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How did the COVID-19 pandemic affect road crashes and crash outcomes in Alabama?

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ABSTRACT

With the rising number of cases and deaths from the COVID-19 pandemic, nations and local governments, including many across the U.S., imposed travel restrictions on their citizens. This travel restriction order led to a significant reduction in traffic volumes and a generally lower exposure to crashes. However, recent preliminary statistics in the US suggest an increase in fatal crashes over the period of lockdown in comparison to the same period in previous years. This study sought to investigate how the pandemic affected road crashes and crash outcomes in Alabama. Daily vehicle miles traveled and crashes were obtained and explored. To understand the factors associated with crash outcomes, four crash-severity models were developed: (1) Single-vehicle (SV) crashes prior to lockdown order (Normal times SV); (2) multi-vehicle (MV) crashes prior to lockdown order (Normal times MV); (3) Single-vehicle crashes after lockdown order (COVID times SV); and (4) Multi-vehicle crashes after lockdown order (COVID times MV). The models were developed using the first 28 weeks of crashes recorded in 2020. The findings of the study reveal that although traffic volumes and vehicle miles traveled had significantly dropped during the lockdown, there was an increase in the total number of crashes and major injury crashes compared to the period prior to the lockdown order, with speeding, DUI, and weekends accounting for a significant proportion of these crashes. These observations provide useful lessons for road safety improvements during extreme events that may require statewide lockdown, as has been done with the COVID-19 pandemic. Traffic management around shopping areas and other areas that may experience increased traffic volumes provide opportunities for road safety stakeholders to reduce the occurrence of crashes in the weeks leading to an announcement of any future statewide or local lockdowns. Additionally, increased law enforcement efforts can help to reduce risky driving activities as traffic volumes decrease.

1. Introduction

The outbreak of the coronavirus disease 2019 (COVID-19) caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) was declared a public health emergency in January 2020 and upgraded to a pandemic in March 2020. Response to the COVID-19 pandemic has had tremendous effects on the global economy and social life, and it has significantly disrupted transportation systems across the world. With the rising number of cases and deaths from the pandemic, nations and local governments, including many across the U.S., imposed travel restrictions on their citizens. These measures have reduced travel and lowered the risk of collisions. However, recent preliminary statistics in the US suggest an increase in fatal crashes over the period of the lockdown in comparison to the same period in previous years. This was established by Brown (2020), who looked not only at fatal crashes but several other crash types.

Indeed, reports point to similar increases in other countries during the COVID-19 pandemic (Australian Road Safety Foundation, 2020; BBC, 2020; City News, 2020). In the US, Carter (2020) and Lockwood et al (2020) observed that the proportion of speeding-related crashes and fatalities had increased during the pandemic lockdown in North Carolina and Virginia, respectively. Vingilis et al (2020) identified personal factors, such as: (1) the propensity for risky behaviors, (2) situational and structural factors such as gas price changes, and (3) reduced law enforcement, as potential factors that affected road safety performance during the pandemic. The pandemic has also been characterized by increased alcohol sale and use (Benzie, 2020; Sharpe, 2020), potentially as a result of reported increase in stress, anxiety, and depression among...
certain population groups (e.g., Liu et al., 2020). With these factors known to be risk factors in road crashes (Wickens et al., 2014), the impacts of the pandemic on road safety appear to be multifactorial requiring an interdisciplinary approach to unravel.

In this study, we investigated the pattern of crashes that occurred in the state of Alabama for the first 28 weeks of 2020. The state announced a stay-at-home (or lockdown) order on March 11, 2020 (week 11) and so, the crash data has been segmented into crashes that occurred prior to March 11, as Normal times and those that occurred after March 11 as COVID times. This order strongly recommended that travel be restricted to only essential trips and this generally impacted traffic volumes and likelihood of crash occurrence. To understand the effect of the stay-at-home order on the trend and primary contributing factors of crashes in the state, the preliminary analysis included historical crash data for the same period in 2018 and 2019. Additionally, we performed injury-severity analyses to understand the association between various crash factors and crash outcomes before and after the lockdown order in the state. This was done to assess whether the factors that influenced crash outcomes differed before and after the lockdown order. As such, only the crash data for the first 28 weeks of 2020 were used for the injury-severity analysis. The 2020 data was further segmented into single-vehicle and multi-vehicle crashes for the period before and after the lockdown order went into effect. Subsets of the crash data were considered to unravel the complex relationships within the injury-severity analysis with regards to the effects of the manner of collision and the lockdown order. Latent Class Multinomial Logit (LC-MNL) and random parameters logit with heterogeneity in means and variances modeling approaches were adopted to address the limitations in the crash data that have the potential to bias the results and the resulting decisions. Segmentation of the crash data for modeling purposes helped to better understand how the crash factors influenced crash outcomes under different scenarios and this provides an opportunity for state officials to target specific countermeasure efforts in a more efficient manner.

