

Time period	Severe injury frequency (%)	Minor injury frequency (%)	No injury frequency (%)	Total (%)
Morning (2010–13)	35 (2.10)	449 (26.98)	1180 (70.91)	1664
Morning (2014–17)	31 (1.98)	453 (28.93)	1082 (69.09)	1566
Afternoon (2010–13)	39 (3.01)	486 (37.50)	771 (59.49)	1296
Afternoon (2014–17)	44 (3.63)	463 (38.23)	284 (58.13)	1211
Total (%)	149 (2.60)	1851 (32.26)	3737 (65.14)	5737 (100)

has on the injury-severity outcome probabilities, were also calculated to further interpret the model estimation results (Washington et al., 2011).

5. Empirical setting

The data used for this study were collected from police-reported crashes that involved large trucks in Los Angeles over an eight-year period from January 1, 2010 to December 31, 2017. In addition to resulting injury severities, the available crash data provided comprehensive information on crash-related factors (such as primary cause of crash and events contributing to crash), driver attributes (such as age, gender, and physical condition), vehicle characteristics (such as type of the vehicle and model year of the vehicle), roadway, weather, and environmental conditions (such as road surface condition and light), and time and location of the crash.

6. Temporal stability tests

After extensive empirical testing[7], it was determined that models that produced the best statistical results were, for different times of day, morning (6:00–11:59 A.M.) and afternoon (12:00–5:59 P.M.)[8], and for the years from 2010 to 2013 and from 2014 to 2017. Table 3 presents the injury distribution in these time-of-day and time-period combinations. Table 4 provides the summary statistics for variables found to be statistically significant in the estimated models, and Tables 5–8 present the model estimation results for the four time-of-day/time-period combinations. To statistically test if injury-severities in crashes involving large trucks were significantly different across different times during the day (morning and afternoon) and different time periods (2010–13 and 2014–17), a series of likelihood ratio tests were conducted. The test statistic is (see Washington et al., 2011),

$$X^2 = -2\left[LL(\boldsymbol{\beta}_{m_2 m_1}) - LL(\boldsymbol{\beta}_{m_1})\right] \tag{4}$$

where $LL(\boldsymbol{\beta}_{m_2 m_1})$ is the log-likelihood at convergence of a model containing converged parameters of time-of-day/time-period data m_2, while using data from time-of-day/time-period data m_1, and $LL(\boldsymbol{\beta}_{m_1})$ is the log-likelihood at convergence of the model using time-of-day/time-period data m_1, with the same explanatory variables but with parameters no longer restricted to the converged parameters of time-of-day/time-period data m_2. This process is repeated for all combinations of the four time-of-day/time-period data sets giving a total of 12 likelihood ratio tests. The resulting value X^2 in Eq. (4) is χ^2 distributed, with degrees of freedom equal to the number of estimated parameters, and can be used to determine if the null hypothesis that the parameters are equal between any two time-of-day/time-period data sets can be rejected. The results of these 12 tests are presented in Table 9. This table shows that in all cases the null hypothesis that the 12 time-of-day/time-period combinations tested produced equal parameters can be rejected with over 99% confidence, suggesting that separate models are warranted for the time-of-day and time-periods used in this analysis. These results are in line with the findings of previous research efforts that have studied of crash-injury severity models across different time periods while considering crashes involving all vehicle types, large trucks and all others (Alnawmasi and Mannering, 2019; Behnood and Mannering, 2015, 2016).

7. Discussion of estimation results

The estimation results provided in Tables 5 through 8 show plausible parameter sign and very good overall model fit with ρ^2 values exceeding 0.60 in three of the models and exceeding 0.50 in the fourth. It should be noted that, although heterogeneity in the means of random parameters was found to be statistically significant in some of the models, heterogeneity in the variances of random parameters was not found to be statistically significant in any of the estimated models.

[7] With regard to time-of-day, we focused on the time periods to cover morning peak hours and afternoon peak hours. For yearly classification of the data, several scenarios were assumed and tested for potential temporal stability using likelihood ratio tests. The classifications used in this study included: (a) 2010–2011, 2012–2013, 2014–2015, and 2016–2017; (b) 2010–2011, 2012–2015, and 2016–2017, and (c) 2010–2013 and 2014–2017. Of these, the classification of data into the years from 2010 to 2013 and from 2014 to 2017 provided the most statistically defensible results as indicated by likelihood ratio tests.

[8] Other times of day (late evening and early morning) produced too few observations to reliably test for temporal stability.

Table 4
Descriptive statistics of the variables used in the estimations.

