Investigating rural and urban differences in single-vehicle crash severity determinants: a time-of-day analysis using random parameter models

by

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Abstract

This study investigates the factors associated with single-vehicle crash injury severity accounting for urban-rural differences and time-of-day variations. We estimate mixed (randomparameter) logit models (with the pseudo direct elasticity values) using five-year (2014 - 2018)crash data for five periods of the day: 12 am - 5 am, 5 am - 9 am, 9 am - 2 pm, 2 pm - 7 pm, and 7 pm - 12 am. Log-likelihood tests confirm the statistical validity of the time-of-day grouping of the crash severity models and the urban-rural separation. Our results indicate variations in effects of factors across time-of-day (e.g., rural roads with ice increase the probability of serious injury for 9 am -2 pm and 2 pm -7 pm models and increase fatality probability for the 9 am -2 pm model; rural road crashes involving oversteering by drivers increases the probability of serious injury for the 12 am -5 am model, and the 5 am -9 am models. This variable is found to decrease the probability of serious injury for the 9 am -2 pm model and for the 7 pm - 12 am model; female drivers in rural crash models are found to be less prone to fatality except for the 12 am to 5 am model, and the effect of this variable is found as random in the 5 am - 9 am, 9 am - 2 pm and 2 pm - 7 pm models. The findings of this research can be applied to improve state-specific Crash Modification Factors (CMFs) and Safety Performance Functions (SPFs).

Keywords: Single Vehicle Crashes, Injury-Severity, Time of Day, Temporal Instability, Logit Model, SPF and CMF

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MOTIVATION AND BACKGROUND

Despite extensive efforts in engineering, enforcement, public health, emergency medicine, and education, thousands of people lose lives due to traffic crashes every year. The US had 36,096 traffic-related fatalities in 2019 alone and single-vehicle crash deaths account for 53 percent of the total fatalities nationwide (*1*)and had been consistently around 40 - 50 percent for the last few decades. The data from FARS and IIHS (*1*, *2*) reveals the non-homogenous distribution of fatalities across urban and rural roads. Traffic fatalities per 100 million vehicle-miles-traveled were about twice as high in rural areas (1.89) compared to urban areas (1.00) in 2019. Time-of-day variations are also evident—the number of fatal crashes was highest from 8 pm to midnight during spring and summer months and from 4 pm to 8 pm during winter months in 2019 (*3*). Traffic crash data for Kentucky follows a similar pattern. Among the 732 traffic fatalities in Kentucky(2), 49 percent (total 357) were caused by single-vehicle crashes and 69 percent (total 532) occurred on rural roads. Thus, crash data suggest that time-of-day variations and the urban-rural differences influence crash frequency and severity.

Time-of-Day Variation

Previous studies (4)(5)(6)(7) provide some information on the influence of time-of-day variations on crash occurrence and severity outcomes. Temporal variation can be long (years), or short (week, month, day, or even hours). Most studies show temporal variation using year-toyear models (8)(5) while studies of shorter duration (different hours of a day) are less common (4, 7). Individual driving behavior varies over time and can be correlated with the timedependent influence of crash contributing factors (9). Temporal variation can be an artifact of the greater availability of urban crash data, the change in police-reporting systems, new safety

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measures and improved technology, and the effect of the macroeconomic shocks such as recession (8). Pahukula (4) estimated separate injury severity models for different times of a day for large truck crashes and found that the effects of some of the explanatory variables (e.g. speeding, changing lanes, light condition) varied from one time of a day to another. Behnood and Mannering (7) found differences in the influence of variables on severity outcomes including drivers younger than 31 years old and object-struck crashes at different times of a day.

Urban-Rural Differences

Only a few studies analyzed the differences in contributing factors between urban and rural crashes. For instance, (10) concluded that rural crashes involving tractor-trailer combinations may increase the probability of severe injury or fatality by 26 percent compared to crashes involving single-unit trucks. For urban areas, the same probability was found to be increased by 700 percent. (11) showed that tractor semi-trailers decrease the probability of any major injury for rural-dark conditions and increase the probability of minor injury for urban daylight conditions. This study also found that the age of occupants aged between 35 and 45 was significant for rural crashes while those with ages between 55 and 65 were significant only for urban crashes. Rural crashes involving drug and alcohol use were found to increase the probability of fatality or severe injury by 250 percent, whereas the increased probability was 800 percent for urban crashes (10). In yet another study, factors such as rainy weather conditions and no passing zones were found to increase injury severity only for rural crashes while usage of drugs and curved and multilane highways were found to increase injury severity for urban crashes (12). This study also found similarities between urban and rural crash determinants such as female and senior drivers (65 years or older), driving under the influence, and collision with

fixed objects. Female drivers and the speed limit of 55 mph were found to increase the probability of non-incapacitating injury for run-off-road crashes for large trucks in rural areas, while these parameters were found to increase the probability of property damage only crashes for urban roadways with raised medians and specific population density (10,001-25,000)(*13*). "Time of day" was found as a significant factor for contributing to crash injury-severity for urban-rural fringe(*14*). In this study, 55.23% of the fatal crashes occurred in the 5pm to 5am period of a day.

Without the consideration of time-of-day variations and urban-rural differences, it is possible to under(over)estimate the effects of safety countermeasures. Consider a before-after study to assess the impact of reducing the speed limit on crash occurrences (frequency). A road segment might have fewer crashes in the morning compared to the afternoon peak period. If a reduced speed limit is introduced on that road segment, that might be able to reduce the number of crashes in the afternoon but might increase delays in the morning with higher traffic flows. In such scenarios, variable speed limits can be introduced, setting lower speed limit in the afternoon and higher speed limit in the morning and other time periods. It shows the importance of the time dependent effect of the variables. A similar analogy can be drawn for the geographical variation—crashes occurring on urban vs. rural roads. In addition, unobserved heterogeneity should also be accounted for.

In general, existing studies lack an integrated focus on time-of-day and urban-rural differences within the same model. Only a few studies accounted for the unobserved heterogeneity through the estimation of random parameter models. For the empirical analysis, we used five years of

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police crash data (from 2014 to 2018) collected from Kentucky Traffic Safety Data Services, a program of Kentucky Transportation Center (KTC). As the study is based on Kentucky crash data, Kentucky has 3 distinct regions which are mountain, urban and farm(rural), so it can be considered as a microcosm of the USA. This research aims to analyze the factors associated with single-vehicle crashes accounting for variation regarding time-of-day and urban-rural differences using random-parameter (mixed) logit models.

To this end, the specific research goals are to:

- a) Investigate the potential determinants of severity outcomes for single-vehicle crashes for the urban and rural roads of Kentucky using 2014 – 2018 traffic crash data,
- b) Evaluate the variation in the influence of these determinants at different times of a day, and
- c) Compare the effects of the contributing factors across urban and rural roads.

FACTORS CONTRIBUTING TO CRASH SEVERITY OUTCOME Age, Gender, and Race

Individuals aged 65 and over have been found to have a higher probability of severe injury outcomes compared to the younger age groups(5, 15, 16). Also, individuals over 45 years old were found to increase the probability of fatality (17). In crashes involving trucks, individuals younger than 31 years old are more likely to have a severe injury outcome (7, 18). Drivers below 21 years old involved in roll-over single-vehicle crashes are more prone to fatality and severe injury (18). Studies also indicate a varying influence of age on the injury severity outcomes(19–

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21). This may be attributed to the heterogeneity in the health conditions across identical age groups.