2. Review of previous studies

Human factors have previously been shown to be the leading contributing factor in crash occurrence (Tillmann and Hobbs, 1949; Treat, 1977; Hendricks et al., 2001). The National Highway Traffic Safety Administration (NHTSA) has identified DUI (drunk and drug-impaired driving), speeding, failure to seat belts, and drowsy and distracted driving to be the major risky driver behaviors that contribute to crashes. While factors such as DUI, contribute to crash occurrence, speeding increases the severity of the crash. Similarly, although failure to use seatbelt does not in itself cause crashes, it increases the probability of being injured in a crash (Evans, 1996; Abdel-Aty, 2003; Wang and Jiang, 2003; Kim et al., 2013; Adanu and Jones, 2017). Nonetheless, many studies have found a strong correlation between serious injury crash outcomes and risky behaviors such as DUI (e.g., Tavris et al., 2001; Abdel-Aty, 2003; Dabbour, 2017), aggressive driving (Paleti et al., 2010; Dahlen et al., 2012; Islam and Mannering, 2020), and driving without a valid license (Blows et al., 2005; Adanu et al., 2018). The propensity of certain road user groups to engage in risky driving behaviors have been linked to many factors such as age (e.g., Elander et al., 1993; Chiaoutakis et al., 2000; Adanu et al., 2017), gender (e.g., Miller et al., 1998; Turner and McClure, 2003; Adanu et al., 2018), socioeconomic status (e.g., Abdalla et al., 1997; Liu et al., 1998), personality (e.g., Yu and Wilfiford, 1993; Nicholson et al., 2005), type of vehicle being driven (e.g., Ulfirenson and Mannering, 2004), and even regional culture and systems (e.g., Lund and Rundmo, 2009; Atchley et al., 2014; Adanu et al., 2017; Adanu et al., 2019). It has also been observed that risky drivers often engage in multiple traffic violations (Kweon and Kokceman, 2010; Briggs et al., 2008; Phillips and Brewer, 2011; Pulido et al., 2011; Stübig et al., 2012; NHTSA, 2012). For instance, Begstrand et al (2015) observed that a higher proportion of alcohol impaired drivers were less likely to use seatbelt and more likely to speed. They also found that a large proportion of drivers who engage in drunk or drugged driving are repeat offenders. Methodologically, a wide range of discrete-outcome models have been used to analyze crash severity due to the classification of the severities into discrete outcomes (see Savolainen et al., 2011; Mannering and Bhat, 2014 for injury-severity methodology reviews). To account for unobserved heterogeneity (Manning et al., 2016), recent crash studies have used random parameters (mixed) logit models (e.g. Milton et al., 2008; Kim et al., 2013; Anastasopoulos and Mannering, 2011; Morgan and Mannering, 2011; Cervero et al., 2014; Islam et al., 2014; Behnood and Mannering, 2016; Seraneeparkarn et al., 2017; Waseem et al., 2019), latent class models (Eluru et al., 2012; Xiong and Mannering, 2013; Cervero et al., 2014; Shaheed and Gkritza, 2014; Yasmin et al., 2014; Adanu et al., 2018; Fountas et al., 2018b; Fountas et al., 2018b; Adanu et al., 2019), Markov switching models (Malyshkina and Mannering, 2009), Markov switching with random parameters (Xiong et al., 2014), bivariate/multivariate models with random parameters (Abay et al., 2013; Russo et al., 2014), random parameters generalized ordered probability with heterogeneity in means and variances (Xin et al., 2017), random thresholds random parameters hierarchical ordered probit (Fountas and Anastasopoulos, 2017), and correlated random parameters ordered probit (Fountas et al., 2018a; Fountas et al., 2018b). Anastasopoulos and Mannering (2011) observed that while injury severity models that do not use detailed crash-specific data underperform compared to those that do, random parameter models using less detailed data can provide a reasonable level of accuracy. Recent studies have also explored the temporal stability of factors that affect crash injury severities (e.g., Behnood and Mannering, 2015; Mannering, 2018; Islam and Mannering, 2020).

3. Data

The study was based on crash data obtained from the Critical Analysis Reporting Environment (CARE) system developed by the Center for Advanced Public Safety (CAPS) at the University of Alabama. The CARE database serves as the primary source of historical crash data for research and policy decision-making in the State of Alabama. For ease of comparison of crash factors across the years in order to understand the impact of the COVID-19 pandemic on crash trends, the database was queried to select crashes that occurred in the first 28 weeks for 2018, 2019, and 2020, as crash data for 2020 was only available for the first 28 weeks at the time of this study. Daily county vehicle miles travelled (VMT) was also obtained as a measure of exposure to crashes. To explore the differences in factors that influenced crash injury severity before and after the lockdown order, the crash data for 2020 was segmented into crashes that occurred before March 11 as Normal times and those that occurred after March 11 as COVID times. The data was further divided by crash mechanism as: (1) Single-vehicle (SV) crashes before the lockdown order (Normal times SV); (2) multi-vehicle (MV) crashes before the lockdown order (Normal times MV); (3) Single-vehicle crashes after the lockdown order (COVID times SV); and (4) Multi-vehicle crashes after the lockdown order (COVID times MV).

Figs. 1 and 2 present the distribution of crashes per daily county VMT before and after the lockdown order, respectively. Fig. 3 shows that the highest number of crashes occurred in week 11, which coincides with the week when the lockdown order was announced. After week 11, both VMT and number of crashes decreased significantly. This reduction lasted until week 15 when crashes began to increase again but not reaching the numbers recorded prior to the lockdown order, although VMT was approaching those prior to week 11. Figs. 4–12 show the comparative historical trend of crashes for the first 28 weeks of 2018, 2019, and 2020, by injury severity and contributing factors.

It can be observed from Fig. 4 that the total number of crashes prior to week 11 in 2020 followed the same pattern as 2018 and 2019. However, the crash fatalities (see Fig. 5) did not follow any particular pattern. For example, it can be observed that the fatality numbers for
weeks 6 and 10 in 2020 were higher compared to those in 2018 and 2019, and the lowest number of fatalities in 2020 occurred in week 14 (three weeks after the lockdown order). By the 20th week of 2020, crash fatalities had increased to a level higher than those recorded around the same period in 2018 and 2019.

The number of people who sustained severe or incapacitating injury crashes in the first 28 weeks of 2020 had a trend similar to that of 2019 until week 11, and by week 19 the number of severe injuries returned to the levels recorded in 2019. With regard to the contributing factors (see Figs. 7–11), crashes involving DUI, aggressive driving, distracted driving, and drowsy driving were lower after week 11 in 2020 compared to 2018 and 2019, but this trend lasted for only a few weeks. However, there has not been any significant difference in speeding-related crashes across the three years. Similarly, failure to use safety equipment (predominantly seatbelt) has not seen any major change due to the lockdown.
Table 1 shows the distribution of the crash severities by crash mechanism and period of crash occurrence. From this table, it can be observed that the highest number of major injury (both SV and MV) crashes occurred during the lockdown period when traffic volumes were low.

Table 2 presents the descriptive statistics of the variables found to be statistically significant during model estimation. From Table 2, it can be observed that the proportions of SV crashes that occurred on interstate highways and those that occurred in rural areas in the first 28 weeks of 2020 are about 10 percentage points and 40 percentage points, respectively higher than MV crashes. This means that a higher proportion of SV crashes occurred on interstates and in rural areas of the state compared to MV crashes.

Analysis of the data as shown in Table 2 also revealed that more than half of the MV crashes occurred at shopping areas and intersection-related crashes make up about 65% of all MV crashes. About 20% of SV crashes involved speeding while less than 3% of MV crashes involved speeding. Similarly, nearly 8% of SV crashes involved DUI and less than 2% of MV crashes involved DUI. However, in absolute terms, more speeding and DUI crashes occurred after the lockdown order. Also, more aggressive driving crashes occurred during the stay at home order. More drivers involved in SV crashes failed to wear seatbelt compared to MV crashes, with the highest proportions happening during the lockdown period. Additionally, more than 10% of the drivers involved in crashes prior to the lockdown order did not have a valid license while 16.8% and 13.8% of drivers involved in SV and MV crashes, respectively during the lockdown did not have a valid license. Drivers aged more than 65 years were involved in more MV crashes than in SV crashes.