Variable	Morning 2010–2013		Morning 2014–2017		Afternoon 2010–2013		Afternoon 2014–2017	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Weekday (1 if crash occurred during the weekday; 0 otherwise)	0.938	0.242	0.934	0.249	0.892	0.310	0.903	0.295
Weekend (1 if crash occurred during the weekend; 0 otherwise)	0.063	0.242	0.066	0.249	0.108	0.310	0.097	0.295
At fault (1 if truck driver is at fault; 0 otherwise)	0.517	0.500	0.525	0.499	0.522	0.500	0.500	0.500
Male (1 if truck driver is male; 0 otherwise)	0.959	0.198	0.958	0.201	0.939	0.239	0.936	0.246
Young-age (1 if truck driver is younger than 31 years old; 0 otherwise)	0.120	0.325	0.127	0.333	0.145	0.352	0.158	0.365
Middle age (1 if truck driver is younger than 51 years old and older than 30 years old; 0 otherwise)	0.560	0.496	0.493	0.500	0.525	0.499	0.486	0.500
Old-age (1 if truck driver is older than 50 years old; 0 otherwise)	0.320	0.467	0.380	0.485	0.329	0.470	0.357	0.479
Had not been drinking (1 if apparent physical condition of driver is had not been drinking; 0 otherwise)	0.949	0.220	0.923	0.267	0.927	0.259	0.898	0.302
Had been drinking, under influence (1 if apparent physical condition of driver is had been drinking and under influence; 0 otherwise)	0.002	0.049	0.003	0.050	0.011	0.103	0.008	0.091
Stopped (1 if movement preceding collision is stopped; 0 otherwise)	0.133	0.340	0.148	0.355	0.102	0.302	0.124	0.329
Proceeding straight (1 if movement preceding collision is proceeding straight; 0 otherwise)	0.416	0.493	0.429	0.495	0.458	0.498	0.449	0.497
Making right turn (1 if movement preceding collision is making right turn; 0 otherwise)	0.127	0.333	0.115	0.319	0.140	0.347	0.120	0.325
Making left turn (1 if movement preceding collision is making left turn; 0 otherwise)	0.092	0.289	0.080	0.271	0.100	0.299	0.089	0.285
Making U-turn (1 if movement preceding collision is making U-turn; 0 otherwise)	0.009	0.095	0.011	0.104	0.012	0.110	0.010	0.099
Backing (1 if movement preceding collision is backing; 0 otherwise)	0.098	0.297	0.102	0.303	0.073	0.259	0.083	0.277
Asian (1 if truck driver is Asian; 0 otherwise)	0.012	0.109	0.008	0.091	0.013	0.114	0.015	0.121
Black (1 if truck driver is Black; 0 otherwise)	0.213	0.409	0.218	0.413	0.166	0.372	0.181	0.385
Hispanic (1 if truck driver is Hispanic; 0 otherwise)	0.505	0.500	0.550	0.498	0.492	0.500	0.528	0.499
White (1 if truck driver is White; 0 otherwise)	0.216	0.411	0.156	0.363	0.258	0.437	0.183	0.387
New truck (1 if truck is less than 6 years old; 0 otherwise)	0.363	0.481	0.355	0.479	0.357	0.479	0.372	0.484
Old truck (1 if truck is above 15 years old; 0 otherwise)	0.077	0.266	0.112	0.315	0.137	0.344	0.142	0.349
Intersection (1 if intersection-related crash; 0 otherwise)	0.205	0.404	0.201	0.401	0.225	0.418	0.237	0.425
Clear (1 if weather condition is clear; 0 otherwise)	0.846	0.361	0.881	0.324	0.899	0.301	0.919	0.273
Cloudy (1 if weather condition is cloudy; 0 otherwise)	0.125	0.331	0.097	0.296	0.069	0.253	0.064	0.244
Rainy (1 if weather condition is rainy; 0 otherwise)	0.025	0.155	0.015	0.120	0.022	0.148	0.013	0.114
Driving under the influence of alcohol or drug (1 if violation category is driving under the influence of alcohol or drug; 0 otherwise	0.009	0.095	0.006	0.080	0.019	0.135	0.015	0.121
Unsafe speed (1 if violation category is unsafe speed; 0 otherwise)	0.165	0.371	0.167	0.373	0.160	0.367	0.167	0.373
Wrong side of road (1 if violation category is wrong side of road; 0 otherwise)	0.038	0.191	0.027	0.162	0.034	0.181	0.037	0.189
Improper passing (1 if violation category is improper passing; 0 otherwise)	0.084	0.277	0.073	0.260	0.052	0.223	0.042	0.201
Unsafe lane change (1 if violation category is unsafe lane change; 0 otherwise)	0.124	0.329	0.125	0.331	0.137	0.344	0.120	0.325
Improper turning (1 if violation category is improper turning; 0 otherwise)	0.150	0.357	0.178	0.382	0.133	0.340	0.160	0.367
Truck right of way (1 if violation category is truck right of way; 0 otherwise)	0.085	0.279	0.075	0.263	0.122	0.327	0.121	0.327
Traffic signals and signs (1 if violation category is traffic signals and signs; 0 otherwise)	0.032	0.177	0.043	0.202	0.042	0.202	0.037	0.189
Felony (1 if crash is felony hit-and-run; 0 otherwise)	0.005	0.069	0.014	0.118	0.016	0.126	0.019	0.137
Misdemeanor (1 if crash is misdemeanor hit-and-run; 0 otherwise)	0.099	0.298	0.096	0.294	0.083	0.276	0.112	0.316
Not Hit and Run (1 if crash is not hit-and-run; 0 otherwise)	0.897	0.304	0.890	0.313	0.900	0.299	0.869	0.338
Head-on (1 if type of crash is head-on; 0 otherwise)	0.031	0.174	0.029	0.167	0.037	0.189	0.040	0.197
Sideswipe (1 if type of crash is sideswipe; 0 otherwise)	0.488	0.500	0.462	0.499	0.408	0.492	0.403	0.491
Rear end (1 if type of crash is rear end; 0 otherwise)	0.144	0.351	0.160	0.366	0.180	0.384	0.187	0.390
Broadside (1 if type of crash is broadside; 0 otherwise)	0.152	0.359	0.144	0.351	0.181	0.385	0.191	0.393
Hit object (1 if type of crash is hit object; 0 otherwise)	0.098	0.297	0.109	0.311	0.113	0.316	0.094	0.292
Pedestrian (1 if truck is involved with Pedestrian; 0 otherwise)	0.023	0.149	0.025	0.156	0.033	0.179	0.026	0.160
Other motor vehicle (1 if truck is involved with other motor vehicle; 0 otherwise)	0.657	0.475	0.656	0.475	0.679	0.467	0.675	0.468
Parked motor vehicle (1 if truck is involved with parked motor vehicle; 0 otherwise)	0.132	0.338	0.142	0.349	0.100	0.300	0.131	0.338
Bicycle (1 if truck is involved with bicycle; 0 otherwise)	0.019	0.135	0.017	0.130	0.024	0.153	0.017	0.127
Fixed object (1 if truck is involved with fixed object; 0 otherwise)	0.118	0.322	0.123	0.328	0.127	0.333	0.120	0.325
Dry (1 if road surface condition is dry; 0 otherwise)	0.942	0.234	0.960	0.197	0.944	0.231	0.961	0.193
Wet (1 if road surface condition is wet; 0 otherwise)	0.052	0.221	0.031	0.174	0.041	0.198	0.029	0.168
Daylight (1 if light condition is daylight; 0 otherwise)	0.975	0.157	0.976	0.154	0.962	0.191	0.957	0.203
Dark – street lights (1 if light condition is dark – street lights; 0 otherwise)	0.005	0.069	0.005	0.071	0.022	0.148	0.024	0.153
Passenger car/station wagon (1 if at fault vehicle type is passenger car/station wagon; 0 otherwise)	0.225	0.417	0.226	0.418	0.214	0.410	0.249	0.433
Truck or truck tractor (1 if at fault vehicle type is truck or truck tractor; 0 otherwise)	0.518	0.500	0.526	0.499	0.523	0.500	0.501	0.500

Table 5
Random parameters logit model (allowing for possible heterogeneity in means and variances) results of large-truck crash injury-severities during the morning time, 2010–2013.

Variable	Parameter estimate	t-Stat.	Marginal effects		
			No injury	Minor injury	Severe injury
Defined for severe injury					
Constant	−0.672	−0.64			
Hispanic (1 if truck driver is Hispanic; 0 otherwise)	1.319	0.62	−0.0027	−0.0013	0.0039
Standard deviation of "Hispanic"	*1.858*	*1.74*			
Sideswipe (1 if type of crash is sideswipe; 0 otherwise)	−1.412	−1.64	0.0013	0.0003	−0.0016
Other motor vehicle (1 if truck is involved with other motor vehicle; 0 otherwise)	−2.205	−4.69	0.0097	0.0077	−0.0174
Daylight (1 if light condition is daylight; 0 otherwise)	−1.949	−2.34	0.0142	0.0127	−0.0269
Defined for minor injury					
Male (1 if truck driver is male; 0 otherwise)	−2.209	−3.61	0.0700	−0.0847	0.0147
Standard deviation of "Male"	*1.859*	*2.63*			
At fault (1 if truck driver is at fault; 0 otherwise)	0.441	1.79	0.3675	−0.3383	−0.0292
Traffic signals and signs (1 if violation category is traffic signals and signs; 0 otherwise)	0.990	1.62	−0.0027	0.0032	−0.0005
Felony (1 if crash is felony hit-and-run; 0 otherwise)	8.530	3.57	−0.0018	0.0019	−0.0001
Head-on (1 if type of crash is head-on; 0 otherwise)	1.306	2.08	−0.0040	0.0045	−0.0005
Pedestrian (1 if truck is involved with Pedestrian; 0 otherwise)	1.567	2.23	−0.0023	0.0041	−0.0018
Bicycle (1 if truck is involved with bicycle; 0 otherwise)	2.368	2.88	−0.0027	0.0046	−0.0019
Dry (1 if road surface condition is dry; 0 otherwise)	−0.808	−1.77	0.0575	−0.0629	0.0053
Defined for no injury					
Constant	−0.437	−0.40			
Parked motor vehicle (1 if truck is involved with parked motor vehicle; 0 otherwise)	4.256	2.41	0.0049	−0.0044	−0.0005
Standard deviation of "Parked motor vehicle"	*2.941*	*1.82*			
Weekday (1 if crash occurred during the weekday; 0 otherwise)	1.615	3.28	0.1264	−0.1146	−0.0119
Stopped (1 if movement preceding collision is stopped; 0 otherwise)	1.640	3.58	0.0182	−0.0163	−0.0019
Proceeding straight (1 if movement preceding collision is proceeding straight; 0 otherwise)	2.313	3.72	0.0822	−0.0766	−0.0056
Backing (1 if movement preceding collision is backing; 0 otherwise)	4.215	4.90	0.0171	−0.0162	−0.0009
Black (1 if truck driver is Black; 0 otherwise)	1.491	3.89	0.0210	−0.0189	−0.0021
White (1 if truck driver is White; 0 otherwise)	0.621	2.10	0.0108	−0.0094	−0.0014
Intersection (1 if intersection-related crash; 0 otherwise)	−0.756	−2.86	−0.0158	0.0138	0.0020
Improper passing (1 if violation category is improper passing; 0 otherwise)	0.911	1.90	0.0042	−0.0041	−0.0002
Not Hit and Run (1 if crash is not hit-and-run; 0 otherwise)	−5.069	−4.58	−0.4169	0.3785	0.0384
Sideswipe (1 if type of crash is sideswipe; 0 otherwise)	2.375	4.95	0.0824	−0.0803	−0.0021
Hit object (1 if type of crash is hit object; 0 otherwise)	2.724	3.57	0.0075	−0.0061	−0.0013
Fixed object (1 if truck is involved with fixed object; 0 otherwise)	3.491	4.43	0.0116	−0.0093	−0.0022
Heterogeneity in the mean of the random parameters					
Male: Proceeding straight (1 if movement preceding collision is proceeding straight; 0 otherwise)	1.621	2.66			
Hispanic: Proceeding straight (1 if movement preceding collision is proceeding straight; 0 otherwise)	1.796	2.01			
Hispanic: Not Hit and Run (1 if crash is not hit-and-run; 0 otherwise)	−3.806	−2.21			
Model statistics					
Number of observations			1664		
Log-likelihood at zero, $LL(0)$			−1828.09		
Log-likelihood at convergence, $LL(\boldsymbol{\beta})$			−724.12		
$\rho^2 = 1 - LL(\boldsymbol{\beta})/LL(0)$			0.604		

