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Crash harm before and during the COVID-19 pandemic: Evidence for spatial heterogeneity in Tennessee

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ABSTRACT

Major concerns have been raised about road safety during the COVID-19 pandemic in the US, as the crash fatalities have increased, despite the substantial reduction in traffic. However, a comprehensive analysis of safety–critical events on roadways based on a broader set of traffic safety metrics and their correlates is needed. In addition to fatalities, this study uses changes in total crashes and total monetary harm as additional measures of safety. A comprehensive and unique time-series database of crashes and socio-economic variables is created at the county level in Tennessee. Statistics show that while fatal crashes increase by 8.2%, total crashes decrease by 15.3%, and the total harm cost is lower by about $1.76 billion during COVID-19 (2020) compared with pre-COVID-19 conditions (2019). Several models, including generalized least squares linear, Poisson, and geographically weighted regression models using the differences between 2020 and 2019 values, are estimated to rigorously quantify the correlates of fatalities, crashes, and crash harm. The results indicate that compared to the pre-pandemic periods, fatal crashes that occurred during the pandemic are associated with more speeding & reckless behaviors and varied across jurisdictions. Fatal crashes are more likely to happen on interstates and dark-not-lighted roads and involve commercial trucks. These same factors largely contribute to crash harm. In addition, a greater number of long trips per person not staying home during COVID-19 is found to be associated with more crashes and crash harm. These results can inform policymaking to strengthen traffic law enforcement through appropriate countermeasures, such as the placement of warning signs and the reduction of the speed limit in hotspots.

1. Introduction

The novel coronavirus 2019 (COVID-19) pandemic has undoubtedly impacted the whole world with unparalleled destruction. However, free-flowing traffic can be considered one of the silver linings of the pandemic. Stay-at-home orders, voluntary isolation, working from home, and the fear of contracting the virus contributed to a substantial reduction in traffic flow (Vingilis et al., 2020; Patwary and Khattak, 2022b). In the US, people drove 13 % fewer miles in 2020 than in 2019 (Brodeur et al., 2021). Active travel (walking and bicycling) has been increased with the reduction in total trips, followed by the variation in COVID-19 case severity initially (Zhang et al., 2021b). In Tennessee, total vehicle miles traveled (VMT) have been reduced by 20 % in 2020 compared to 2019 (FHWA, 2020). Reduced traffic flow has produced a noticeable decline in congestion and emissions (Vingilis et al., 2020). Thus, there should be a decrease in the total number of crashes after the pandemic. However, recent information suggests while there are fewer crashes now than in 2019, the fatality rate has increased (Walker, 2020).

The national safety council (NSC) reported an 8 % increase in fatalities across the U.S. from 2019 to 2020, with over 4,200 fatalities (NSC, 2021). Tennessee experienced a more than 7 % increase in fatalities in 2020. The increase in the fatality rate from 2019 to 2020 is the highest estimated year-to-year jump in the US in over 96 years (Palazzo, 2021). This unprecedented situation is raising some serious safety concerns. While COVID-19′s impacts on road safety are relatively unknown, some factors brought about by the pandemic may shed some light. For example, the combination of risky drivers and near-empty streets may result in faster driving, which in turn increases the likelihood of fatality during a crash. Researchers and policymakers are concerned that the new traffic pattern during the pandemic could lead to excessive speeding (Vingilis et al., 2020). Reports suggest that speeding cases in the U.S. have risen by 20 %, and the number of speeding tickets has more than

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doubled (Harris, 2020; Palazzo, 2021). It is also reported that fewer drivers were wearing a seatbelt on the road during the pandemic (Palazzo, 2021). Moreover, more seriously impaired drivers are found on roads, making the roads more vulnerable to fatal crashes (Vingilis et al., 2020). The pandemic has increased alcohol and cannabis sales (CCSA, 2020). It is also reported that stress, anxiety, and depressive traits have been prevalent during the pandemic (Liu et al., 2020), and these have been identified for reckless driving behavior in the past (Wickens et al., 2014).