4. Method

Road crash occurrence is complex in nature and may involve a variety of factors; many of which may be unknown and not recorded by the reporting police officer. It is therefore not possible to include all probable crash factors in the standard crash report form. This limitation can affect the accuracy of results from traditional statistical analyses of crash data, hence leading to biased parameter estimates which may affect the accuracy of decisions made from such crash models. Various statistical methods (see Savolainen et al., 2011; Mannering and Bhat, 2014 for injury-severity methodology reviews) can be used to overcome this inherent problem typically referred to as unobserved heterogeneity in crash data and analysis (Mannering et al., 2016). For instance, recent studies have used random parameters (mixed logit) models (Milton et al., 2008; Morgan and Mannering, 2011; Anastasopoulos and Mannering, 2011; Kim et al., 2013) and latent class (finite mixture) models (Yasmin et al., 2014; Shaheed and Gkritza, 2014; Lidbe et al., 2020) to
capture unobserved heterogeneity (defined as the existence of variations in the effect of variables across the sample population that maybe unknown to the analyst) in crash data (Mannering et al., 2016). Whereas the random parameters approach uses continuous mixing distributions (for example, normal, lognormal, uniform, triangular, etc.) to capture heterogeneity, the latent class approach identifies unobserved classes by replacing the continuous distribution assumption of random parameter model with a discrete distribution in which unobserved heterogeneity is captured by the membership of distinct classes (Mannering and Bhat, 2014).

This study used both latent class multinomial logit (LC-MNL) (e.g., Shaheed and Gkritza, 2014; Adanu et al., 2018; Lidbe et al., 2020) and random parameters with heterogeneity in means and variances models (e.g. Venkataraman et al. 2014; Behnoon and Manning, 2017; Adanu et al., 2021; Damsere-Derry et al., 2021) to account for unobserved heterogeneity across the crash observations, as these methods have been shown to perform better than the traditional multinomial logit and random parameters logit models (Shaheed and Gkritza, 2014; Adanu and Jones, 2017). The models were developed using the first 28 weeks of crashes recorded in 2020. Single-vehicle (SV) models were developed to eliminate the influence of other vehicles/drivers on the crash occurrence and outcome. Also, separate crash severity models were developed based on the period of the crash in order to understand whether the lockdown order issued in the state on March 11, 2020 had any effects on the crash mechanisms and outcomes. The study used three crash injury-severity categories: severe injury (fatal or incapacitating injury), minor injury (non-incapacitating injury or possible injury), and no injury (property damage only).

To obtain an estimable model, a crash severity function $S_i$ that determines the probability that crash $n$ will result in injury severity $i$ is defined as (McFadden, 1981):

$$S_i = \beta_i X_{in} + \epsilon_{in}$$

(1)

where $\beta_i$ is a vector of estimable parameter for crash outcome $i$ (major injury, minor injury, or no injury), $X_{in}$ is a vector of explanatory variables that affect the likelihood of damage outcome $i$ in crash $n$ and $\epsilon_{in}$ is

| Table 1 | Trend of crash outcomes by crash type and period. |
|---|---|
| Crash severity | Normal SV | COVID SV | Normal MV | COVID MV |
| Minor injury | 301 | 5.5% | 667 | 8.8% | 358 | 1.8% | 543 | 2.4% |
| No injury | 4042 | 73.4% | 5220 | 68.5% | 15,785 | 81.1% | 17,952 | 79.8% |
| Total | 5509 | 100.0% | 7622 | 100.0% | 19,459 | 100.0% | 22,491 | 100.0% |

| Table 2 | Descriptive statistics of variables used in model estimation. |
|---|---|
| Variables | Normal SV | COVID SV | Normal MV | COVID MV |
| Crash location | | | | |
| Interstate highway | 1030 | 18.7% | 1380 | 18.1% | 356 | 16.1% | 3133 | 16.1% |
| Rural area | 3096 | 56.2% | 4444 | 58.3% | 3133 | 16.1% | 3913 | 17.4% |
| Intersection | 2054 | 37.3% | 2621 | 34.4% | 12,843 | 66.0% | 14,799 | 65.8% |
| Shopping area | 753 | 13.7% | 1008 | 13.2% | 10,761 | 55.3% | 11,830 | 52.6% |
| Residential area | 1323 | 24.0% | 1894 | 24.8% | 3717 | 19.1% | 4993 | 22.2% |
| Contributing circumstances | | | | |
| Speeding | 1135 | 20.6% | 1486 | 19.5% | 564 | 2.9% | 562 | 2.5% |
| DUI | 413 | 7.5% | 671 | 8.8% | 311 | 1.6% | 450 | 2.0% |
| Aggressive driving | 121 | 2.2% | 282 | 3.7% | 195 | 1.0% | 315 | 1.4% |
| Drowsy driving | 288 | 5.2% | 511 | 6.7% | 116 | 0.6% | 157 | 0.7% |
| Distracted driving | 534 | 9.7% | 487 | 6.4% | 1342 | 6.9% | 1668 | 7.4% |
| Temporal factors | | | | |
| Between midnight and 6AM | 992 | 18.0% | 1311 | 17.2% | 584 | 3.0% | 630 | 2.8% |
| Between midday and 6PM | 1565 | 28.4% | 2401 | 31.5% | 9574 | 49.2% | 12,393 | 55.1% |
| Between 6PM and midnight | 1476 | 28.6% | 2256 | 29.6% | 3425 | 17.6% | 3846 | 17.1% |
| Weekend | 1543 | 28.0% | 2271 | 29.8% | 5585 | 28.7% | 7040 | 31.3% |
| Six weeks after lockdown | 2248 | 29.5% | 8529 | 43.8% | 9779 | 43.5% | 1223 | 22.2% |
| Three weeks before lockdown | 1223 | 22.2% | 8893 | 45.7% | 9424 | 41.9% | 1223 | 22.2% |
| Manner of crash | | | | |
| Rear-end collision | 4573 | 23.5% | 5488 | 24.4% | 2335 | 12.0% | 2744 | 12.2% |
| Side impact | 2115 | 38.4% | 2599 | 34.1% | 8795 | 45.2% | 9446 | 42.0% |
| Sideswipe | 2231 | 40.5% | 3186 | 41.8% | 7064 | 36.3% | 8322 | 37.0% |
| Driver demographics and behavioral factors | | | | |
| Female driver | 3041 | 55.2% | 3910 | 51.3% | 10,469 | 53.8% | 11,538 | 51.3% |
| Driver less than 25 years | 1559 | 28.3% | 2271 | 29.8% | 5487 | 28.2% | 6118 | 27.2% |
| Driver age between 25 and 45 years | 2231 | 40.5% | 3186 | 41.8% | 7064 | 36.3% | 8322 | 37.0% |
| Driver between 45 and 65 years | 1339 | 24.3% | 1684 | 22.1% | 4378 | 22.5% | 5285 | 23.5% |
| Driver aged 65 years or more | 380 | 6.9% | 434 | 5.7% | 2355 | 12.1% | 2586 | 11.5% |
| Employed | 3041 | 55.2% | 3910 | 51.3% | 10,469 | 53.8% | 11,538 | 51.3% |
| Unemployed | 970 | 17.6% | 1619 | 21.2% | 2160 | 11.1% | 2969 | 13.2% |
| Self-employed | 220 | 4.0% | 366 | 4.8% | 720 | 3.7% | 900 | 4.0% |
| No seatbelt | 446 | 8.1% | 808 | 10.6% | 331 | 1.7% | 517 | 2.3% |
| Invalid license | 600 | 10.9% | 1280 | 16.8% | 2004 | 10.3% | 3104 | 13.8% |
| Vehicle type | | | | |
| SUV | 1140 | 20.7% | 1502 | 19.7% | 4690 | 24.1% | 5038 | 22.4% |
| Pickup truck | 959 | 17.4% | 1479 | 19.4% | 3405 | 17.5% | 4498 | 20.0% |
Based on Eqs. (4) and (5), the LC-MNL model for class where