Tables 5 through 8 also show considerable variation in the variables found to be statistically significant in the four time-of-day/time-period combinations. To better illustrate these differences, Table 10 provides a side-by-side presentation of the marginal effects of explanatory variables (organized by variable category) for the four time-of-day/time-period models, of day and across the two time periods. A discussion of model results by variable category is presented below.

7.1. Driver characteristics

With regard to driver's characteristics, black drivers consistently were involved in crashes that resulted in less severe injuries (positive marginal effects for no injury and negative marginal effects for minor injury and severe injury) in both morning and afternoon and across time periods, relative to other ethnicities (see Table 10). White drivers also tended to be involved in crashes that resulted in less severe injuries, although the white indicator variable was not statistically significant in the 2014–17 morning time period. Hispanic drivers were involved in more severe injury crashes in the 2010–13 morning period (this was a random parameter in this period) and the 2014–17 afternoon period. However, for these ethnic-

Table 6
Random parameters logit model (allowing for possible heterogeneity in means and variances) results of large-truck crash injury-severities during the afternoon time, 2010–2013.

Variable	Parameter estimate	t-Stat.	Marginal effects		
			No injury	Minor injury	Severe injury
Defined for severe injury					
Constant	−2.791	−2.69			
Weekday (1 if crash occurred during the weekday; 0 otherwise)	1.895	1.83	−0.0168	−0.0312	0.0480
At fault (1 if truck driver is at fault; 0 otherwise)	−1.107	−2.90	0.0037	0.0072	−0.0109
Old truck (1 if truck is above 15 years old; 0 otherwise)	1.083	2.81	−0.0028	−0.0052	0.0080
Sideswipe (1 if type of crash is sideswipe; 0 otherwise)	−1.452	−3.05	0.0042	0.0023	−0.0065
Rear end (1 if type of crash is rear end; 0 otherwise)	−2.435	−3.26	0.0013	0.0024	−0.0037
Passenger car/station wagon (1 if at fault vehicle type is passenger car/station wagon; 0 otherwise)	−1.727	−3.24	0.0018	0.0045	−0.0063
Defined for minor injury					
Making U-turn (1 if movement preceding collision is making U-turn; 0 otherwise)	1.564	1.93	−0.0480	0.0847	−0.0367
Rainy (1 if weather condition is rainy; 0 otherwise)	1.865	1.91	−0.0043	0.0046	−0.0002
Automobile right of way (1 if violation category is automobile right of way; 0 otherwise)	0.818	3.41	−0.0116	0.0148	−0.0033
Pedestrian (1 if truck is involved with Pedestrian; 0 otherwise)	0.681	1.80	−0.0025	0.0041	−0.0016
Defined for no injury					
Constant	−1.400	−6.93			
Wet (1 if road surface condition is wet; 0 otherwise)	1.120	1.40	0.0040	−0.0039	−0.0001
Standard deviation of "Wet"	*2.373*	*2.02*			
Stopped (1 if movement preceding collision is stopped; 0 otherwise)	0.753	2.84	0.0128	−0.0123	−0.0006
Proceeding straight (1 if movement preceding collision is proceeding straight; 0 otherwise)	0.581	3.25	0.0378	−0.0353	−0.0025
Backing (1 if movement preceding collision is backing; 0 otherwise)	2.249	6.03	0.0162	−0.0149	−0.0012
Black (1 if truck driver is Black; 0 otherwise)	0.684	3.17	0.0147	−0.0137	−0.0011
White (1 if truck driver is White; 0 otherwise)	0.468	2.58	0.0160	−0.0151	−0.0009
Intersection (1 if intersection-related crash; 0 otherwise)	−0.353	−1.86	−0.0110	0.0101	0.0009
Improper passing (1 if violation category is improper passing; 0 otherwise)	1.236	3.19	0.0072	−0.0068	−0.0004
Unsafe lane change (1 if violation category is unsafe lane change; 0 otherwise)	0.506	2.16	0.0106	−0.0100	−0.0005
Misdemeanor (1 if crash is misdemeanor hit-and-run; 0 otherwise)	4.275	5.35	0.0057	−0.0053	−0.0004
Sideswipe (1 if type of crash is sideswipe; 0 otherwise)	1.473	8.09	0.0850	−0.0807	−0.0043
Hit object (1 if type of crash is hit object; 0 otherwise)	1.895	3.86	0.0100	−0.0083	−0.0017
Parked motor vehicle (1 if truck is involved with parked motor vehicle; 0 otherwise)	2.238	5.33	0.0107	−0.0098	−0.0009
Fixed object (1 if truck is involved with fixed object; 0 otherwise)	2.514	5.33	0.0155	−0.0136	−0.0019
Model statistics					
Number of observations			1296		
Log-likelihood at zero, $LL(0)$			−1423.80		
Log-likelihood at convergence, $LL(\boldsymbol{\beta})$			−674.97		
$\rho^2 = 1 - LL(\boldsymbol{\beta})/LL(0)$			0.526		

ity results, some caution should be exercised in their interpretation because various ethnicities of drivers may be more likely to be assigned to certain routes and at certain times of day. Thus, this finding could be reflecting truck routing and delivery characteristics (some with higher or lower risk) rather than ethnicity itself.

In the 2010–13 mornings, male drivers (comprising 96% of all drivers) were more likely to be involved in either severe injury or no-injury crashes than their female counterparts, but this effect was from a random parameter (suggesting variability across observations) and was statistically insignificant in other time-of-day/time-period categories. As with ethnicity, this finding could also be related to different truck routing and delivery characteristics assignments that may vary by gender.

The young-age indicator, middle-age indicator and non-drinking indicator did not produce results that were consistent across time-of-day/time-period combinations. However, relative to their older counterparts, drivers younger than 31 years of age were involved in less severe crash outcomes in the 2014–17 time period. Interestingly, the marginal effect for no-injury in the afternoon was more than 2.5 times the marginal effect for no-injury in the morning, making no-injury crash outcomes involving younger drivers much more likely in the afternoon than morning (the magnitude of the afternoon marginal effect of 0.4724 is substantial, and well above other no-injury marginal effects). This finding suggests trucking firms may want to check the routes of younger drivers (morning versus afternoon) and consider that they may be more susceptible to time-of-day variations in performance relative to their older counterparts.