Male drivers were found to be involved in more fatal crashes than female drivers (*16*). Female drivers were found to have a higher probability of no injury outcomes than male drivers (*15*, *21*). At the same time, female drivers are more prone to severe injuries in low-risk segments (*16*) (e.g. segments with higher driver populations share with lower probability of fatality and severe injury). Male drivers were found to increase the probability of property damage only crashes(*8*). Male truck drivers were found to be involved in severe injuries (*7*). Black truck drivers were more likely to be involved in less severe injuries and Hispanic drivers were found to be involved in more severe injuries during morning and afternoon time according to (*7*).

Driving Behavior

Involvement of alcohol or illicit drugs is found to increase the probability of fatality and severe injury outcomes (5, 8, 10, 15, 18, 22). Behnood et al. (17) found that alcohol-impaired driving increases the probability for less severe injuries for male drivers less than 31 years old but was found to increase the probability of severe injury for the female of the same age group and had no significant effect on drivers over 31 years old. Further, fatigue, the effect of medication, reduced visibility due to aging, falling asleep, or fainted are found to increase the probability of severe injury outcomes (8, 16, 18, 21). Distraction involving cellphone usage was found to increase the probability of fatality(15). Speeding was found to increase the probability of fatality across all ages and genders (15, 18, 22).

Geometric and Roadway Attributes:

The existence of median width between 51 and 75 ft was found to be positively correlated with minor injury outcomes during the mid-day (10:00 am to 3 pm) period (4). Dabbour (18) found that crashes occurring on two-lane highways more likely lead to fatality. Concrete median barriers may reduce the probability of severe injury and fatality significantly (10). Dry road surface conditions may increase the probability of property damage only crashes (7, 21). Contradicting to that (23) found drivers under 45 years experienced a decrease in no injury and severe injury probability on wet surface and snowy surface but higher probabilities of minor or severe injury on the dry surface. Wet surfaces reduced the risk of fatal injury but increased the probability of no injury or minor injury (15). Dry road surface increases fatal injury outcomes for passenger cars (5) that might be correlated with the higher-risk taking behavior under dry conditions. Traffic control devices and stop or yield signs were found to decrease the probability of severe injury outcomes due to a reduction in speed (16).

Weather and Lighting Condition:

Rain, snow, and cloudy weather conditions are found to influence severe injury and fatality outcomes (16) (15) (21). Clear weather was found to increase the probability of severe injury (5, 21) and property damage only outcome (21) compared to fatality. Daylight was found to decrease severe injury outcomes except for days where the morning time is short (winter and fall) (7). Roads without streetlight during nighttime was found to increase the probability of severe injury outcome, but this effect was found to be reduced with streetlights (5, 15, 16). Dabbour (18) indicates dark lighting conditions may increase fatality outcome probability.

Vehicle Characteristics:

Motorcyclists are prone to more severe injury outcomes than passenger cars or light-duty trucks because of exposure to the crash without an energy-dissipating structure (24). Commercial vehicles were found to increase the probability of severe injury, while passenger cars were found to decrease the probability of severe injury (8). Light-duty vehicles excluding passenger cars positively influenced severe injury outcomes (18)(5). Tractors with or without trailers were found to increase the probability of fatality and severe injury both in urban and rural roads (10). Older vehicles are found to have a positive correlation with fatal injury outcomes in all the models (5, 18). Vehicle age was found to be an influential factor for severe injury(25, 26). Truck age was found to be statistically significant in different time periods, and the effect of this variable was not temporally stable across all the time periods (7). Using seat belts was found to significantly decrease the probability of severe injury outcomes (5, 15, 17, 21, 26, 27). Airbag deployment was found to decrease the probability of severe injury outcomes (17).

Given the vast literature on single-vehicle crash severity analysis, we acknowledge that this is not an exhaustive review. More information can be found in (28, 29).

METHODOLOGY

Past studies suggest crash injury severities have been modeled using the diverse modeling approaches: multinomial logit model (*10*), latent class model (*17*, *30*), mixed (random parameters) logit model (*8*, *31*, *32*), ordered probit or logit model (*33*, *34*), random parameters ordered probit model(*35*), nested logit model(*36*, *37*), heteroskedastic ordered probit model(*38*),

Bayesian binary logit model(39), and Markov switching models (40–42). It is important to select modeling frameworks that can capture potential unobserved heterogeneity (43). Our study used random parameters multinomial logit model (31, 44, 45) to study the effect of time-of-day and urban-rural differences on the variables of injury severity outcomes. The model begins by defining a probability function as follows(20, 44, 46):

$$S_{in} = \beta_i X_{in} + \varepsilon_{in} \tag{1}$$

Where S_{in} is a function that determines the probability of individual injury outcome *i* in crash *n*, β_i is a vector of estimable parameters for injury-severity outcome *i*, X_{in} is a vector of the observable characteristics that impact the injury severity for observation *n*, and ε_{in} is an error term that is an extreme value (Type-I) distributed. The outcome probabilities of a random parameters logit model which takes into consideration unobserved heterogeneity in the data can be written as below:

$$P_n(i) = \int \frac{EXP(\beta_i X_{in})}{\sum_{\forall K} EXP(\beta_i X_{in})} f(\beta|\varphi) d\beta \qquad (2)$$

Where " $P_n(i)$ " is the probability of observation n having injury-severity outcome *i*, " $f(\beta|\varphi)$ " is the density function of β with φ referring to the vector of parameters (mean and variance) of that density function, and all other terms have definitions as before.

To statistically verify whether injury-severities of single-vehicle crashes were significantly different across different times on a day, a series of likelihood ratio tests were conducted. The formulation for this is as below:

$$\chi^{2} = -2[LL(\beta_{m_{2}m_{1}}) - LL(\beta_{m_{1}})]$$
(3)

Where $LL(\beta_{m_2m_1})$ is the log-likelihood at the convergence of a model containing converged parameters of time of day data m_2 while using data from the period m_1 , and $LL(\beta_{(m_1)})$ is the loglikelihood at the convergence of the model using time of day data m_1 , with the same explanatory variables but with parameters no longer restricted to the converged parameters of time of day data m_2 .

For simulation-based maximum likelihood estimation, 200 Halton draws will be used (47). Further, the direct pseudo-elasticity of the probability concerning the explanatory variables was calculated using the elasticity equation for each of the variables for each model. The elasticity equation can be shown as below (22, 48, 49):

$$E_{x_{mi}}^{P_{(i)}} = \frac{\partial P(i)}{\partial x_{mi}} \times \frac{x_{mi}}{P(i)}$$
(4)

Where P(i) is the probability of discrete crash severity outcome i and x_{mi} is the value of variable m for the outcome i. Elasticity values represents the percent effect that a unit percent change in x_{mi} has on the crash severity outcome probability P(i). However, elasticity calculation for indicator variables using this equation is inaccurate because these variables take only value of either zero or one, which is unable to show a one percent change in a specific variable. In a

situation like this, pseudo-elasticity of binary indicator variables should be estimated, which shows the change in percentage in the probability of that crash severity category when that specific variable is changed from zero to one. It follows the following equation(*12*, *22*, *49*):

$$E_{x_{nk}}^{P_{ni}} = \frac{P_{ni}[given \, x_{nk} = 1] - P_{ni}[given x_{nk} = 0]}{P_{ni}[given x_{nk} = 0]}$$
(5)

DATA DESCRIPTION

The empirical analysis is based on the five years (2014 - 2018) crash data in Kentucky. After cleaning, we used a total of 75,980 rural crashes and 19,154 urban crashes. Although initially we had higher crash occurrences for urban roads, we found urban crash records to have significant portions of missing values. **Figure 1** and **Figure 2** show the distribution of urban and rural crashes for different age groups for two different times of a day. It is found that age group 1 drivers (0 to <25 years old) sustained more fatal and serious injuries in rural roadways than urban roadways. Age group 3 drivers (over 50 years old) sustained more fatal and serious injuries during the 9 am to 2 pm period than age group 2 drivers (25 to 50 years old) for both urban and rural roadways. Also, age group 2 drivers (25 to 50 years old) sustained more fatal and serious injuries during the 12 am to 5 am period. It is clear from the figure that distribution varies significantly with different times and geological locations (urban-rural) across three age groups.