\[
P_c(i) = \int \frac{\exp(\beta_{ic} \epsilon_i)}{\sum_{k} \exp(\beta_{ik} \epsilon_i)} f(\phi) d\phi \tag{2}
\]

where \( f(\phi) \) is the density of \( \beta \) and \( \phi \) corresponding to a vector of parameters of the density function (mean and variance), \( P_c(i) \) is the probability of crash severity \( i \) in crash conditioned on \( f(\phi) \). With this formulation, \( \beta \) can now account for observation-specific variations in the effect of \( X \) on crash outcome probabilities, with \( f(\phi) \) used to determine \( \phi \). Mixed-logit probabilities are then a weighted average for different values of \( \beta \) across observations where some elements of \( \beta \) can be fixed across observations and some may vary across observations (known as random parameters). This model is estimated by simulated maximum likelihood estimation with the logit probabilities shown in Eq. (3) approximated by drawing values of \( \beta \) from \( f(\phi) \) for given values of \( \phi \), using Halton draws (Halton, 1960; Bhat, 2003; Train, 1999). Heterogeneity in means and variances of random parameters is accounted for by allowing \( \beta \) to vary across crashes as (Seranneprakarn et al., 2017):

\[
\beta_i = \beta + \Theta Z_i + \sigma \exp(\omega_i W_i) u_i
\tag{3}
\]

where \( \beta \) is the mean parameter estimate across all crashes, \( Z_i \) is a vector of attributes that capture heterogeneity in the mean, \( \Theta \) is a corresponding vector of estimable parameters, \( W_i \) is a vector of attributes that capture heterogeneity in standard deviation \( \sigma \) with corresponding parameter vector \( \omega_i \) and a disturbance term \( u_i \), and \( Z_i \) and \( W_i \) may contain crash attributes or other sources of heterogeneity which may not be captured by variables recorded in the crash database.

In contrast, the LC-MNL model allows the crash severity, based on Eq. (1), to have \( C \) different classes so that each of the classes will have its own parameters, with the probability given by (Behnoood et al., 2014):

\[
P_c(c) = \frac{\exp(\alpha_i Z_c)}{\sum_{c_i} \exp(\alpha_i Z_c)}
\tag{4}
\]

where \( Z_c \) represents a vector that shows the probabilities of \( c \) for crash, \( C \) is the possible classes, and \( \alpha_i \) represents the estimable parameters (class specific parameters). The unconditional probability that a crash will result in severity \( i \) is given by:

\[
P_c(i) = \sum_{c} P_c(c) \times P_i(i/c)
\tag{5}
\]

where \( P_c(i/c) \) is the probability of crash \( n \) to result in severity \( i \) in class \( c \). Based on Eqs. (4) and (5), the LC-MNL model for class \( c \) will be:

\[
P_c(i/c) = \frac{\exp(\beta_{ic} \epsilon_i)}{\sum_{j} \exp(\beta_{ij} \epsilon_i)}
\tag{6}
\]

where \( I \) represents the possible number of crash severity levels and \( \beta_{ic} \) is a class-specific parameter vector that takes a finite set of values.

Marginal effects were computed to assess the effect of the crash-contributing factors on the likelihood of crash-severity outcomes (Washington et al 2011). In this study, all the explanatory variables are coded as indicator variables. As such, the marginal effects are calculated as:

\[
ME_{\epsilon_i} = P_i(X_{\epsilon_i} = 1) - P_i(X_{\epsilon_i} = 0)
\tag{7}
\]

The probabilities specific to each severity level \( i \) for crash \( j \), are calculated when the \( k^{th} \) indicator variable, \( X_{ijk} \) equals to 1 or 0, respectively. Specifically, a marginal effect for \( X_{ijk} \) is the difference in probabilities when \( X_{ijk} \) changes from 0 to 1 while all other variables remain constant. For variables with random parameter across all observations, only the estimated mean value of the coefficients is used in the utility function to calculate the marginal effects. The marginal effect for each parameter is calculated by averaging the marginal effects over all crash observations.

5. Results

Four crash-severity models (single-vehicle crashes prior to lockdown order (Normal times SV), multi-vehicle crashes prior to lockdown order (Normal times MV), single-vehicle crashes after lockdown order (COVID times SV) and multi-vehicle crashes after lockdown order (COVID times MV)) were developed using LC-MNL and random parameters with heterogeneity in means and variances approaches. A comparison of the model fit statistics revealed that the LC-MNL model was superior to the random parameters with heterogeneity in means and variances model in three out of the four scenarios (COVID times SV, Normal times MV, and COVID times MV). The Normal times SV random parameters with heterogeneity in means and variances model performed better than the LC-MNL model. The random parameters multinomial logit with heterogeneity in means and variances model was estimated by simulated maximum likelihood with 500 Halton draws (McFadden and Train, 2000). The normal probability density function was used for random parameters (e.g. Milton et al. 2008; Behnoood and Manning, 2016). With respect to the LC-MNL models, two distinct classes with homogeneous attributes were found significant; Latent Class 1 with probability 0.62 and Latent Class 2 with probability 0.38, for the Normal times MV model, Latent Class 1 with probability 0.54 and Latent Class 2 with probability 0.46, for the COVID times MV model, and Latent Class 1 with probability 0.63 and Latent Class 2 with probability 0.37, for the COVID times SV model. Estimation results with more than two latent classes did not statistically improve the models in terms of data fit.

The class-specific probabilities are a set of fixed constants since segmentation based on crash-specific characteristics did not produce a superior model. Tables 3–6 present the best model estimation results for all the four scenarios considered and Table 7 presents a comparative summary of how the variables influence the likelihood of major injury outcome. The model estimation results for each latent class crash severity model show that each variable has two sets of parameters associated with it. However, it can be observed that some of the parameters have the same sign between the two latent classes (e.g., rural area, shopping area, residential area in the COVID MV model; rural area, aggressive driving, no seatbelt in the COVID SV model, rural area; and DUI, sideswipe in the Normal times MV model). Others were found to have opposite signs (e.g., intersection, DUI in the COVID MV model, crash time between midday and 6PM in the COVID SV model, self-employed driver in the Normal times MV model) or are not significant in both classes (e.g., interstate highway and DUI in the COVID MV model, driver less than 25 years, unemployed driver in the COVID SV model, no seatbelt in the Normal times MV model). This indicates that there is heterogeneity between the two classes. For this reason, it would be inaccurate to base the interpretation of the model on the magnitude and sign of the parameters. Rather, model interpretation and comparison of variable effects on crash outcomes across all models are more appropriately based on examining the marginal effects.