In 2014–17 for middle-aged drivers had a lower probability of a no-injury crash in the afternoon than in the morning, but this was a random parameter suggesting significant variation in the effect of this variable across crashes.

Table 7
Random parameters logit model (allowing for possible heterogeneity in means and variances) results of large-truck crash injury-severities during the morning time, 2014–2017.

Variable	Parameter estimate	t-Stat.	Marginal effects		
			No injury	Minor injury	Severe injury
Defined for severe injury					
Constant	1.053	0.91			
Middle age (1 if truck driver is younger than 51 years old and older than 30 years old; 0 otherwise)	−3.262	−1.70	−0.0017	−0.0008	0.0025
Standard deviation of "Middle age"	*2.662*	*2.06*			
Weekday (1 if crash occurred during the weekday; 0 otherwise)	−1.490	−2.03	0.0061	0.0119	−0.0179
At fault (1 if truck driver is at fault; 0 otherwise)	−1.629	−3.08	0.0036	0.0051	−0.0087
Sideswipe (1 if type of crash is sideswipe; 0 otherwise)	−1.685	−2.34	0.0015	0.0016	−0.0030
Rear end (1 if type of crash is rear end; 0 otherwise)	−2.547	−2.40	0.0007	0.0014	−0.0021
Other motor vehicle (1 if truck is involved with other motor vehicle; 0 otherwise)	−1.780	−3.20	0.0040	0.0088	−0.0128
Bicycle (1 if truck is involved with bicycle; 0 otherwise)	−1.767	−1.93	0.0001	0.0018	−0.0019
Dark – street lights (1 if light condition is dark – street lights; 0 otherwise)	3.992	2.55	−0.0008	−0.0005	0.0013
Passenger car/station wagon (1 if at fault vehicle type is passenger car/station wagon; 0 otherwise)	−1.948	−2.27	0.0015	0.0036	−0.0051
Defined for minor injury					
Young-age (1 if truck driver is younger than 31 years old; 0 otherwise)	1.388	4.62	0.1536	−0.1221	−0.0316
Passing another vehicle (1 if movement preceding collision is passing another vehicle; 0 otherwise)	0.738	2.56	−0.0068	0.0077	−0.0009
Pedestrian (1 if truck is involved with Pedestrian; 0 otherwise)	1.622	3.31	−0.0034	0.0061	−0.0027
Dry (1 if road surface condition is dry; 0 otherwise)	−1.415	−1.76	0.1085	−0.1211	0.0126
Defined for no injury					
Constant	−1.787	−2.20			
Old truck (1 if truck is above 15 years old; 0 otherwise)	−1.753	−3.91	−0.0128	0.0119	0.0009
Standard deviation of "Old truck"	*1.852*	*2.92*			
Sideswipe (1 if type of crash is sideswipe; 0 otherwise)	3.402	5.25	0.0230	−0.0223	−0.0006
Standard deviation of "Sideswipe"	*2.763*	*3.59*			
Stopped (1 if movement preceding collision is stopped; 0 otherwise)	1.012	3.92	0.0152	−0.0147	−0.0005
Backing (1 if movement preceding collision is backing; 0 otherwise)	2.743	6.76	0.0166	−0.0152	−0.0014
Black (1 if truck driver is Black; 0 otherwise)	0.747	2.61	0.0105	−0.0099	−0.0006
New truck (1 if truck is less than 6 years old; 0 otherwise)	−0.452	−2.19	−0.0138	0.0130	0.0008
Wrong side of road (1 if violation category is wrong side of road; 0 otherwise)	−1.706	−2.42	−0.0037	0.0036	0.0002
Improper passing (1 if violation category is improper passing; 0 otherwise)	3.618	2.30	0.0125	−0.0121	−0.0004
Traffic signals and signs (1 if violation category is traffic signals and signs; 0 otherwise)	−1.531	−3.40	−0.0057	0.0053	0.0004
Felony (1 if crash is felony hit-and-run; 0 otherwise)	−7.512	−2.63	−0.0017	0.0016	0.0001
Misdemeanor (1 if crash is misdemeanor hit-and-run; 0 otherwise)	5.113	4.87	0.0047	−0.0044	−0.0004
Hit object (1 if type of crash is hit object; 0 otherwise)	3.256	5.64	0.0116	−0.0075	−0.0041
Parked motor vehicle (1 if truck is involved with parked motor vehicle; 0 otherwise)	3.254	5.65	0.0124	−0.0109	−0.0015
Bicycle (1 if truck is involved with bicycle; 0otherwise)	−3.623	−2.59	−0.0019	0.0018	0.0001
Fixed object (1 if truck is involved with fixed object; 0otherwise)	1.789	3.52	0.0081	−0.0060	−0.0021
Wet (1 if road surface condition is wet; 0 otherwise)	2.698	2.78	0.0064	−0.0063	−0.0002
Heterogeneity in the mean of the random parameters					
Sideswipe: Backing (1 if movement preceding collision is backing; 0 otherwise)	−4.125	−3.05			
Sideswipe: Black (1 if truck driver is Black; 0 otherwise)	1.298	1.80			
Sideswipe: Improper passing (1 if violation category is improper passing; 0 otherwise)	−2.786	−1.62			
Sideswipe: Passenger car/station wagon (1 if at fault vehicle type is passenger car/station wagon; 0 otherwise)	−1.027	−1.96			
Model statistics					
Number of observations			1566		
Log-likelihood at zero, $LL(0)$			−1720.43		
Log-likelihood at convergence, $LL(\boldsymbol{\beta})$			−637.04		
$\rho^2 = 1 - LL(\boldsymbol{\beta})/LL(0)$			0.630		

7.2. Driver actions

Table 10 shows that being stopped before the collision generally resulted in less severe crash outcomes (positive marginal effects for no injury and negative marginal effects for minor injury and severe injury) in all time-of-day/time-period combinations except for the afternoons in 2014–17. Proceeding straight before the collision also resulted in less severe crash outcomes in general, except for the mornings in 2014–17 where it was statistically insignificant.

Backing (1 if movement preceding collision is backing; 0 otherwise) consistently resulted in less severe injuries (likely because of the low speed involved) in all time-of-day/time-period combinations, without much change across time-of-

Table 8
Random parameters logit model (allowing for possible heterogeneity in means and variances) results of large-truck crash injury-severities during the afternoon time, 2014–2017.