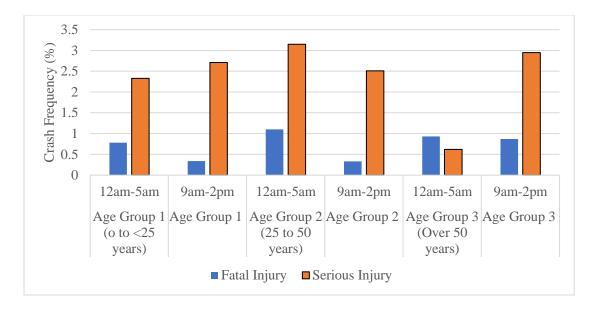


Figure 1: Distribution of urban crashes for three age groups for two different times of a day

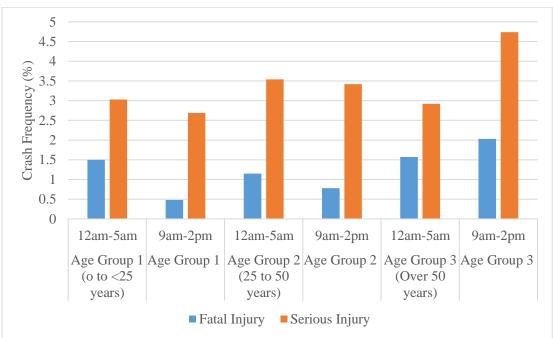


Figure 2: Distribution of rural crashes for three age groups for two different times of a day

The cleaned data are divided into five different datasets based on five different time periods of a day which are: 12 am - 5 am, 5 am - 9 am, 9 am - 2 pm, 2 pm - 7 pm, and 7 pm - 12 am. Previous time-of-day studies divided a day into different segments such as morning and afternoon (7), AM-PM peaks, and off-peak times (6). Our goal was to divide a day in such a way that we could divide the whole 24 hours into separate time periods. Of course, the morning and afternoon peak periods can be captured in the divided time period (5 am - 9 am and 2 pm - 7 pm respectively) and off-peak periods can be captured in other time periods. Later, these twelve individual datasets were used in mixed logit (random parameter) modeling approach. Elasticity values for each variable for all the datasets were also calculated. We had a total of five severity classes which are fatal injury, serious injury, minor injury, possible injury and property damage only crashes. Here we show the results for fatal and serious crashes only. **Table 1** shows the descriptive statistics of the variables used in the study.

Indicator variable	Time: 12	2am-5am	Time: 5am	n-9am	Time: 9a	am-2pm	Time: 2pt	m-7pm	Time:7p	m-12am	Time: W	hole day
(1 if present, 0	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
otherwise)	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
Roadway												
Characteristics												
Curve & Grade	0.1305	0.1487	0.1406	0.1968	0.1590	0.2234	0.1470	0.1972	0.1468	0.1581	0.1461	0.1888
Curve & Hillcrest	0.0275	0.0355	0.0289	0.0447	0.0302	0.0497	0.0290	0.0480	0.0339	0.0391	0.0301	0.0445
Curve & Level	0.1813	0.1673	0.1741	0.1829	0.1621	0.2065	0.1532	0.2001	0.1453	0.1822	0.1611	0.1907
Straight & Grade	0.1210	0.1692	0.1629	0.1724	0.1513	0.1577	0.1358	0.1581	0.1455	0.1597	0.1441	0.1622
Straight & Hillcrest	0.0286	0.0487	0.0324	0.0437	0.0281	0.0392	0.0373	0.0440	0.0322	0.0451	0.0321	0.0437
Straight & Level	0.5111	0.4307	0.4612	0.3595	0.4693	0.3234	0.4978	0.3527	0.4963	0.4158	0.4864	0.3702
Roadway Condition												
Dry	0.6855	0.7024	0.5514	0.5647	0.6118	0.5817	0.6514	0.6288	0.6460	0.6933	0.6281	0.6288
Ice	0.0351	0.0381	0.1011	0.1039	0.0326	0.0366	0.0195	0.0229	0.0334	0.0263	0.0423	0.0436
Other	0.0011	0.0010	0.0020	0.0020	0.0005	0.0019	0.0006	0.0012	0.0020	0.0011	0.0012	0.0014
Sand, Mud, Dirt, Oil,	0.0008	0.0001	0.0014	0.0012	0.0024	0.0020	0.0008	0.0018	0.0007	0.0011	0.0013	0.0014
Gravel												
Snow/Slush	0.0378	0.0257	0.0627	0.0486	0.0554	0.0568	0.0308	0.0349	0.0332	0.0273	0.0434	0.0394
Wet	0.2397	0.2325	0.2814	0.2797	0.2974	0.3210	0.2968	0.3104	0.2847	0.2509	0.2838	0.2854
Weather Condition												
Blowing Sand, Soil,	0.0122	0.0063	0.0137	0.0098	0.0118	0.0106	0.0083	0.0091	0.0064	0.0076	0.0102	0.0089
Dirt, Snow												
Clear	0.6134	0.6070	0.4626	0.4793	0.4868	0.4990	0.5363	0.5394	0.5639	0.6099	0.5285	0.5423
Cloudy	0.1740	0.1767	0.2451	0.2393	0.2528	0.2412	0.2080	0.1995	0.1792	0.1782	0.2138	0.2086
Fog with Rain	0.0031	0.0099	0.0031	0.0071	0.0022	0.0028	0.0014	0.0044	0.0035	0.0073	0.0026	0.0058
Fog/Smog/Smoke	0.0080	0.0370	0.0120	0.0410	0.0012	0.0019	0.0010	0.0012	0.0040	0.0061	0.0046	0.0138
Other	0.0008	0.0013	0.0040	0.0018	0.0007	0.0010	0.0006	0.0009	0.0015	0.0014	0.0015	0.0013
Raining	0.1481	0.1237	0.1798	0.1611	0.1983	0.1940	0.2118	0.2055	0.1936	0.1521	0.1905	0.1742
Severe Crosswinds	0.0000	0.0013	0.0017	0.0012	0.0007	0.0016	0.0004	0.0016	0.0007	0.0017	0.0007	0.0015
Sleet/Hail	0.0092	0.0094	0.0109	0.0139	0.0029	0.0086	0.0058	0.0089	0.0149	0.0101	0.0085	0.0101
Snowing	0.0313	0.0275	0.0670	0.0455	0.0427	0.0392	0.0263	0.0294	0.0324	0.0255	0.0393	0.0335
Lighting Condition												
Darkness - Highway	0.6137	0.0977	0.1781	0.0194	0.0041	0.0009	0.0621	0.0117	0.4700	0.0636	0.2321	0.0315
Lighted/On												
Darkness - Highway not Lighted	0.2824	0.7900	0.0910	0.2133	0.0031	0.0129	0.0520	0.1458	0.2713	0.7018	0.1262	0.3227

 Table 1: Descriptive statistics of variables for urban and rural roads on different time periods