The marginal effects shown in Table 3 reveal that the probability of major injury increased by 0.0007 for crashes involving aggressive driving while the “no seatbelt” indicator variable increased the probability of major injury by 0.023. The results further show that the likelihood of major injury increased by 0.007 for crashes that occurred within three weeks of when the statewide lockdown order was announced. The variable associated with crashes that occurred within this period was found to be random with mean of −2.16 and standard deviation of 2.11. These numbers plotted on the normal distribution curve indicate that the probability of minor injury was lower in 15.3% of the crashes recorded within three weeks of the lockdown order (this implies increased likelihood of major injury or no injury) and the
probability of minor injury was higher in 84.7% of the crashes.

One variable (indicator variable for dark and unlit roadway condition) and two variables (indicator variable for car and indicator variable for open country) were found to produce random parameters with means and variances, respectively. For the “three weeks to lockdown” crash indicator, crashes that occurred under dark and unlit roadway conditions had an increase in their mean making minor injury more likely (relative to crashes that occurred under daylight or lit roadway conditions). Regarding the heterogeneity in variance of random parameters, SV crashes that occurred prior to the lockdown period in open country was found to increase the variance. The results further show that SV crashes that occurred prior to the lockdown period on interstate highways and in rural areas were less likely to result in major injury. Similarly, SV crashes involving speeding, distracted driving, DUI and those that occurred on weekends were more likely to record minor injury but not major injury. The employed driver and unemployed driver indicator variables decrease the likelihood of major injury, but they increase the likelihood of minor injury by 0.0075 and 0.0028, respectively.

During the lockdown period, Table 4 shows that SV crashes that occurred on interstate highways were less likely to record major injury, whereas the probability of major injury increased by 0.0457 for crashes that occurred in rural areas. Speeding, aggressive driving, and drowsy driving indicator variables increased the likelihood of major injury by 0.0087, 0.004, and 0.0011, respectively. DUI was less likely to be primary contributing factor in major injury SV crashes after the lockdown order. The weekend crash indicator increased the probability of major injury by 0.006 and minor injury was more likely to be recorded between 6PM and midnight. By the sixth week after the lockdown order, the chance of injury was reduced by 0.0027 for major injury and 0.0012 for minor injury. SV crashes that occurred during the lockdown involving drivers aged 25–45 and 45–65 years were more likely to record major injury. Also, the no seatbelt indicator variable was found to increase the probability of major injury by 0.0378. The employed driver variable decreased the likelihood of major injury but increased the likelihood of minor injury by 0.0019, while the unemployed driver variable decreased the probability of injury in general.

With respect to Normal MV crashes, Table 5 revealed that injury outcome was less likely for crashes that occurred on Interstate highways. The probability of major injury in MV crashes that occurred in rural areas increased by 0.0125 before the lockdown order. The intersection indicator and shopping area indicator variables also increased the probability of major injury by 0.0291 and 0.0008, respectively. MV crashes that involved speeding, DUI, and aggressive driving were more likely to result in major injury prior to the lockdown order than after it.

Table 3
Model estimation results for Normal SV crashes.

| Variable | In severity function of | Parameter estimate | t-statistics | Marginal effects |
|----------|-------------------------|--------------------|-------------|------------------|
| Constant | Minor injury            | –1.06              | –17.47      |                  |
| Random parameter (normally distributed) | Major injury | –2.16 | –3.12 | 0.007 | –0.0016 | –0.0054 |
| Three weeks before lockdown | Major injury | 2.11 | 3.21 | |
| Standard deviation of “Three weeks before lockdown” | Major injury | 0.86 | 1.87 | |
| Heterogeneity in means | Major injury | 0.40 | 2.10 | |
| Three weeks before lockdown: Dark roadway condition | Major injury | –0.26 | –1.81 | |
| Heterogeneity in variance | Major injury | –1.14 | –5.27 | –0.0054 | 0.0013 | 0.0041 |
| Crash location | Major injury | –0.45 | –3.26 | –0.0116 | 0.0027 | 0.0089 |
| Interstate highway | Major injury | –1.14 | –5.27 | –0.0054 | 0.0013 | 0.0041 |
| Rural area | Major injury | –0.45 | –3.26 | –0.0116 | 0.0027 | 0.0089 |
| Contributing circumstances | Major injury | 0.26 | 3.26 | –0.0007 | 0.0098 | –0.0091 |
| Speeding | Minor injury | 0.39 | 3.16 | –0.061 | 0.0762 | –0.0152 |
| DUI | Minor injury | –0.41 | –2.12 | 0.0007 | 0.0013 | –0.002 |
| Aggressive driving | No injury | –0.40 | –1.87 | –0.0017 | 0.0003 | 0.0013 |
| Distracted driving | Major injury | 0.32 | 3.64 | –0.0027 | –0.0076 | 0.0103 |
| Temporal factors | No injury | 0.12 | 1.64 | –0.0016 | –0.0049 | 0.0065 |
| Between midnight and 6AM | No injury | –0.89 | –6.08 | –0.0101 | 0.0025 | 0.0076 |
| Between 6PM and midnight | Major injury | –0.72 | –5.15 | –0.0088 | 0.0021 | 0.0067 |
| Weekend | Major injury | –0.93 | –6.64 | –0.0124 | 0.0029 | 0.0095 |
| Driver demographics and behavioral factors | Major injury | 0.30 | 4.03 | –0.0033 | –0.0123 | 0.0156 |
| Female driver | No injury | 0.23 | 2.90 | –0.0024 | –0.0077 | 0.0102 |
| Driver less than 25 years | Major injury | –1.76 | –12.27 | –0.0322 | 0.0075 | 0.0248 |
| Driver between 45 and 65 years | Major injury | –1.23 | –6.65 | –0.0114 | 0.0028 | 0.0086 |
| Driver aged 65 years or more | No injury | 0.84 | 4.74 | –0.0024 | –0.0028 | 0.0052 |
| Employed | Major injury | 1.95 | 13.70 | 0.023 | –0.0057 | –0.0173 |
| Unemployed | Minor injury | 0.28 | 2.76 | –0.0007 | 0.0057 | –0.005 |
| Self-employed | Major injury | –0.80 | –4.48 | –0.0058 | 0.0014 | 0.0044 |
| No seatbelt | No injury | 0.21 | 2.45 | –0.002 | –0.0047 | 0.0067 |
| Invalid license | Minor injury | –0.80 | –4.48 | –0.0058 | 0.0014 | 0.0044 |
| Vehicle type | Major injury | 0.21 | 2.45 | –0.002 | –0.0047 | 0.0067 |
| Model fit statistics | Number of observations | 6509 | | | |
| Log likelihood function | –3999.3871 | | | | |
| Log likelihood at zero | –6052.2551 | | | | |
| McFadden pseudo R-sq | 0.35 | | | | |
Major injury was more likely to be recorded between 6PM and 6AM and on weekends. The indicator variables for driver aged 25–45 years and 45–65 years increased the probability of major injury by 0.0012 and 0.0002, respectively. Failure to wear seatbelt was also found to increase the likelihood of major injury in MV crashes that occurred before the lockdown.