Variable	Parameter estimate	t-Stat.	Marginal effects		
			No injury	Minor injury	Severe injury
Defined for severe injury					
Constant	−0.499	−1.12			
At fault (1 if truck driver is at fault; 0 otherwise)	−0.630	−1.61	0.0022	0.0049	−0.0072
Making left turn (1 if movement preceding collision is making left turn; 0 otherwise)	1.154	2.46	−0.0015	−0.0054	0.0069
Hispanic (1 if truck driver is Hispanic; 0 otherwise)	0.780	1.93	−0.0045	−0.0112	0.0156
Sideswipe (1 if type of crash is sideswipe; 0 otherwise)	−2.277	−3.57	0.0035	0.0035	−0.0070
Rear end (1 if type of crash is rear end; 0 otherwise)	−3.073	−3.60	0.0015	0.0031	−0.0047
Broadside (1 if type of crash is broadside; 0 otherwise)	−1.289	−2.56	0.0024	0.0089	−0.0113
Other motor vehicle (1 if truck is involved with other motor vehicle; 0 otherwise)	−1.636	−2.89	0.0070	0.0171	−0.0241
Defined for minor injury					
Middle age (1 if truck driver is younger than 51 years old and older than 30 years old; 0 otherwise)	0.632	3.03	−0.0245	0.0254	−0.0009
Standard deviation of "middle aged"	*0.973*	*2.13*			
Young-age (1 if truck driver is younger than 31 years old; 0 otherwise)	0.702	2.63	0.4724	−0.4185	−0.0539
New truck (1 if truck is less than 6 years old; 0 otherwise)	0.327	1.77	−0.0135	0.0152	−0.0016
Rainy (1 if weather condition is rainy; 0 otherwise)	−1.353	−2.03	0.0025	−0.0031	0.0006
Automobile right of way (1 if violation category is automobile right of way; 0 otherwise)	0.923	3.17	−0.0121	0.0149	−0.0028
Head-on (1 if type of crash is head-on; 0 otherwise)	0.822	1.79	−0.0025	0.0043	−0.0018
Other motor vehicle (1 if truck is involved with other motor vehicle; 0 otherwise)	−0.806	−2.06	0.0708	−0.0793	0.0084
Defined for no injury					
Constant	−1.652	−3.12			
Old truck (1 if truck is above 15 years old; 0 otherwise)	−1.356	−3.74	−0.0141	0.0127	0.0014
Standard deviation of "old truck"	*1.197*	*1.61*			
Fixed object (1 if truck is involved with fixed object; 0 otherwise)	4.305	2.46	0.0059	−0.0044	−0.0015
Standard deviation of "fixed object"	*3.558*	*2.02*			
Had not been drinking (1 if apparent physical condition of driver is had not been drinking; 0 otherwise)	0.655	1.95	0.0677	−0.0627	−0.0050
Proceeding straight (1 if movement preceding collision is proceeding straight; 0 otherwise)	0.339	1.78	0.0186	−0.0174	−0.0012
Making U-turn (1 if movement preceding collision is making U-turn; 0 otherwise)	−3.330	−1.89	−0.0019	0.0015	0.0004
Backing (1 if movement preceding collision is backing; 0 otherwise)	1.987	4.61	0.0132	−0.0118	−0.0015
Black (1 if truck driver is Black; 0 otherwise)	0.959	3.81	0.0193	−0.0185	−0.0008
White (1 if truck driver is White; 0 otherwise)	0.776	3.04	0.0155	−0.0145	−0.0010
Intersection (1 if intersection-related crash; 0 otherwise)	−0.481	−2.01	−0.0129	0.0118	0.0011
Unsafe speed (1 if violation category is unsafe speed; 0 otherwise)	−1.702	−5.03	−0.0307	0.0278	0.0029
Wrong side of road (1 if violation category is wrong side of road; 0 otherwise)	−1.046	−2.26	−0.0049	0.0045	0.0004
Traffic signals and signs (1 if violation category is traffic signals and signs; 0 otherwise)	−1.504	−2.51	−0.0044	0.0040	0.0004
Misdemeanor (1 if crash is misdemeanor hit-and-run; 0 otherwise)	5.529	6.59	0.0086	−0.0081	−0.0006
Sideswipe (1 if type of crash is sideswipe; 0 otherwise)	1.453	6.31	0.0682	−0.0660	−0.0023
Hit object (1 if type of crash is hit object; 0 otherwise)	3.014	3.31	0.0123	−0.0089	−0.0034
Parked motor vehicle (1 if truck is involved with parked motor vehicle; 0 otherwise)	3.296	5.94	0.0243	−0.0213	−0.0030
Bicycle (1 if truck is involved with bicycle; 0 otherwise)	−2.174	−1.85	−0.0015	0.0013	0.0002
Heterogeneity in the mean of the random parameters					
Middle age: Unsafe speed (1 if violation category is unsafe speed; 0 otherwise)	−1.201	−2.81			
Model statistics					
Number of observations			1211		
Log-likelihood at zero, $LL(0)$			−1330.42		
Log-likelihood at convergence, $LL(\boldsymbol{\beta})$			−600.17		
$\rho^2 = 1 - LL(\boldsymbol{\beta})/LL(0)$			0.549		

day/time-period combinations. Interestingly, trucks making a U-turn resulted in a higher probability of minor injury in the afternoons across years, but trucks making a U-turn did not significantly affect injury-severity probabilities in the morning. This may be a function of traffic conditions and other related factors but may be worth safety-conscious trucking companies investigating further.

Table 10 shows that making a left turn results in more severe crash outcomes in the afternoons of 2014–17 and passing a vehicle results in a higher probability of minor injury in the morning of 2014–17. Neither of these variables had a statistically significant effect on injury severities in 2010–13.

Table 9
Likelihood ratio test results between morning and afternoon in different time periods (χ^2 values with degrees of freedom in parenthesis and confidence level in brackets, see Equation 4 for reference).

m_1	m_2 Morning 2010–13	Afternoon 2010–13	Morning 2014–17	Afternoon 2014–17
Morning 2010–13	–	117.46 (27) [>99.99%]	183.36 (34) [>99.99%]	298.81 (37) [>99.99%]
Afternoon 2010–13	526.44 (33) [>99.99%]	–	293.18 (37) [>99.99%]	97.12 (36) [>99.97%]
Morning 2014–17	77.06 (30) [>99.99%]	101.42 (27) [>99.99%]	–	230.74 (37) [>99.99%]
Afternoon 2014–17	748.46 (33) [>99.99%]	58.00 (27) [>99.95%]	241.68 (37) [>99.99%]	–

7.3. Crash characteristics

Table 10 shows that a wide variety of crash characteristics were found to be significant in one or more of the time-of-day/time-period models. Of these, several were statistically significant in all models. Sideswipe crashes consistently resulted in less severe injuries (positive marginal effects for no injury and negative marginal effects for minor injury and severe injury) in all models. The hit-object indicator also consistently resulted in less severe crashes in all models (with little variation by time of day). A collision with a parked vehicle consistently resulted in a higher probability of no injury and lower probabilities of minor injuries and severe injuries (although this variable produced a random parameter in the 2010–13 morning model). It is also interesting to note that the effect of this variable on injury-outcome probabilities is about twice in the afternoon as it is in the morning across the two time periods.

Collisions with fixed objects consistently resulted in less severe crashes (a higher likelihood of no injury and a lower likelihood of minor and severe injury) but produced a random parameter for the 2014–17 afternoon model. There was comparatively little difference in the marginal effects of this variable between morning and afternoon periods.

While other explanatory variables in this category mostly show considerable variation in their effect on injury severities across the time-of-day/time-period models, there were some exceptions. For example, the indicator variable for automobiles violating the right of way consistently resulted in a higher likelihood of minor injury over the years, but only in the afternoon time period. In contrast, crashes that were classified as hit-and-run felonies resulted in a higher likelihood of minor injury over the years, but only for the morning time period. These findings underscore important morning/afternoon differences even when effects were generally unstable over the years.

7.4. Crash time

Table 10 shows the indicator variables for daylight, dark-street lights and weekdays do not generally produce consistent findings across time-of-day/time-period combinations. It is important to note here that because we consider times 6:00 a.m. to 5:59 p.m., daylight and dark-streetlight will only be contrasted with non-daylight and non-dark streetlight in the late fall and winter months when the daylight time is short. Table 10 marginal effects show daylight significantly decreases severe injury crash outcomes in the mornings of 2010–13 (relative to non-daylight conditions), and in 2014–17, dark with street lights increases severe-injury crash outcomes (relative to non-dark streetlight conditions). So, these variables were capturing the same morning effect across the two time periods in that dark mornings (occurring in late fall and winter) result in more severe crash outcomes.

The weekday-indicator marginal effects show that, in the morning, weekdays resulted in less severe morning crash outcomes in 2010–13 (a higher likelihood of no injury and lower likelihoods if minor injury and severe injury) relative to weekend crashes. But in the afternoons of the 2010–13 period, weekday crashes resulted in more severe crash outcomes (a higher likelihood of severe injury with a lower likelihood of no injury and minor injury), relative to weekend crashes. The morning time period in 2014–17 resulted in a somewhat different findings with weekdays resulting in a higher likelihood of minor injury and lower likelihoods of no injury and severe injury relative to weekend crashes. The afternoon effect of weekday crashes was statistically insignificant in 2014–17 (no significant difference between weekday and weekend crashes).