This extraordinary situation is also contributing to more economic damage. Road crashes alone cost about $1 trillion in the loss of life and productivity each year in the US, where each crash fatality costs an average of $1.4 million (Blincoe et al., 2015). However, this loss in value may not necessarily reflect the true scenarios in the wake of worsened road safety arising from the reduced mobility during COVID-19. Hence, there should be an in-depth investigation of road crashes and the overall economic impacts due to COVID-19. This investigation would help us design more effective and safe interventions for the current and forthcoming pandemic waves and similar outbreaks. Furthermore, understanding how COVID-19 has impacted road safety is imperative for the vision zero goals, as we seek to eliminate traffic fatalities and severe injuries while increasing safe mobility. Specifically, this study attempts to examine the factors associated with crashes and the increased crash fatalities within the state of Tennessee during COVID-19. The study also makes an effort to analyze how the economic harm in a crash has changed during the pandemic.

2. Literature review

Quantifying the changes in travel and safety during the pandemic can be challenging. Positive impacts of the stay-at-home pandemic order may include less mobility, less congestion, fewer traffic crashes and fatalities, fewer emissions, and less vehicular energy consumption (Khan and Odoi, 2023; Saladié et al., 2020; Vingilis et al., 2020). Some previous studies showed a positive association between congestion and injury crashes (Hughes et al., 2022; Inada et al., 2021; Gao et al., 2020). The number of crashes increases moderately with the increase of traffic in an uncongested roadway segment (Khattak et al., 2022). However, when the critical traffic density is attained, the number of crashes starts to surge rapidly with the traffic (Kononov et al., 2008; Quddus et al., 2010). Therefore, in a congestion-free environment, the number of crashes should decline. During the pandemic, statewide stay-at-home policies lead to a 20 % decline in road crashes in the US (Brodeur et al., 2021; Sutherland et al., 2020). Some states experienced a higher reduction in crashes. For example, total crashes are decreased by 50 % in North Carolina compared to the pre-pandemic era (Carter, 2020). Although the number of crashes has decreased, there are contradictory reports about the number of fatalities during the pandemic. In some cases, minor injury crashes decreased, whereas severe and fatal crashes stayed the same (Lin et al., 2020) (Table 1). Moreover, the number of fatalities decreased in some states; Hawaii, Wyoming, Delaware, and Nebraska have experienced a decline of 20 %, 13 %, 11 %, and 9 %, respectively. In contrast, fatalities increased in some other states and contributed to the overall 8 % increase across the US (NSC, 2021; OHS, 2020).

The association between negative safety effects and reduced congestion from the pre-pandemic era has been studied (Noland & Quddus, 2005; Wang et al., 2013). Since congestion is usually localized, specific time analysis may be needed to form a better association. Exposure tends to be a key confounding factor, especially for vulnerable road users' activities. Traffic exposure can be measured in vehicle miles travel (VMT), average annual daily traffic (AADT), and the number of trips in a certain unit of time in a certain region (Kononov et al., 2008). A few earlier studies explored the cross-sectional relationship between VMT and fatal crashes and found both positive and negative associations (Clark & Cushing, 2004; Yeo et al., 2015) (Table 1). For example, Doucette et al. (2021b) found that the crash rate more than quadrupled after accounting for the VMT reductions during COVID-19 in Connecticut. Average speed is another exposure used in the literature. A higher speed is associated with more fatal and severe injury crashes (Hughes et al., 2022; Vingilis et al., 2020). For instance, California experienced little to no reduction in fatalities with the decline of VMT because of speeding during the pandemic (Hughes et al., 2022). A 10-mile-*per*-hour (mph) higher speed limit increases the chance of fatal crashes between 15 % and 60 % (Van Benthem, 2015). However, this can largely differ across locations over time because traffic flows in urban areas are often limited by congestion rather than speed limits. It is observed that during COVID-19, the speed effect is generally the largest in locations with some pre-existing level of congestion (Hughes et al., 2022; Vingilis et al., 2020). This effect can partially offset the reduced traffic flow on fatal crashes. Therefore, regional differences in terms of topography, roadway type, lighting conditions, or weather could be explored as possible input variables on fatal crashes. Empty roads trigger speed-related violations (e.g., speeding, red-light running, failure to comply with stop signs, failure to yield to other drivers or vulnerable road users) (Inada et al., 2021) (Fig. 1). For example, crashes remain low

Table 1
Summary of the Selected Literature.