The marginal effects in Table 6 show that the interstate highway indicator variable increased the likelihood of major injury by 0.0047 in MV crashes during lockdown, while the rural area indicator increased the likelihood of major injury by 0.0104. During the lockdown, the chance of major injury was lower at intersections, shopping areas and residential areas. However, the probability of injury increased for crashes involving speeding, DUI, aggressive driving and drowsy driving. The likelihood of major injury increased by 0.0014, 0.0012, 0.001, and 0.0002, for crashes involving speeding, DUI, aggressive driving, and drowsy driving, respectively. The likelihood of minor injury decreased by 0.0001 for speeding, but it increased by 0.0002, 0.0009, and 0.001 for DUI, aggressive driving, and drowsy driving, respectively. It was also found that MV crashes that occurred during the lockdown order were more likely to record major injury between 6PM and 6AM and during weekends. The side-impact indicator variable also increased the probability of major injury by 0.0005 and minor injury by 0.03 while rear-end crashes and sideswipes were more likely to result in minor injury.

A comparison of variables across all four models show some consistency and variations in how variables influence crash severity based on the period and manner of crash. For instance, the female driver and younger driver indicators decreased the probability of major injury, with the female driver indicator increasing the likelihood of minor injury across all four models. Older drivers were found to be less likely to be involved in injury crashes except for SV crashes that occurred before lockdown. Also, it was found that in exception of MV crashes during the lockdown, drivers with no valid license were less likely to be involved in major injury crashes. Drivers of SUVs were found to have higher chances of sustaining minor injury in SV crashes prior to and during the lockdown. The southern area of the state was more prone to crashes involving two or more vehicles and had higher likelihood of minor injury compared to SV crashes. Intersection crashes and shopping area crashes involving two or more vehicles had higher likelihood of major injury compared to others.

Table 7 was further developed to isolate and better understand how the variables compare in terms of their contribution to major injury outcome. It can be observed that the probability of major injury on interstate highways was only high for MV crashes that occurred after the lockdown order, and rural area MV crashes were generally more likely to record major injury outcome compared to SV crashes. Intersection crashes and shopping area crashes involving two or more vehicles had higher likelihood of minor injury compared to others. The self-employed drivers were found to be less likely to be involved in major injury crashes compared to the employed drivers. The likelihood of minor injury increased by 0.0029, 0.019, and 0.0016 for crashes involving speeding, DUI, and aggressive driving, respectively. For crashes involving drowsy driving, the likelihood of major injury increased by 0.0047, 0.0012, 0.0002, and 0.0001 for rural areas, intersections, residential areas, and week-ends, respectively. The likelihood of minor injury decreased by 0.0001 for speeding, and increased by 0.0002, 0.0009, and 0.001 for DUI, aggressive driving, and drowsy driving, respectively. It was also found that MV crashes that occurred during the lockdown order were more likely to record major injury between 6PM and 6AM and during weekends. The side-impact indicator variable also increased the probability of major injury by 0.0005 and minor injury by 0.03 while rear-end crashes and sideswipes were more likely to result in minor injury.
higher chances of recording major injury prior to the lockdown. With regard to primary crash contributing factor, aggressive driving was more associated with major injury outcomes across all four models, while speeding and DUI were linked with major injury in only three (SV during lockdown, MV prior to lockdown and MV during lockdown) and two models (MV prior to lockdown and MV during lockdown), respectively. The lockdown order that has been placed on states across the US during the COVID-19 global pandemic has caused a decline in travel activities. In Alabama, Fig. 3 shows a significant drop in VMT and total crashes after the week when the stay-at-home order was issued (March 11 i.e., week 11). This observation affirms the relationship between exposure (measured as VMT) and crashes. Table 5 presents the model estimation results for COVID SV crashes.

### Table 5

| Variable                                | In severity function of | Parameter estimate | Latent Class 1 | Parameter estimate | Latent Class 2 | Marginal effects |
|------------------------------------------|-------------------------|-------------------|-----------------|-------------------|-----------------|-----------------|
| Constant                                 | Major injury            | −1.90             | −8.20           | −2.21             | −5.90           |                 |
| Crash location                           |                         |                   |                 |                   |                 |                 |
| Interstate highway                       | Major injury            | −1.05             | −3.51           | 0.07              | 0.23            | −0.0035         |
| Rural area                               | Major injury            | 0.97              | 4.90            | 1.04              | 3.67            | 0.0457          |
| **Contributing circumstances**           |                         |                   |                 |                   |                 |                 |
| **Speeding**                             | Major injury            | 0.99              | 4.41            | −0.36             | −0.92           | 0.0087          |
| **DUI**                                  | No injury               | 0.61              | 2.43            | −0.27             | −1.05           | 0.0021          |
| **Aggressive**                           | Major injury            | 0.99              | 2.89            | 0.81              | 1.65            | 0.004           |
| **Drowsy driving**                       | Major injury            | 0.62              | 1.85            | −0.44             | −0.86           | 0.0011          |
| **Temporal factors**                     |                         |                   |                 |                   |                 |                 |
| Between midnight and 6AM                 | Minor injury            | −3.94             | −1.47           | 0.43              | 1.86            | −0.0472         |
| Between midday and 6PM                   | No injury               | 0.74              | 3.56            | −0.50             | −2.22           | −0.0027         |
| Between 6PM and midnight                 | Major injury            | 4.40              | 2.25            | −0.53             | −1.52           | 0.0567          |
| Between 6PM and midnight                 | No injury               | 4.38              | 1.25            | −0.33             | −1.94           | −0.0586         |
| Weekend                                  | Major injury            | 0.25              | 1.84            | 0.31              | 1.27            | 0.0006          |
| Six weeks after lockdown                  | No injury               | 0.28              | 1.75            | −0.01             | −0.04           | −0.0027         |
| **Driver demographics and behavioral factors** |                       |                   |                 |                   |                 |                 |
| Female driver                            | Major injury            | 0.16              | 0.8             | −1.23             | −3.11           | −0.0034         |
| Driver less than 25 years                | No injury               | 1.15              | 6.24            | 0.16              | 0.68            | −0.0076         |
| Driver age between 25 and 45 years       | Minor injury            | −2.64             | −5.38           | −0.15             | −0.74           | 0.0029          |
| Driver between 45 and 65 years           | Minor injury            | −2.16             | −4.36           | −0.22             | −0.99           | 0.0019          |
| Driver aged 65 years or more             | No injury               | 1.79              | 3.99            | −0.60             | −1.18           | −0.0015         |
| Employed                                 | Major injury            | −1.90             | −7.15           | −0.07             | −0.22           | −0.026          |
| Unemployed                               | Major injury            | −1.47             | −5.03           | 0.40              | 1.08            | −0.0089         |
| Self employed                            | No injury               | 1.39              | 3.85            | 0.23              | 0.84            | −0.003          |
| No seathelt                              | Major injury            | 2.76              | 10.06           | 1.08              | 2.52            | 0.0378          |
| Invalid license                          | Minor injury            | −1.93             | −2.04           | 0.62              | 2.99            | −0.0014         |
| **Vehicle type**                         |                         |                   |                 |                   |                 |                 |
| SUV                                      | Minor injury            | −4.81             | −0.47           | 0.18              | 2.08            | −0.0005         |
| Pickup truck                             | No injury               | 0.35              | 1.77            | 0.38              | 2.26            | −0.0033         |
| **Model fit statistics**                 |                         |                   |                 |                   |                 |                 |
| Class membership probability            | 0.63                    | 12.76            | 0.37            | 7.64              |                 |                 |
| Number of observations                   | 7622                    |                   |                 |                   |                 |                 |
| Log likelihood function                  | −5731.08                |                   |                 |                   |                 |                 |
| Log likelihood at zero                   | −973.6229               |                   |                 |                   |                 |                 |
| McFadden pseudo R-sq                     | 0.32                    |                   |                 |                   |                 |                 |