Indicator variable	Time: 12	2am-5am	Time: 5am	n-9am	Time: 9a	am-2pm	Time: 2p	m-7pm	Time:7p	m-12am	Time: WI	nole day
(1 if present, 0	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
otherwise)	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
Darkness-Highway	0.0863	0.0912	0.0312	0.0280	0.0007	0.0019	0.0166	0.0201	0.0866	0.0881	0.0401	0.0404
Lighted/Off												
Dawn	0.0027	0.0053	0.1824	0.2022	0.0024	0.0054	0.0033	0.0035	0.0015	0.0022	0.0353	0.0421
Daylight	0.0038	0.0113	0.5102	0.5271	0.9887	0.9780	0.8257	0.7728	0.1156	0.0939	0.5415	0.5369
Dusk	0.0111	0.0044	0.0072	0.0099	0.0010	0.0008	0.0404	0.0461	0.0550	0.0504	0.0248	0.0264
Unit Type												
Bus	0.0004	0.0004	0.0023	0.0016	0.0034	0.0010	0.0021	0.0013	0.0005	0.0000	0.0018	0.0009
Emergency Vehicle in	0.0057	0.0046	0.0023	0.0007	0.0022	0.0012	0.0010	0.0015	0.0020	0.0031	0.0023	0.0020
Response												
Emergency Vehicle	0.0164	0.0152	0.0074	0.0042	0.0036	0.0027	0.0050	0.0030	0.0111	0.0087	0.0080	0.0057
Non-Response												
Farm Tractor and/or	0.0000	0.0001	0.0003	0.0001	0.0002	0.0012	0.0006	0.0010	0.0000	0.0002	0.0003	0.0006
Farm Equipment												
Go-Cart	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0001	0.0000	0.0001	0.0000	0.0001
Hit & Run/Unknown	0.0008	0.0006	0.0003	0.0001	0.0000	0.0001	0.0008	0.0002	0.0015	0.0001	0.0007	0.0002
Lt. Truck	0.2496	0.3373	0.3255	0.3957	0.3204	0.3616	0.3022	0.3587	0.2673	0.3544	0.2959	0.3632
Military Vehicle	0.0000	0.0001	0.0006	0.0006	0.0002	0.0003	0.0006	0.0003	0.0002	0.0003	0.0004	0.0003
Motor	0.0004	0.0009	0.0009	0.0006	0.0010	0.0023	0.0002	0.0014	0.0007	0.0015	0.0006	0.0014
Home/Recreational												
Vehicle												
Motor Scooter or Motor	0.0004	0.0005	0.0009	0.0001	0.0024	0.0008	0.0064	0.0016	0.0022	0.0008	0.0028	0.0009
Bicycle												
Motorcycle	0.0153	0.0072	0.0092	0.0062	0.0197	0.0270	0.0310	0.0367	0.0290	0.0200	0.0220	0.0221
Other	0.0004	0.0015	0.0009	0.0004	0.0002	0.0008	0.0006	0.0021	0.0005	0.0020	0.0005	0.0014
Other Public Owned	0.0011	0.0008	0.0006	0.0006	0.0012	0.0009	0.0006	0.0008	0.0002	0.0007	0.0007	0.0008
Vehicle												
Passenger Car	0.6500	0.5449	0.5875	0.5178	0.5365	0.4946	0.5701	0.5295	0.6304	0.5664	0.5896	0.5299
Passenger Car & Trailer	0.0008	0.0019	0.0009	0.0021	0.0043	0.0035	0.0033	0.0033	0.0027	0.0030	0.0026	0.0029
School Bus	0.0000	0.0000	0.0029	0.0021	0.0005	0.0008	0.0010	0.0012	0.0000	0.0002	0.0009	0.0009
Taxicab	0.0015	0.0003	0.0009	0.0001	0.0007	0.0001	0.0002	0.0000	0.0012	0.0001	0.0008	0.0001
Truck & Tractor	0.0088	0.0163	0.0129	0.0122	0.0266	0.0214	0.0205	0.0126	0.0124	0.0105	0.0171	0.0143
Truck Tractor & Semi-	0.0393	0.0564	0.0315	0.0376	0.0484	0.0470	0.0356	0.0286	0.0309	0.0225	0.0372	0.0357
Trailer												
Truck-Other	0.0031	0.0016	0.0011	0.0021	0.0038	0.0042	0.0014	0.0021	0.0012	0.0011	0.0021	0.0023
Combination												
Truck Single Unit	0.0061	0.0093	0.0115	0.0151	0.0247	0.0284	0.0166	0.0139	0.0057	0.0043	0.0137	0.0145

Indicator variable	Time: 12	2am-5am	Time: 5an	n-9am	Time: 9a	am-2pm	Time: 2p	m-7pm	Time:7p	m-12am	Time: WI	nole day
(1 if present, 0	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
otherwise)	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
Age Group												
AgeGrp1:0-25 years	0.3924	0.3529	0.2797	0.2949	0.2832	0.2807	0.2937	0.3000	0.3347	0.3341	0.3110	0.3081
AgeGrp2:26-50 years	0.4844	0.4794	0.5107	0.4916	0.4400	0.4193	0.4515	0.4350	0.4661	0.4551	0.4674	0.4518
AgeGrp3: Over 50	0.1233	0.1677	0.2096	0.2135	0.2767	0.3000	0.2548	0.2650	0.1993	0.2107	0.2216	0.2401
years												
Driver Gender												
Female	0.2805	0.2888	0.4091	0.3990	0.4216	0.4142	0.3937	0.4059	0.3567	0.3849	0.3793	0.3893
Male	0.7191	0.7112	0.5909	0.6009	0.5784	0.5856	0.6063	0.5939	0.6431	0.6151	0.6206	0.6106
Human												
Characteristics												
Alcohol Involvement	0.2111	0.1263	0.0186	0.0153	0.0132	0.0166	0.0342	0.0401	0.0938	0.0778	0.0635	0.0479
Cell Phone	0.0137	0.0063	0.0052	0.0041	0.0062	0.0061	0.0072	0.0072	0.0089	0.0062	0.0079	0.0061
Disregard Traffic	0.0031	0.0046	0.0026	0.0021	0.0058	0.0018	0.0031	0.0020	0.0037	0.0036	0.0037	0.0026
Control												
Distraction	0.0477	0.0257	0.0218	0.0203	0.0312	0.0355	0.0323	0.0325	0.0369	0.0228	0.0332	0.0279
Drug Involvement	0.0344	0.0281	0.0100	0.0109	0.0211	0.0173	0.0253	0.0225	0.0319	0.0281	0.0242	0.0210
Emotional	0.0099	0.0049	0.0020	0.0015	0.0048	0.0026	0.0035	0.0038	0.0062	0.0051	0.0050	0.0035
Exceeded Stated Speed	0.0496	0.0214	0.0112	0.0088	0.0132	0.0111	0.0221	0.0135	0.0292	0.0160	0.0234	0.0135
Limit												
Failed to Yield Right of	0.0027	0.0004	0.0020	0.0003	0.0026	0.0004	0.0025	0.0005	0.0007	0.0001	0.0021	0.0004
Way												
Fatigue	0.0366	0.0308	0.0186	0.0203	0.0072	0.0087	0.0058	0.0088	0.0079	0.0064	0.0131	0.0127
Fell Asleep	0.0618	0.0665	0.0487	0.0544	0.0209	0.0225	0.0151	0.0227	0.0134	0.0151	0.0285	0.0316
Following Too Close	0.0027	0.0008	0.0057	0.0011	0.0067	0.0014	0.0087	0.0022	0.0025	0.0007	0.0056	0.0013
Improper Backing	0.0015	0.0010	0.0014	0.0005	0.0048	0.0008	0.0019	0.0007	0.0017	0.0007	0.0023	0.0008
Improper Passing	0.0008	0.0003	0.0026	0.0012	0.0010	0.0017	0.0027	0.0023	0.0020	0.0011	0.0019	0.0015
Inattention	0.1378	0.1080	0.1134	0.1013	0.1453	0.1506	0.1455	0.1419	0.1319	0.1028	0.1357	0.1237
Lost	0.0073	0.0065	0.0157	0.0067	0.0252	0.0188	0.0209	0.0129	0.0119	0.0054	0.0171	0.0106
Consciousness/Fainted												
Medication	0.0015	0.0015	0.0034	0.0010	0.0043	0.0019	0.0050	0.0030	0.0042	0.0021	0.0039	0.0020
Misjudge Clearance	0.0172	0.0106	0.0338	0.0159	0.0671	0.0271	0.0528	0.0227	0.0329	0.0166	0.0434	0.0197
Not Under Proper	0.2126	0.1865	0.2419	0.2024	0.2782	0.2785	0.2606	0.2487	0.2213	0.1828	0.2462	0.2248
Control												
Overcorrecting/Overste	0.0679	0.0793	0.0696	0.0852	0.0873	0.1141	0.0807	0.1008	0.0696	0.0699	0.0760	0.0914
ering												
Physical Disability	0.0023	0.0013	0.0029	0.0010	0.0041	0.0028	0.0060	0.0026	0.0027	0.0009	0.0038	0.0018