7.5. Other variables

Table 10 shows that if the truck driver was deemed to be at fault, there is a higher probability of no injury and lower probability of severe injury in all time-of-day/time-period combinations. This may suggest that truck-driver training may provide them the skills to mitigate crash consequences after they made a driving error. Interestingly, dry road-surface conditions

Table 10
The marginal effects of the explanatory variables in different time periods of the day (italic value indicates random parameter).

Variable	No Injury				Minor Injury				Severe Injury			
	Morning 2010–13	Afternoon 2010–13	Morning 2014–17	Afternoon 2014–17	Morning 2010–13	Afternoon 2010–13	Morning 2014–17	Afternoon 2014–17	Morning 2010–13	Afternoon 2010–13	Morning 2014–17	Afternoon 2014–17
Driver characteristics												
Black (1 if truck driver is Black; 0 otherwise)	0.0210	0.0147	0.0105	0.0193	−0.0189	−0.0137	−0.0099	−0.0185	−0.0021	−0.0011	−0.0006	−0.0008
White (1 if truck driver is White; 0 otherwise)	0.0108	0.0160	–	0.0155	−0.0094	−0.0151	–	−0.0145	−0.0014	−0.0009	–	−0.0010
Hispanic (1 if truck driver is Hispanic; 0 otherwise)	*−0.0027*	–	–	−0.0045	*−0.0013*	–	–	−0.0112	*0.0039*	–	–	0.0156
Male (1 if truck driver is male; 0 otherwise)	*0.0700*	–	–		*−0.0847*	–	–		*0.0147*	–	–	0.0156
Young-age (1 if truck driver is younger than 31 years old; 0 otherwise)	–	–	0.1536	0.4724	–	–	−0.1221	−0.4185	–	–	−0.0316	−0.0539
Middle age (1 if truck driver is younger than 51 years old and older than 30 years old; 0 otherwise)	–	–	*−0.0017*	*−0.0245*	–	–	*−0.0008*	*0.0254*	–	–	*0.0025*	*−0.0009*
Had not been drinking (1 if apparent physical condition of driver is had not been drinking; 0 otherwise)	–	–	–	0.0677	–	–	–	−0.0627	–	–	–	−0.0050
Driver actions												
Stopped (1 if movement preceding collision is stopped; 0 otherwise)	0.0182	0.0128	0.0152	–	−0.0163	−0.0123	−0.0147	–	−0.0019	−0.0006	−0.0005	–
Proceeding straight (1 if movement preceding collision is proceeding straight; 0 otherwise)	0.0822	0.0378	–	0.0186	−0.0766	−0.0353	–	−0.0174	−0.0056	−0.0025	–	−0.0012
Backing (1 if movement preceding collision is backing; 0 otherwise)	0.0171	0.0162	0.0166	0.0132	−0.0162	−0.0149	−0.0152	−0.0118	−0.0009	−0.0012	−0.0014	−0.0015
Making U-turn (1 if movement preceding collision is making U-turn; 0 otherwise)	–	−0.0480	–	−0.0019	–	0.0847	–	0.0015	–	−0.0367	–	0.0004
Making left turn (1 if movement preceding collision is making left turn; 0 otherwise)	–	–	–	−0.0015	–	–	–	−0.0054	–	–	–	0.0069
Passing another vehicle (1 if movement preceding collision is passing another vehicle; 0 otherwise)	–	–	−0.0068	–	–	–	0.0077		–	–	−0.0009	–
Crash characteristics												
Sideswipe (1 if type of crash is sideswipe; 0 otherwise)	0.0837	0.0892	0.0245	0.0711	−0.0800	−0.0784	−0.0207	−0.0625	−0.0037	−0.0108	−0.0036	−0.0093
Head-on (1 if type of crash is head-on; 0 otherwise)	−0.0040	–	–	−0.0025	0.0045	–	–	0.0043	−0.0005	–	–	−0.0018
Hit object (1 if type of crash is hit object; 0 otherwise)	0.0075	0.0100	0.0116	0.0123	−0.0061	−0.0083	−0.0075	−0.0089	−0.0013	−0.0017	−0.0041	−0.0034
Rear end (1 if type of crash is rear end; 0 otherwise)	–	0.0013	0.0007	–	–	0.0024	0.0014	–	–	−0.0037	−0.0021	–
Parked motor vehicle (1 if truck is involved with parked motor vehicle; 0 otherwise)	*0.0049*	0.0107	0.0124	0.0243	*−0.0044*	−0.0098	−0.0109	−0.0213	*−0.0005*	−0.0009	−0.0015	−0.0030
Other motor vehicle (1 if truck is involved with other motor vehicle; 0 otherwise)	0.0097	–	0.0040	0.0708	0.0077	–	0.0088	−0.0793	−0.0174	–	−0.0128	0.0084
Pedestrian (1 if truck is involved with Pedestrian; 0 otherwise)	−0.0023	−0.0025	−0.0034	–	0.0041	0.0041	0.0061	–	−0.0018	−0.0016	−0.0027	–
Bicycle (1 if truck is involved with bicycle; 0 otherwise)	−0.0027	–	0.0017	−0.0015	0.0046	–	0.0036	0.0013	−0.0019	–	−0.0019	0.0002
Fixed object (1 if truck is involved with fixed object; 0 otherwise)	0.0116	0.0155	0.0081	*0.0059*	−0.0093	−0.0136	−0.0060	*−0.0044*	−0.0022	−0.0019	−0.0021	*−0.0015*
Traffic signals and signs (1 if violation category is traffic signals and signs; 0 otherwise)	−0.0027	–	−0.0057	−0.0044	0.0032	–	0.0053	0.0040	−0.0005	–	0.0004	0.0004

(*continued on next page*)

Table 10 (*continued*)