**6. Discussion and recommendations for traffic safety management during pandemics**

The rate of road crashes is predominantly influenced by traffic characteristics such as traffic volume and VMT. Generally, as traffic volume and VMT increase, the likelihood and frequency of crashes are expected to increase (as examples, refer to Figs. 1 and 2 where the correlation coefficients for daily county VMT and number of crashes in Alabama are 0.771 and 0.851 for COVID times and normal times respectively). The lockdown order that has been placed on states across the US during the COVID-19 global pandemic has caused a decline in travel activities. In Alabama, Fig. 3 shows a significant drop in VMT and total crashes after the week when the stay-at-home order was issued (March 11 i.e., week 11). This observation affirms the relationship between exposure (measured as VMT) and crashes.

A comparative analysis of the pattern of crashes that occurred within the first 28 weeks in the last three years revealed that crashes attributed to DUI, aggressive driving, distraction, and drowsy driving appeared to follow a similar pattern in 2018, 2019, and the first 11 weeks of 2020. After the stay-at-home order was issued in week 11, there was a general drop in the number of crashes until about week 17 where the number of crashes began to increase. A remarkable departure from this trend was observed for speeding crashes and crashes in which the driver failed to use seatbelt. These crashes appeared not to have been significantly impacted by the stay-at-home order. In fact, these risky behaviors contributed to a higher proportion of crashes that occurred after the lockdown than prior to the lockdown order. This observation may perhaps be due to the reduced traffic volumes and reduced law enforcement. Indeed, this finding is consistent with previous studies. For instance, according to Adanu et al. (2019), risky driver behaviors and

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the crashes they contribute to may be influenced by situational and regional factors/systems such as traffic laws and rigor of traffic law enforcement. Further analysis of the 2020 crash data revealed that more than half of all multi-vehicle crashes occurred at intersections and at shopping areas compared to open country and more crashes occurred in residential areas during the stay-at-home order than the period prior to the lockdown. These findings reflect the events leading to the lockdown where panic-buying was at a peak, with increased traffic activities at shopping areas compared to open country and more crashes occurred in residential areas during the lockdown period and in multi-vehicle crashes prior to the lockdown order. These major injury outcome crashes were more likely to result in major injury.

Aggressive driving was found to be associated with major injury crash outcome irrespective of when the crash occurred. Similarly, crashes involving drivers who failed to use seatbelt were more likely to record major injury irrespective of the time of the crash. While these findings are generally consistent with previous studies, it is important to recognize the influence of the lockdown order on crashes and crash outcomes. Although traffic volumes and VMT had significantly dropped during extreme events that may require statewide lockdown, as has been recognized the influence of the lockdown order on crashes and crash outcomes. Although traffic volumes and VMT had significantly dropped during extreme events that may require statewide lockdown, as has been observed to be significantly associated with major injury crash outcome in crashes that occurred during the lockdown period and in multi-vehicle crashes prior to the lockdown order. These major injury outcome crashes were more likely to involve drivers aged between 25 and 65 years and there was also higher probability that these crashes occurred in the rural areas of the state and between 6PM and 6AM. Female drivers and younger drivers were less likely to be involved in major injury crashes. For single-vehicle crashes that occurred within three weeks to the lockdown order, the chances of recording major injury were high, whereas crashes that occurred six weeks into the lockdown period, the likelihood of major injury was low. Multi-vehicle crashes in which SUV was at fault during the lockdown were more likely to result in major injury.

Aggressive driving was found to be associated with major injury crash outcome irrespective of when the crash occurred. Similarly, crashes involving drivers who failed to use seatbelt were more likely to record major injury irrespective of the time of the crash. While these findings are generally consistent with previous studies, it is important to recognize the influence of the lockdown order on crashes and crash outcomes. Although traffic volumes and VMT had significantly dropped during the lockdown, there have been an increase in the total number of crashes and major injury crashes compared to the period prior to the lockdown order, with speeding, DUI, and weekends accounting for a significant proportion of these crashes.

These findings provide useful lessons for road safety improvements during extreme events that may require statewide lockdown, as has been observed to be significantly associated with major injury crash outcome in crashes that occurred during the lockdown period and in multi-vehicle crashes prior to the lockdown order.