Indicator variable	Time: 12	2am-5am	Time: 5am	-9am	Time: 9a	um-2pm	Time: 2pi	n-7pm	Time:7p	m-12am	Time: Wh	nole day
(1 if present, 0	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
otherwise)	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
Sick	0.0050	0.0030	0.0066	0.0027	0.0115	0.0061	0.0112	0.0054	0.0040	0.0026	0.0080	0.0042
Too Fast for Conditions	0.0916	0.0592	0.1268	0.0839	0.1096	0.0921	0.0898	0.0768	0.0948	0.0557	0.1022	0.0748
Turning Improperly	0.0019	0.0018	0.0026	0.0006	0.0036	0.0015	0.0039	0.0016	0.0050	0.0008	0.0036	0.0012
Weaving in Traffic	0.0027	0.0000	0.0014	0.0003	0.0007	0.0008	0.0010	0.0008	0.0030	0.0005	0.0017	0.0006
Other	0.0473	0.0314	0.0736	0.0347	0.0887	0.0438	0.0714	0.0424	0.0421	0.0282	0.0661	0.0369
None Detected	0.3248	0.4745	0.3576	0.4964	0.2731	0.3591	0.3347	0.4100	0.4134	0.5513	0.3407	0.4543

RESULTS AND DISCUSSIONS

Log Likelihood-Ratio Test for Time-of-Day and Urban-Rural Models

The null hypothesis for the log-likelihood ratio test is that the combined model including all time frames of a day does not have significantly lower log-likelihood compared to the separate models built for different times of a day, which in turn indicates a lack of significant difference between the combined model and separate models. The test statistics is χ^2 distributed with *n* degrees of freedom.

$$LR = -2[LL(\beta_{all}) - LL(\beta_1) - LL(\beta_2) - LL(\beta_3) - LL(\beta_4) - LL(\beta_5)]$$
(5)

 $LL(\beta_{all})$ = Log-likelihood value for all time-of-day model $LL(\beta_1)$ = Log-likelihood value for 12 am to 5 am model $LL(\beta_2)$ = Log-likelihood value for 5 am to 9 am model $LL(\beta_3)$ = Log-likelihood value for 9 am to 2 pm model $LL(\beta_4)$ = Log-likelihood value for 2 pm to 7 pm model $LL(\beta_5)$ = Log-likelihood value for 7 pm to 12 am model For urban crash models:

 $LR_{urban} = -2(-12981.47 + 1834.83 + 2258.83 + 2978.41 + 3323.23 + 2539.44)$

 $=93.46 > \chi^2_{59,99.99\%}$ (87.16)

For rural crash models:

 $LR_{Rural} = -2(-57645.77 + 5899.81 + 10110.16 + 13476.54 + 16747.94 + 11148.20)$ $= 524.7 > \chi^{2}_{112.99.99\%} (152.162)$

From the above calculation, it was found that we can reject the null hypothesis for both urban and rural crash models. A similar test was conducted to justify the need to model crashes on urban and rural roads separately (for brevity we do not report the results for these two models here).

$$LR_{separate} = -2(-70785.15 + 57645.77 + 12979.07)$$
$$= 320.62 > \chi^{2}_{30,99.99\%} (50.89)$$

Roadway Attributes:

Table 2 and **Table 3** show the estimates for fatal and serious injury for rural and urban crashes respectively. The estimates for minor injury, possible injury, and property damage only crashes were not shown for the lack of space. **Table 2** indicates hilly roads with curves are found to positively influence the probability of a fatal crash during 12 am - 5 am on rural roads. Straight (grade) roads are found to increase the fatal injury outcome during 12 am - 5 am and 5 am - 9 am. Dry Road surface has a significant positive correlation with fatal and serious injury outcomes (9 am - 2 pm). This is similar to findings by (7) where truck drivers experienced fatality or serious injury, and by (5) where passenger cars experienced serious injury on dry roads during the morning time. Roads with ice increase the probability of serious injury for 9 am - 2 pm and 2 pm - 7 pm models and increase fatality probability for the 9 am - 2 pm model.

Table 3 (urban road crashes) also reports that dry road surface has a positive correlation with fatality, serious injury, or both in all the models except the 2 pm - 7 pm model. The effect of dry road surface in the 2 pm - 7 pm model is found to be a random parameter with a mean of 2.48 and a standard deviation of 2.24. Using these values in a normal distribution curve, this variable is found to decrease the probability of fatality by 13.41 percent. Icy Road surface is found to increase the probability of serious injury outcome for the 5 am - 9 am model.

Weather Condition:

Table 2 (rural road crashes) reports that cloudy weather increases the probability of serious injury for the 7 pm – 12 am model. The study (*15*) also found that cloudy weather significantly increases the probability of fatality or serious injury. This might be due to the lower visibility in cloudy conditions and reduced color contrasts compared to clear skies. The effect of cloudy weather in the 5 am – 9 am model is found to be a random parameter with a mean of 2.75 and a standard deviation of 1.78. Using these values in a normal distribution curve, this variable is found to decrease the probability of serious injury for 6.1 percent of the sample (decrease for the rest93.9 percent). For urban road crashes (**Table 3**), cloudy weather has a positive correlation with serious injury for the 9 am – 2 pm model.

Lighting Condition:

Table 2 indicates that rural crashes during daylight have a positive correlation with fatality for the 2 pm - 7 pm and 7 pm - 12 am models; however, exhibits a negative correlation with fatality for the 9 am - 2 pm model. This finding can be explained by a previous study(*16*) which showed that daylight reduces severe injury outcomes except for days where the morning time is short (winter and fall). Also, darkness with streetlights being turned on is found to decrease serious injury outcome probability for rural crashes in the 2 pm – 7 pm and 7 pm – 12 am models. In **Table 3** (urban road crashes), this variable is found to negatively influence serious injury outcomes for urban crashes for the 2 pm – 7 pm and the 7 pm – 12 am models. Daylight reduction due to season change was not considered here.

Driver Age:

From **Table 2** (rural road crashes), young drivers less than 25 years old (Age Group 1) are found to have a lower probability of fatality or serious injury or both for all rural time of day models (except for 5 - 9 am). This finding is similar to the finding of (*16*) where crashes involving young drivers were found to decrease the probability of serious injury outcomes due to having much more physiological strength than older drivers. Further, the effect of this young driver variable in the 7 pm – 12 am model is found as a random parameter for serious injury outcome with a mean of 1.61 and standard deviation of 2.66.