Variable	No Injury				Minor Injury				Severe Injury			
	Morning 2010–13	Afternoon 2010–13	Morning 2014–17	Afternoon 2014–17	Morning 2010–13	Afternoon 2010–13	Morning 2014–17	Afternoon 2014–17	Morning 2010–13	Afternoon 2010–13	Morning 2014–17	Afternoon 2014–17
Improper passing (1 if violation category is improper passing; 0 otherwise)	0.0042	0.0072	0.0125	–	−0.0041	−0.0068	−0.0121	–	−0.0002	−0.0004	−0.0004	–
Unsafe lane change (1 if violation category is unsafe lane change; 0 otherwise)	–	0.0106	–	–	–	−0.0100	–	–	–	−0.0005	–	–
Automobile right of way (1 if violation category is automobile right of way; 0 otherwise)	–	−0.0116	–	−0.0121	–	0.0148	–	0.0149	–	−0.0033	–	−0.0028
Wrong side of road (1 if violation category is wrong side of road; 0 otherwise)	–	–	−0.0037	−0.0049	–	–	0.0036	0.0045	–	–	0.0002	0.0004
Unsafe speed (1 if violation category is unsafe speed; 0 otherwise)	–	–	–	−0.0307	–	–	–	0.0278	–	–	–	0.0029
Felony (1 if crash is felony hit-and-run; 0 otherwise)	−0.0018	–	−0.0017	–	0.0019	–	0.0016	–	−0.0001	–	0.0001	–
Not Hit and Run (1 if crash is not hit-and-run; 0 otherwise)	−0.4169	–	–	–	0.3785	–		–	0.0384	–	–	–
Misdemeanor (1 if crash is misdemeanor hit-and-run; 0 otherwise)	–	0.0057	0.0047	0.0086	–	−0.0053	−0.0044	−0.0081	–	−0.0004	−0.0004	−0.0006
Passenger car/station wagon (1 if at fault vehicle type is passenger car/station wagon; 0 otherwise)	–	0.0018	0.0015	–	–	0.0045	0.0036	–	–	−0.0063	−0.0051	–
Crash time												
Daylight (1 if light condition is daylight; 0 otherwise)	0.0142	–	–	–	0.0127	–	–	–	−0.0269	–	–	–
Dark – street lights (1 if light condition is dark – street lights; 0 otherwise)	–	–	−0.0008	–	–	–	−0.0005	–	–	–	0.0013	–
Weekday (1 if crash occurred during the weekday; 0 otherwise)	0.1264	−0.0168	0.0061	–	−0.1146	−0.0312	0.0119	–	−0.0119	0.0480	−0.0179	–
Other variables												
At fault (1 if truck driver is at fault; 0 otherwise)	0.3675	0.0037	0.0036	0.0022	−0.3383	0.0072	0.0051	0.0049	−0.0292	−0.0109	−0.0087	−0.0072
Dry (1 if road surface condition is dry; 0 otherwise)	0.0575	–	0.1085	–	−0.0629	–	−0.1211	–	0.0053	–	0.0126	–
Wet (1 if road surface condition is wet; 0 otherwise)	–	0.0040	0.0064	–	–	−0.0039	−0.0063	–	–	−0.0001	−0.0002	–
Rainy (1 if weather condition is rainy; 0 otherwise)	–	−0.0043	–	0.0025	–	0.0046	–	−0.0031	–	−0.0002	–	0.0006
Intersection (1 if intersection-related crash; 0 otherwise)	−0.0158	−0.0110	–	−0.0129	0.0138	0.0101	–	0.0118	0.0020	0.0009	–	0.0011
Old truck (1 if truck is above 15 years old; 0 otherwise)	–	−0.0028	*−0.0128*	*−0.0141*	–	−0.0052	*0.0119*	*0.0127*	–	0.0080	*0.0009*	*0.0014*
New truck (1 if truck is less than 6 years old; 0 otherwise)	–	–	−0.0138	−0.0135	–	–	0.0130	0.0152	–	–	0.0008	−0.0016

increased the probability of both no-injury and severe injury crashes, but only in the morning time period. This may suggest a high variance in morning-driver behavior in dry-road conditions with conservative and aggressive behaviors, a finding that is consistent with earlier research that explored the effect of road surface conditions on injury severity (Morgan and Mannering, 2011). In contrast, the wet-road condition indicator and the rain indicators were significant in several afternoon periods but did not produce consistent marginal effects (Table 10).

Intersection-related crashes generally resulted in more severe crash outcomes (lower probability of no injury and higher probabilities of minor and severe injuries) but were statistically insignificant in the afternoons in the 2014–17 time period. Finally, truck age was statistically significant in several time periods (and with random parameters in both daily time periods in 2014–17) but did not produce temporally stable results.

7.6. Heterogeneity in the means of random parameters

Table 5 shows that, in 2010–23 morning model, two variables were found to produce random parameters with heterogeneity in means; an indicator variable for male drivers and an indicator variable for Hispanic drivers. For the male-indicator and Hispanic-indicator, proceeding straight before collision resulted in an increase in their mean, making no injuries more likely (relative to other types of movements preceding collision). For the Hispanic-indicator, non-hit-and-run crashes decreased its mean, making no injuries less likely.

As indicated in Table 6, none of the explanatory variables were found to significantly affect the mean or variance of the random parameter in 2010–13 afternoon model.

With regard to the 2014–17 morning model (Table 7), the sideswipe indicator variable was found to produce a random parameter with heterogeneity in mean. For this variable, backing or improper passing resulted in a decrease in the mean (making no injuries less likely) while black drivers had an increase in the mean (making no injuries more likely). Passenger cars/station wagons, when being at fault, were also found to decrease the mean of sideswipe-indicator, making severe injuries less likely.

As shown in Table 8, in 2014–17 afternoon model, and indicator variable for middle age drivers (1 if truck driver is younger than 51 years old and older than 30 years old; 0 otherwise) produced a random parameter with heterogeneity in mean. Unsafe speed decreased the mean of this variable, making no injuries less likely.

8. Summary and conclusions

Using data on large truck crashes in Los Angeles from January 1, 2010 to December 31, 2017, this paper examined the effect of time-of-day and time periods on resulting injury severities in large-truck crashes. With three possible crash-injury severity outcomes (measured by the most severely injured individual in the crash) of no injury, minor injury, and severe injury, a wide range of possible factors affecting large-truck crash-injury severities such as driver's characteristics, driver' actions, crash characteristics, and roadway and environmental conditions were considered in the analysis.

Likelihood ratio tests show that the effect of factors that determine injury severity varies significantly across time-of-day/time-period combinations. However, there were several explanatory variables that do produce temporally stable effects in terms of their impact on resulting injury severities. Black drivers, crashes occurring while backing, sideswipe crashes, hit-object crashes, parked-vehicle crashes, fixed-object crashes, and truck-driver at fault crashes all consistently produced less severe crashes across all times-of-day/time-periods combinations. There were also some interesting time-of-day effects. For example, 2014–17 models show that younger truck drivers were more likely to have a no-injury crash outcome in the afternoon than they were in the morning, and the hit-object indicator variable has roughly twice the effect on injury probabilities in the afternoon time period relative to the morning time period.

The findings of this research underscore the importance of accounting for the time-dependent effect that variables have on resulting injury-severity outcomes in crashes involving large trucks. The findings of this research should be of value to decision makers and trucking companies seeking to improve truck safety, and also serve as a starting point for future research in this topic that may explore this temporal phenomenon in different regions of the country and in other parts of the world. Future research can also benefit from combining severity models with frequency models since decreasing the number of crashes (even those with less severe injuries) provides considerable economic advantages to the society and trucking companies.

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References

Abay, K., Paleti, R., Bhat, C., 2013. The joint analysis of injury severity of drivers in two-vehicle crashes accommodating seat belt use endogeneity. Transportation Research Part B 50, 74–89.