### Table 6

| Variable                          | In severity function of          | Latent Class 1 Parameter estimate | t-statistics | Latent Class 2 Parameter estimate | t-statistics | Marginal effects |
|-----------------------------------|----------------------------------|----------------------------------|--------------|----------------------------------|--------------|-----------------|
| Constant                          | Major injury                     | –8.19                            | –2.06        | –2.23                            | –14.07       |                 |
| Crash location                    |                                  |                                  |              |                                  |              |                 |
| Interstate highway               | Major injury                     | 5.16                             | 1.29         | –1.21                            | –2.53        | 0.0047          | –0.0016         | –0.0031 |
| Rural area                        | Major injury                     | 1.14                             | 2.15         | 1.45                             | 12.3         | 0.0104          | –0.0005         | –0.0099 |
| Intersection                      | Minor injury                     | 0.13                             | 2.07         | –2.77                            | –2.11        | –0.0019         | 0.0083           | 0.0063 |
| Shopping area                     | Minor injury                     | –0.10                            | –1.69        | –2.46                            | –2.31        | –0.0005         | –0.0072         | 0.0077 |
| Residential area                  | No injury                        | 0.20                             | 2.87         | 0.57                             | 2.93         | –0.0013         | –0.0053         | 0.0067 |

#### Contributing circumstances

- **Speeding**
  - Major injury: 0.25 (0.28, 1.45) 5.28
- **DUI**
  - Major injury: –4.83 (–0.23, 1.50) 5.58
- **Aggressive**
  - Major injury: 0.88 (0.66, 1.41) 4.64
- **Drowsy driving**
  - Minor injury: 1.46 (4.11, –0.29) –1.17

#### Temporal factors

- Between midnight and 6AM
  - Major injury: 0.06 (0.44, –2.69) –1.68
- Between midnight and 6PM
  - No injury: 0.19 (4.05, 0.41) 3.59
- Between 6PM and midnight
  - Major injury: 1.40 (2.67, 0.35) 2.44
- Weekend
  - Major injury: 0.01 (0.09, –2.81) –1.96

#### Manner of crash

- Rear-end collision
  - Major injury: 0.34 (0.44, –1.46) –10.22
- Side impact
  - Minor injury: 0.94 (11.29, –2.79) –1.25
- Sideswipe
  - Major injury: –0.31 (–0.33, –2.19) –7.55

#### Driver demographics and behavioral factors

- Female driver
  - Major injury: 0.20 (0.38, –0.19) –1.67
- Driver less than 25 years
  - No injury: 0.96 (7.69, 0.45) 3.61
- Driver age between 25 and 45 years
  - Minor injury: –0.90 (–6.93, –2.10) –3.56
- Driver between 45 and 65 years
  - Minor injury: –0.97 (–7.51, –2.50) –3.08
- Driver aged 65 years or more
  - No injury: 1.03 (7.68, 0.41) 2.43
- Employed
  - Major injury: –1.63 (–3.02, –0.51) –4.09
- Unemployed
  - Major injury: –0.31 (–0.64, –0.14) –1.83
- Self-employed
  - No injury: 0.11 (1.89, 0.24) 0.92
- No seatbelt
  - Major injury: 1.29 (1.31, 2.79) 10.79
- Invalid license
  - Minor injury: 0.39 (5.41, –3.52) –1.32

#### Vehicle type

- SUV
  - Minor injury: –0.02 (–0.32, –0.92) –1.82
- Pickup truck
  - No injury: 0.11 (1.84, 0.52) 2.43

#### Model fit statistics

- Class membership probability: 0.54, 10.77, 0.46, 9.08
- Number of observations: 22,491
- Log likelihood function: –12349.644
- Log likelihood at zero: –24708.889
- McFadden pseudo R-sq: 0.50
done with the COVID-19 pandemic. Traffic management around shopping areas and other areas that may experience increased traffic provide opportunities for road safety stakeholders to reduce the occurrence of crashes in the weeks leading to an announcement of any future statewide or local lockdowns. Lessons learned from the COVID-19 pandemic could also help in managing anxiety among citizens that may prompt panic shopping and rushed travel decisions which may have indirect consequences for road safety. Beyond the wholesale traditional road safety and public awareness campaigns, it would be necessary to identify and target messages to road users that have been shown to exhibit risky behaviors. This process should include strategies and appropriate media through which the majority of these road users could be reached in an efficient and effective manner. Also, traffic enforcement could be intensified during weekends and between 6PM and 6AM to reduce risky driving behaviors. Additionally, the use of technology in traffic law enforcement efforts across the state such as red light running and automated speed enforcement cameras, particularly at high risk locations, would ensure continuous enforcement in times when it becomes difficult to deploy law enforcement personnel into the field.

7. Conclusion

The road safety implications of the COVID-19 pandemic are beginning to be understood across various jurisdictions. Despite a significant decrease in traffic volumes and VMT, many regions of the world have reported increases in the number and severity of crashes during the pandemic. This observation offers the opportunity for traffic safety professionals to plan for appropriate countermeasures for a third wave or even future pandemics. However, in order to develop and prioritize the implementation of countermeasures, it is imperative to understand the trends and factors that influence the occurrence and outcome of crashes. Consequently, this study was carried out in the state of Alabama to inform policy and decision makers on the best strategies on how to improve road safety in the midst of a pandemic. The first 28 weeks of crash data in 2020 was obtained from the Critical Analysis Reporting Environment (CARE) system developed by the Center for Advanced Public Safety at the University of Alabama and for the purposes of comparing the crash trends, data for the two previous years were also obtained. However, only the crash data for 2020 was analyzed to understand how the pandemic affected the factors that influenced crash outcomes. The data were segmented into manner of collision and period of the crash. Latent class multinomial logit and random parameters with heterogeneity in means and variances modeling techniques were used to address the challenge of unobserved heterogeneity in the crash data.

The model estimation results generally show that aggressive driving, DUI, drowsy driving, speeding and failure to use seatbelt were more associated with major injury crash outcome. Rural areas and weekends were also found to have higher chances of recording major injury crashes. Multi-vehicle crashes that occurred prior to the lockdown order recorded the highest number of major injury outcomes. Perhaps, this was due to the increased traffic activities that occurred around shopping areas in the days prior to the lockdown order. Younger drivers and senior drivers were less likely to sustain major injury, whereas drivers aged between 25 and 65 years had higher probability of being involved in major injury crashes, particularly during the lockdown. Multi-vehicle crashes that occurred between 6PM and 6AM were also found to be more likely to result in major injury before and during the lockdown.

Segmentation of the data by manner of collision and period of crash provided detailed insight into how various crash factors influenced crash outcomes. The findings of the study further reveal how the COVID-19 pandemic has affected crash trends and outcomes across the state of Alabama. For instance, it was found that while the total number of crashes decreased in the weeks after the lockdown order in comparison to the crashes that occurred during the same period in previous years, the number of fatalities during the lockdown period was similar to those in previous years. With respect to contributing factors, speeding and failure to use seatbelt were observed to play significant roles in the high fatalities recorded over the lockdown period. These observations are expected to provide a data-driven foundation to prioritize road safety strategies in order to minimize the effects of the pandemic on road safety.

CRediT authorship contribution statement

Emmanuel Kofi Adanu: Conceptualization, Methodology, Writing – original draft. David Brown: Data curation, Writing – original draft, Writing – review & editing. Steven Jones: Writing – review & editing. Allen Parrish: Writing – review & editing.

Declaration of Competing Interest

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

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