From **Table 2** (rural road crashes), drivers of Age group 3 (50 years and older) are found to have a positive correlation with serious injury in the 9 am -2 pm model. However, this variable is found to have a negative correlation with fatality in four of the rural crash models, but this variable was found as a random parameter in these models. The positive correlation of this variable with serious injury is supported by the findings of (*15*), (*16*), and (*5*) where drivers aged 65 and over were found to have a positive correlation with serious injury outcomes.

Gender:

Female drivers in rural crash models are found to decrease the probability of fatality (**Table 2**) except for the 12 am to 5 am model, and the effect of this variable is found as random parameters in the 5 am - 9 am, 9 am - 2 pm and 2 pm - 7 pm models. By using the mean and standard deviation values for the respective models, this variable is found to decrease the probability of fatal injury of 2.05 percent of the sample population in the 5 am - 9 am model, decrease the probability of fatal injury of 18.49 percent of the population in the 9 am - 2 pm model and decrease the probability of fatal injury of fatal injury of 22.09 percent of the sample population in

the 7 pm - 12 am model. This finding is similar to (21) and (15) where female drivers were found to increase the probability of no injury (property damage only) outcome.

Table 2 indicates that male drivers have a negative correlation with fatality in the 12 am – 5 am model and have a negative correlation with serious injury in the 7 pm – 12 am. The effect of the male variable is found as a random parameter and this variable is found to decrease the probability of fatality of 17.3 percent of the sample in the 12 am – 5 am model and the probability of serious injury of 31.13 percent of the population in the 7 pm – 12 am model. **Table 3** (urban road crashes) shows that male drivers have a positive correlation with serious injury outcomes for the 5 am – 9 am, 9 am – 2 pm, and the 2 pm – 7 pm models. The finding is similar to (*16*) where male drivers were found to increase the probability of fatality.

Driving Attributes:

Table 2 (rural road crashes) indicates that oversteering by drivers increases the probability of serious injury for the 12 am – 5 am model and the 5 am – 9 am models. This variable is found to decrease the probability of serious injury for the 9 am – 2 pm model and for the 7 pm – 12 am model, although in these two models the effect of this variable was found as a random parameter. Also, results show that losing control of the vehicle increases the probability of fatality or serious injury in all models. From **Table 2** (rural road crashes), driving under influence of alcohol or drugs is found to increase the probability of both fatality and serious injury. From **Table 3** (urban road crashes), this variable is also found to have a positive correlation with the serious injury outcome for the urban 12 am – 5 am and the 7 pm – 12 am model. This result is supported by previous studies where usage of alcohol or illicit drugs was found to increase the probability of fatality or serious injury outcome (*15*)(*22*) (*8*) (*5*) (*10*)(*18*)

Explanatory	12 am-5 am	!	5 am-9 am		9 am-2 pm	!	2 pm-7 pm	!	7 pm-12 ar	n
Variables	Parameters		Parameters		Parameter	.s	Parameter	.s	Parameter	s
	(Z Score)		(Z Score)		(Z Score)		(Z Score)		(Z Score)	
	Fatal	Serious	Fatal	Serious	Fatal	Serious	Fatal	Serious	Fatal	Serious
Constants	-3.91	-2.21	-4.29	-1.98	-3.56	-2.40	-3.98	-2.38	-3.21	-2.66
	(-10.56)	(-13.75)	(-13.64)	(-21.8)	(-4.64)	(-9.87)	(-12.21)	(-7.81)	(-18.35)	(-11.79)
Roadway Characteristics and Conditions										
Curve & hill (1 if	1.04(2.87)									
roadway										
characteristics are										
curve & hill; 0										
otherwise)										
Straight & grade (1 if	0.69(2.04)		0.98							
roadway			(3.91)							
characteristics is										
straight & grade; 0										
otherwise)										
Dry (1 if roadway		0.44			1.84	0.8		1.09		0.40
condition is dry; 0		(2.84)			(2.7)	(3.36)		(3.6)		(2.63)
otherwise)										
Ice (1 if the roadway					1.68	0.73		0.71		
has ice; 0 otherwise)					(2.45)	(2.97)		(2.28)		
Weather Condition										
Cloudy (1 if the				-2.53						0.17
weather condition is				(-1.02)						(1.13)
cloudy; 0 otherwise)										
Standard Deviation –				2.75						
Normal Distribution				(1.78)		_				
Lighting Condition						-		-		
Day (1 if daylight; 0					-1.47		1.08		0.45	
otherwise)					(-3.68)		(3.84)		(1.90)	
Light_on (1 if the								-0.93		-0.35
highway is lighted								(-5.56)		(-2.77)
and light is on; 0										
otherwise)						_				

Table 2: Model outputs for all the models for Fatal Injury and Serious injury outcome for Rural Roads

Explanatory	12 am-5 ar	т	5 am-9 an	n	9 am-2 pn	n	2 pm-7 pn	n	7 pm-12 ai	n
Variables	Parameter	·s	Paramete	rs	Paramete	rs	Paramete	rs	Parameter	s
	(Z Score)		(Z Score)		(Z Score)		(Z Score)		(Z Score)	
	Fatal	Serious	Fatal	Serious	Fatal	Serious	Fatal	Serious	Fatal	Serious
Driver Age										
Age group 1 (1 if		-0.26				-0.32	-0.77	-0.59	-0.58	-1.25
driver age is 0 to 25		(-1.86)				(-2.57)	(-3.27)	(-5.53)	(-2.60)	(-1.81)
years; 0 otherwise)										
Standard Deviation -										1.61
Normal Distribution										(2.66)
Age group 3 (1 if			-0.67		-1.31	0.39	-1.34		-0.77	
driver age is over 50			(-0.52)		(-0.74)	(3.87)	(-0.98)		(-0.60)	
years; 0 otherwise)										
Standard Deviation -			2.04		2.7		2.47		1.76	
Normal Distribution			(2.27)		(2.3)		(2.69)		(1.90)	
Gender										
Male (1 if the driver	-0.84									-0.19
is male; 0 otherwise)	(-0.61)									(-0.42)
Standard Deviation –	1.96									1.24
Normal Distribution	(2.08)									(2.52)
Female (1 if the			-7.92		-3.56		-2.42			
driver is female; 0			(-1.70)		(-2.12)		(-2.01)			
otherwise)										
Standard Deviation –			4.6		2.78		2.00			
Normal Distribution			(2.25)		(3.1)		(2.6)			
Human										
Characteristics	<u> </u>									
Oversteering (1 if the		0.4		0.67		-0.88				-1.82
driver has done		(1.86)		(3.7)		(-0.73)				(-1.06)
oversteering; 0										
otherwise)	_					2.1.4	_			0.07
						2.14				3.27
Standard Deviation –						(2.14)				(2.48)
Normal Distribution	<u> </u>	0.00	1.64	0.62	1.00	0.05	1.25	0.02	1.40	1.00
Control (1 if the		0.69	1.64	0.62	1.00	0.85	1.36	0.93	1.42	1.28
vehicle is not under		(4.79)	(6.70)	(4.65)	(4.63)	(8.89)	(6.49)	(10.43)	(7.69)	(8.45)
proper control; 0										
otherwise)										

Explanatory	12 am-5 an	ı	5 am-9 am		9 am-2 pm		2 pm-7 pm		7 pm-12 am	
Variables	Parameters	ľ	Parameters		Parameters		Parameters		Parameters	
	(Z Score)		(Z Score)	Z Score)			(Z Score)		(Z Score)	
	Fatal	Serious	Fatal	Serious	Fatal	Serious	Fatal	Serious	Fatal	Serious
Alcohol (1 if driver	1.87	1.26	1.85	1.35	1.45	0.64	1.32	1.06	1.39	1.61
was found driving	(5.72)	(8.80)	(4.66)	(4.7)	(3.46)	(2.47)	(5.25)	(8.18)	(6.83)	(9.15)
drunk; 0 otherwise)										