Ahmed, M., Franke, R., Ksaibati, K., Shinstine, D., 2018. Effects of truck traffic on crash injury severity on rural highways in Wyoming using Bayesian binary logit models. Accident Analysis and Prevention 117, 106–113.
Alnawmasi, N., Mannering, F., 2019. A statistical assessment of temporal instability in the factors determining motorcyclist injury severities. Analytic Methods in Accident Research 22, 100090. 1–20.
Anastasopoulos, P., Mannering, F., 2011. An empirical assessment of fixed and random parameter logit models using crash- and non-crash-specific injury data. Accident Analysis and Prevention 43 (3), 1140–1147.
Anastasopoulos, P., Sarwar, M., Shankar, V., 2016. Safety-oriented pavement performance thresholds: accounting for unobserved heterogeneity in a multi-objective optimization and goal programming approach. Analytic Methods in Accident Research 12, 35–47.
Anderson, J., Hernandez, S., 2017. Roadway classifications and the accident injury severities of heavy-vehicle drivers. Analytic Methods in Accident Research 15, 17–28.
Behnood, A., Mannering, F., 2015. The temporal stability of factors affecting driver-injury severities in single-vehicle crashes: some empirical evidence. Analytic Methods in Accident Research 8, 7–32.
Behnood, A., Mannering, F., 2016. An empirical assessment of the effects of economic recessions on pedestrian-injury crashes using mixed and latent-class models. Analytic Methods in Accident Research 12, 1–17.
Behnood, A., Mannering, F., 2017a. The effects of drug and alcohol consumption on driver injury severities in single-vehicle crashes. Traffic Injury Prevention 18 (5), 456–462.
Behnood, A., Mannering, F., 2017b. Determinants of bicyclist injury severities in bicycle-vehicle crashes: a random parameters approach with heterogeneity in means and variances. Analytic Methods in Accident Research 16, 35–47.
Behnood, A., Mannering, F., 2017c. The effect of passengers on driver-injury severities in single-vehicle crashes: a random parameters heterogeneity-in-means approach. Analytic Methods in Accident Research 14, 41–53.
Behnood, A., Roshandeh, A., Mannering, F., 2014. Latent class analysis of the effects of age, gender, and alcohol consumption on driver-injury severities. Analytic Methods in Accident Research 3–4, 56–91.
Cerwick, D., Gkritza, K., Shaheed, M., Hans, Z., 2014. A comparison of the mixed logit and latent class methods for crash severity analysis. Analytic Methods in Accident Research 3–4, 11–27.
Chang, L.-Y., Mannering, F., 1999. Analysis of injury severity and vehicle occupancy in truck- and non-truck-involved accidents. Accident Analysis and Prevention 31 (5), 579–592.
Chen, F., Chen, S., 2011. Injury severities of truck drivers in single- and multi-vehicle accidents on rural highways. Accident Analysis and Prevention 43 (5), 1677–1688.
Fabbri, M., Natale, V., Adan, A., 2008. Effect of time of day on arithmetic fact retrieval in a number-matching task. Acta Psychologica 127 (2), 485–490.
Fountas, G., Anastasopoulos, P.C., 2017. A random thresholds random parameters hierarchical ordered probit analysis of highway accident injury-severities. Analytic Methods in Accident Research 15, 1–16.
Fountas, G., Anastasopoulos, P.C., 2018. Analysis of accident injury-severity outcomes: the zero-inflated hierarchical ordered probit model with correlated disturbances. Analytic Methods in Accident Research 20, 30–45.
Fountas, G., Anastasopoulos, P.C., Mannering, F., 2018a. Analysis of vehicle accident-injury severities: a comparison of segment-versus accident-based latent class ordered probit models with class-probability functions. Analytic Methods in Accident Research 18, 15–32.
Fountas, G., Anastasopoulos, P.C., Abdel-Aty, M., 2018b. Analysis of accident injury-severities using a correlated random parameters ordered probit approach with time variant covariates. Analytic Methods in Accident Research 18, 57–68.
Fountas, G., Pantangi, S., Hulme, K., Anastasopoulos, P.C., 2019. The effects of driver fatigue, gender, and distracted driving on perceived and observed aggressive driving behavior: a correlated grouped random parameters bivariate probit approach. Analytic Methods in Accident Research 22, 100091.
Hao, W., Kamga, C., Yang, X., Ma, J., Thorson, E., Zhong, M., Wu, C., 2016. Driver injury severity study for truck involved accidents at highway-rail grade crossings in the United States. Transportation Research Part F 43, 379–386.
Hasler, B., Forbes, E., Franzen, P., 2014. Time-of-day differences and short-term stability of the neural response to monetary reward: a pilot study. Psychiatry Research: Neuroimaging 224 (1), 22–27.
Islam, M., Hernandez, S., 2013a. Large truck-involved crashes: exploratory injury severity analysis. Journal of Transportation Engineering 139 (6), 596–604.
Islam, M., Hernandez, S., 2013b. Modeling injury outcomes of crashes involving heavy vehicles on Texas highways. Transportation Research Record: Journal of the Transportation Research Board 2388, 28–36.
Khorashadi, A., Niemeier, D., Shankar, V., Mannering, F., 2005. Differences in rural and urban driver-injury severities in accidents involving large-trucks: an exploratory analysis. Accident Analysis and Prevention 37 (5), 910–921.
Lemp, J., Kockelman, K., Unnikrishnan, A., 2011. Analysis of large truck crash severity using heteroskedastic ordered probit models. Accident Analysis and Prevention 43 (1), 370–380.
Leone, M., Slezak, D., Golombek, D., Sigman, M., 2017. Time to decide: diurnal variations on the speed and quality of human decisions. Cognition 158, 44–55.
Malyshkina, N., Mannering, F., 2009. Markov switching multinomial logit model: an application to accident-injury severities. Accident Analysis and Prevention 41 (4), 829–838.
Mannering, F., Bhat, C., 2014. Analytic methods in accident research: methodological frontier and future directions. Analytic Methods in Accident Research 1, 1–22.
Mannering, F., Shankar, V., Bhat, C., 2016. Unobserved heterogeneity and the statistical analysis of highway accident data. Analytic Methods in Accident Research 11, 1–16.
McFadden, D., Train, K., 2000. Mixed MNL models for discrete response. Journal of Applied Econometrics 15, 447–470.
Morgan, A., Mannering, F., 2011. The effects of road-surface conditions, age, and gender on driver-injury severities. Accident Analysis and Prevention 43 (5), 1852–1863.
National Highway Traffic Safety Administration, 2018. Traffic safety facts: Large trucks, 2016 Data. Washington, DC.
Pahukula, J., Hernandez, S., Unnikrishnan, A., 2015. A time of day analysis of crashes involving large trucks in urban areas. Accident Analysis and Prevention 75, 155–163.
Russo, B., Savolainen, P., Schneider, W., Anastasopoulos, P.C., 2014. Comparison of factors affecting injury severity in angle collisions by fault status using a random parameters bivariate ordered probit model. Analytic Methods in Accident Research 2, 21–29.
Sarwar, M., Anastasopoulos, P., 2017. The effect of long term non-invasive pavement deterioration on accident injury-severity rates: a seemingly unrelated and multivariate equations approach. Analytic Methods in Accident Research 13, 1–15.
Savolainen, P., Mannering, F., Lord, D., Quddus, M., 2011. The statistical analysis of highway crash-injury severities: a review and assessment of methodological alternatives. Accident Analysis and Prevention 43 (5), 1666–1676.
Seraneeprakarn, P., Huang, S., Shankar, V., Mannering, F., Venkataraman, N., Milton, J., 2017. Occupant injury severities in hybrid-vehicle involved crashes: a random parameters approach with heterogeneity in means and variances. Analytic Methods in Accident Research 15, 41–55.
U.S. Department of Transportation, 2017. Freight Facts and Figures 2017 – Chapter 2: Freight Moved in Domestic and International Trade. Washington, DC.
Uddin, M., Huynh, N., 2018. Factors influencing injury severity of crashes involving HAZMAT trucks. International Journal of Transportation Science and Technology 7 (1), 1–9.
Waseem, M., Ahmed, A., Saeed, T., 2019. Factors affecting motorcyclists' injury severities: an empirical assessment using random parameters logit model with heterogeneity in means and variances. Accident Analysis and Prevention 123, 12–19.
Washington, S., Karlaftis, M., Mannering, F., 2011. Statistical and Econometric Methods for Transportation Data Analysis. Taylor and Francis, Chapman and Hall/CRC, Boca Raton, FL.

Xiong, Y., Mannering, F., 2013. The heterogeneous effects of guardian supervision on adolescent driver-injury severities: a finite-mixture random-parameters approach. Transportation Research Part B 49, 39–54.
Xiong, Y., Tobias, J., Mannering, F., 2014. The analysis of vehicle crash injury-severity data: a Markov switching approach with road-segment heterogeneity. Transportation Research Part B 67, 109–128.
Yasmin, S., Eluru, N., Bhat, C., Tay, R., 2014. A latent segmentation based generalized ordered logit model to examine factors influencing driver injury severity. Analytic Methods in Accident Research 1, 23–38.
Zheng, Z., Lu, P., Lantz, B., 2018. Commercial truck crash injury severity analysis using gradient boosting data mining model. Journal of Safety Research 65, 115–124.
Zhu, X., Srinivasan, S., 2011. Modeling occupant-level injury severity: an application to large-truck crashes. Accident Analysis and Prevention 43 (4), 1427–1437.
Zou, W., Wang, X., Zhang, D., 2017. Truck crash severity in New York city: an investigation of the spatial and the time of day effects. Accident Analysis and Prevention 99, 249–261.