 Table 3: Model outputs for all the models for Fatal Injury and Serious injury outcome for Urban Road crashes

Explanatory	12 am-5 a	ım	5 am-9 am		9 am-2 pn	n	2 pm-7 pn	ı	7 pm-12 ai	n
Variables	Paramete	rs	Parameter	s	Paramete		Parameter		Parameter	S
	(Z Score)		(Z Score)		(Z Score)		(Z Score)		(Z Score)	
	Fatal	Serious	Fatal	Serious	Fatal	Serious	Fatal	Serious	Fatal	Serious
Constants	-4.27	-2.76	-3.4	-3.52	-5.16	-1.79	-5.5	-2.12	-3.39	-2.16
	(-5.68)	(-7.10)	(-11.04)	(-5.55)	(-4.96)	(-8.25)	(-4.82)	(-7.13)	(-7.50)	(-7.49)
Roadway										
Characteristics and Conditions										
Dry (1 if roadway	1.66	1.08		1.26	2.18		-0.4	0.77		0.51
condition is dry; 0	(2.23)	(2.80)		(2.09)	(2.11)		(-0.18)	(3.03)		(1.76)
otherwise)	. ,			. ,						
Standard Deviation –							2.48			
Normal Distribution							(2.24)			
Ice (1 if the roadway				1.07						
has ice; 0 otherwise)				(1.68)						
Weather Condition										
Cloudy (1 if the						0.57				
weather condition is						(2.85)				
cloudy; 0 otherwise)										
Lighting Condition										
Light_on (1 if the								-1.90		-0.63
highway is lighted								(-1.83)		(-2.25)
and light is on; 0										
otherwise)										
Driver Age										

Explanatory	12 am-5 a	т	5 am-9 am		9 am-2 pm		2 pm-7 pm		7 pm-12 am	
Variables	Parameter	.s	Parameters		Parameters	5	Parameters		Parameters	
	(Z Score)		(Z Score)		(Z Score)		(Z Score)		(Z Score)	
	Fatal	Serious	Fatal	Serious	Fatal	Serious	Fatal	Serious	Fatal	Serious
Age group 1 (1 if							-2.30	-0.56		
driver age is 0 to 25							(-2.01)	(-2.38)		
years; 0 otherwise)										
Gender										
Male (1 if the driver				0.72		0.41		0.35		
is male; 0 otherwise)				(2.33)		(1.98)		(1.72)		
Human										
Characteristics										
Control (1 if vehicle	1.57	1.01		0.67	1.03	0.36	2.19	1.07	1.16	0.76
is not under proper	(3.87)	(3.86)		(2.34)	(2.27)	(1.72)	(3.08)	(5.63)	(2.07)	(3.35)
control; 0 otherwise)										
Alcohol (1 if the		0.75								1.04
driver was found		(2.86)								(4.09)
driving drunk; 0										
otherwise)										
None (1 if no specific									-1.13	
human characteristics									(-1.76)	
were identified; 0										
otherwise)										

Direct Pseudo-Elasticity

Table 4 reports the direct pseudo-elasticity values of the estimates for different injury outcomes specific to the rural and urban time-of-day models. For instance, in urban crash models, drivers of age group 1 are found to decrease the probability of fatality outcome by 65.54 percent for the 2 pm - 7 pm model. This variable is also found to decrease the serious injury probability by 16.02 percent for the 2 pm - 7 pm model. From **Table 4**, female drivers are found to increase the probability of fatality by 84.7 percent in the 5 am – 9 am period, and in the 9 am – 2 pm model, this variable is found to decrease fatality probability by 59.6 percent. From **Table 4**, when streetlights are on, this variable is found to decrease the probability of serious injury by 12.92 percent for the rural 2 pm – 7 pm model, and for the rural 7 pm – 12 am model this variable is found to decrease serious injury probability by 21.77 percent. This finding is similar for the urban roads as well. It shows that during nighttime in both rural and urban roads if streetlights are installed and they are on, the probability of fatality or serious injury is lower. The elasticity values are reflective of the estimates in **Table 2** and **Table 3**, and we have not discussed all the values to avoid repetition.

Urban-Rural Differences

Some interesting findings can be observed for urban-rural differences. Roadway characteristics (e.g., curve and hills, straight and grade) are found to increase the probability of fatal crashes for rural roadways in the 12 am to 5 am and 5 am to 9 am periods, but these parameters were found insignificant for urban crashes. The presence of daylight is found to decrease the fatality probability in the 9 am to 2 pm period while this same variable is found to increase the fatality probability in the 2 pm to 7 pm and the 7 pm to 12 am period. One probable reason might be lack of daylight and presence of darkness in the latter two time periods during the late fall and winter months, which is known to be influential for fatality and serious injury (6, 7). However, daylight is found statistically insignificant for urban roadways. Being a male driver is found to increase the fatality and serious injury probability for both urban and rural crashes, but this variable is found as a random parameter in the rural crash models. For urban roads, male drivers are found to be positively influencing the serious injury probability in the 5 am to 9 am, 9 am to 2 pm, and 2 pm to 7 pm periods while their female counterparts are found as statistically insignificant in urban crash models. This finding does not support the finding of (14) where it was found that female drivers have a higher probability of producing fatality or serious injury when involved in accidents. One possible reason might be the presence of a higher proportion of male truck drivers(7). Oversteering by the driver is found to increase serious injury probability in all the five times of day in rural crash models, but this is found to be insignificant in urban crash models. While alcohol is found to increase the fatality and serious injury probability in all the rural crash models, this is found to increase the serious injury probability in just two urban crash models (12 am to 5 am and 7 pm to 12 am model). It shows that driving under the influence of alcohol has more serious consequences in rural areas than urban areas which might be due to slower EMS response times (50).

Table 5 provides a side-by-side comparison of the major differences in the effect of variables based on the urban-rural setting.

Explanatory Variables	12 am-5	am	5 am-9	ат	9 am-2 p	m	2 pm-7	рт	7 pm-12	2 am
	Elasticit	y (%)	Elastici	ty (%)	Elasticit	y (%)	Elastici	ty (%)	Elastici	ty (%)
	Fatal	Serious	Fatal	Serious	Fatal	Serious	Fatal	Serious	Fatal	Serious
		Rur	al Road	Crashes						
Roadway Characteristics and Conditions										
Curve & hill (1 if roadway characteristics are curve & hill; 0 otherwise)	13.23									
Straight & grade (1 if roadway characteristics is straight & grade; 0 otherwise)	10.07		14.5							
Dry (1 if roadway condition is dry; 0 otherwise)		29.74	33.93		89.06	43.12		62.13		24.46
Ice (1 if the roadway has ice; 0 otherwise)					46.85	21.95		20.23		
Weather Condition										
Cloudy (1 if the weather condition is cloudy; 0 otherwise)				31.92						2.58
Lighting Condition										
Day (1 if daylight; 0 otherwise)					-122.98		75.18		4.08	
Lighton (1 if the highway is lighted and light is on; 0 otherwise)					-122.90		75.10	-12.92	4.00	-21.77
No light (1 if the highway has no light; 0 otherwise)										-4.60
Driver Age										
Age group 1 (1 if driver age is 0 to 25 years; 0 otherwise)		-8.75				-8.42	-22.70	-15.81	-19.11	19.97
Age group 3 (1 if the driver age is over 50 years; 0 otherwise)			36.65		60.21	10.99	51.97		34.64	
Gender										
Male (1 if the driver is male; 0 otherwise)	137.85				1		Ì		1	54.80
Female (1 if the driver is female; 0 otherwise)			84.78		59.61		33.29		-28.42	
Human Characteristics										
Oversteering (1 if the driver has done oversteering; 0 otherwise)		3.01		5.05		14.21		10.85		9.69

Table 4: Elasticity values of parameters for fatality and serious injury for the Rural and Urban crash models

Explanatory Variables	12 am-5 am Elasticity (%)		5 am-9 am Elasticity (%)		9 am-2 pm Elasticity (%)		2 pm-7 pm Elasticity (%)		7 pm-12 am Elasticity (%)	
	Fatal	Serious	Fatal	Serious	Fatal	Serious	Fatal	Serious	Fatal	Serious
Control (1 if the vehicle is not under proper control; 0 otherwise)		12.12	26.83	11.14	23.45	21.43	30.11	19.93	24.75	18.36
Alcohol (1 if driver was found driving drunk; 0 otherwise)	18.82	14.54	2.43	1.78	1.91	0.96	4.47	3.66	10.12	9.58
	•	Urbe	an Road (Crashes		•		•		•
Roadway Characteristics and Conditions										
Dry (1 if roadway condition is dry; 0 otherwise)	112.30	71.86		68.22	132.28		253.46	48.02		32.26
Ice (1 if the roadway has ice; 0 otherwise)				29.66						
Weather Condition										
Cloudy (1 if the weather condition is cloudy; 0 otherwise)						13.09				
Lighting Condition										
Light-on (1 if the highway is lighted and light is on; 0 otherwise)								-9.81		-16.76
Driver Age										
Age group 1 (1 if driver age is 0 to 25 years; 0 otherwise)							-65.54	-16.02		
Gender										
Male (1 if the driver is male; 0 otherwise)				41.91		23.13		20.18		
Human Characteristics										
Control (1 if vehicle is not under proper control; 0 otherwise)	32.58	20.33		15.76	28.41	9.64	50.58	26.5	25.34	16.18
Alcohol (1 if the driver was found driving drunk; 0 otherwise)		15.05								9.21

Table 5: Major differences in the effect of variables for urban-rural setting	Table 5: Majo	r differences in	n the effect (of variables for	urban-rural setting
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Variable	Influence in Urban crashes? (Y/N)	Influence in Rural crashes? (Y/N)	Highest Positive Elasticity (%) (urban)	Lowest Positive Elasticity (%) (urban)	Highest Positive Elasticity (%) (rural)	Lowest Positive Elasticity (%) (rural)	Highest Negative Elasticity (%) (rural)	Lowest Negative Elasticity (%) (Rural)
Curve and hilly (1 if roadway characteristics are curve & hill; 0 otherwise)	N	Y	N/A	N/A	13.23 (fatal) in the 12 am – 5 am period	N/A	N/A	N/A
Straight and grade (1 if roadway characteristics is straight & grade; 0 otherwise)	N	Y	N/A	N/A	14.5 (fatal) in the 5 am – 9 am period	10.07 in the 12 am – 5 am period	N/A	N/A
Daylight (1 if daylight; 0 otherwise)	Ν	Y	N/A	N/A	75.18 (fatal) in the 2 pm - 7 pm period	4.08 (fatal) in the 7 pm – 12 am period	-122.98 in the 9 am – 2 pm period***	N/A
Oversteering (1 if the driver has done oversteering; 0 otherwise)	N	Y	N/A	N/A	14.21 (serious) in the 9 am – 2 pm period	3.01 (serious) in the 12 am - 5 am period	N/A	N/A
Age group 3 (1 if the driver age is over 50 years; 0 otherwise)	N	Y	N/A	N/A	60.21 (fatal) in the 9 am – 2pm period***	10.99 (serious) in the 9 am – 2 pm period	N/A	N/A
Female driver (1 if the driver is female; 0 otherwise)	N	Y	N/A	N/A	84.78 (fatal) in the 5 am – 9 am period	33.29 (fatal) in the 2 pm – 7 pm period	-28.42 (fatal) in the 7 pm – 12 am period	N/A
Alcohol (1 if the driver was found driving drunk; 0 otherwise)	Y	Y	15.05 (serious) in the 12 am – 5 am period	9.21 (serious) in the 7 pm – 12 am period	18.82 (fatal) in the 12 am – 5 am period	0.96 (serious) in the 9 am – 2 pm period	N/A	N/A

CONCLUSION

Using five years of police crash report data from Kentucky, this research examined the effect of time of day on resulting injury severities on single-vehicle crashes on urban and rural roads. Only singlevehicle crashes were considered for this study to better capture the human characteristics of the drivers associated with the crashes. Likelihood ratio test results justified the necessity of building separate models for different times of a day rather than building just one model including all times of a day for urban and rural crashes. However, some variables were found to show a varying effect at different times of the day. For instance, results show that rural crashes during daylight are less likely to produce fatality in the 9 am to 2 pm period but more likely to produce fatality in the 2 pm to 7 pm and the 7 pm to 12 am periods. Also, young drivers were found to have less likelihood to be involved in fatal and serious injury crashes in almost all the rural road models, which contradicts the findings of some previous studies that younger drivers have a higher likelihood of getting involved in fatal or serious injury crashes. Moreover, it was found that rural crashes involving female drivers have a significant positive correlation with fatality and serious injury outcomes in all models except for the 7 pm - 12 am model. Some variables such as alcohol, losing control of the vehicle, oversteering, dry road surface, icy road surface, cloudy environment is found to exhibit a relatively similar and stable effect over all the rural and urban models. The pseudo elasticity values for different variables shown in Table 4 provide us insights regarding prioritizing variables across different injury outcomes. Our findings indicate that rural drivers over 50 years old, male drivers on the urban roads, and drunk driving on rural roads have a higher probability to experience fatality and serious injuries. NHTSA (51) provided guidelines and countermeasures against drunk driving, old driver and young driver fatality, and speeding. Kentucky traffic authorities can revise their existing countermeasure approaches based on the guidelines.

The findings of this research can be used in the improvement of current state-specific Safety Performance Functions (SPFs). For example, we have found rural female drivers, rural older drivers, dry roads, icy roads, drunk driving, losing control of vehicles to have a significant positive correlation with fatality and serious injury in all the models. These variables are more common in crash injury-severity analysis than crash frequency analysis because crash frequency models do not use the information on specific crashes (e.g., characteristics of drivers, specific weather conditions, vehicle information). However, SPFs are developed using crash frequency analysis such as negative binomial regression and EB (Empirical Bayes) method. Police crash reports typically contain geographic coordinates of specific crashes. Plotting those coordinates in a GIS map would show the road segments where those crashes occurred. Then, for any specific segment, we will have information on all the crashes that occurred during a specific period, such as gender frequency of drivers that experienced a crash in that segment, their age, DUI information, information on the frequency of different weather conditions, frequency of different periods of the crashes. After that, following the methodology shown in (*52*), we can see how many of these influential variables also influence the crash frequency and generate SPFs for different road segments, for county level and state level using negative binomial regression. We can also develop SPF for different times of the day and analyze their performance.

The contributions of this research are—first, we have identified and investigated the factors which influence fatality and serious injury outcomes for single-vehicle crashes for urban and rural road crashes in Kentucky separately. Second, the estimated random-parameter models have accounted for any unobserved heterogeneity in the dataset. Finally, we have explored the heterogeneous time-varying effect of the various determinants for urban and rural roads. The methodology can be extended to study crash data in geographical locations other than Kentucky and provides insights for understanding the urban-rural differences in crash severity determinants across different times of the day.

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