Author	Study Approach			Relationship between road safety and congestion	Study relevance
Name and Year	Study Period (B = Before, D = During COVID-19 pandemic)	Location and Sample size	Method	Increase safety (+) or reduces safety (-)	Relevance to the research topic
Lin et al., 2020	D	Los Angeles and New York, N = na	Time series data (January to August 2020), Difference-in-difference analysis	–	High
Doucette et al., 2021b	B + D	Connecticut, N = na	Time Series Data, (January 1st to April 30th in 2017–2020), Interrupted Time-Series Analysis	–	High
Hughes et al., 2022	B + D	California; N = 44 counties	Cross-sectional Data (Mar 2015 to May 2020), Poisson Regression	-/+	Medium
Doucette et al., 2021a	B + D	Connecticut; N = na	Time-series data (January 1st-August 31st, 2017, 2018, 2019, 2020), Interrupted Time-Series Analysis	–	High
Inada et al., 2021	B + D	Japan, N = 121	Monthly time-series data (Jan 2010 to May 2020), ARIMA	–	Medium
Saladié et al., 2020	B + D	Tarragona, Spain; N = 152	Time series (Feb-Apr 2018–2020), Comparative analysis	+	Medium
Quddus et al., 2010	B	UK, N = 72	Road segments data, Ordered Response Models	–	Medium
Kononov et al., 2008	B	CA, CO, TX of US; 5 years crash data	Freeway crash data, Neural Networks	+	Medium

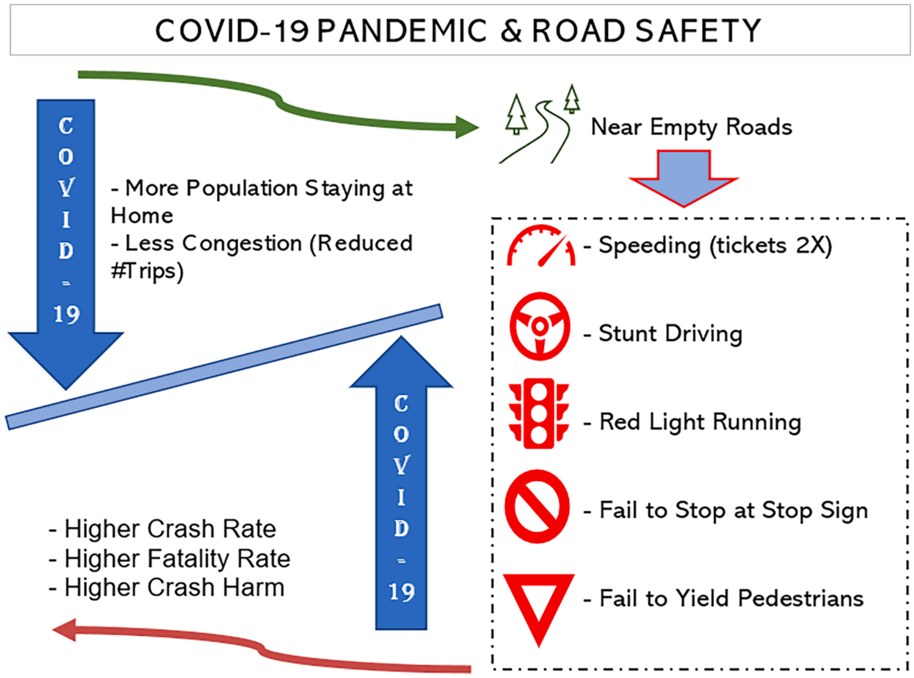


Fig. 1. Graphical Abstract.

in New York City due to low traffic volume. Yet, an increase in severe injury and fatality rate hints at higher traffic speeds, which is supported by an increase of the number of speeding tickets in downtown by 108 % and in school zones by 72 % during the pandemic (Gao et al., 2020). A recent study by Doucette et al. (2021a) on post-stay-at-home periods showed crash rates are slowly starting to return to previous year averages. Overall, measures like speeding, alcohol & drugs, other types of reckless behavior, and trips per person not staying home can be used to analyze the potential behavior of the drivers and their safety consequences. In addition, vehicle factors like the increased use of commercial trucks amid the pandemic could add more insights. All the relevant studies are summarized in Table 1.

Literature suggests that time-series analysis models like seasonal autoregressive integrated moving average (ARIMA) have been used to examine potential changes in fatalities or crashes across time (Inada et al., 2021; Sebego et al., 2014). Linear models have been adopted to explore crash harm resulting from fatalities and crashes (Khattak & Targa, 2004). Generally, count models like Poisson and negative binomial regression are powerful predictive tools that are being applied in crash frequency analysis (Abdulhafedh, 2017; Shankar et al., 1995). Most of the crash data are over-dispersed, which is a condition suggesting the need for correction to Poisson regression assumptions. In that case, the negative binomial often performs better than Poisson regression in crash frequency analysis (Abdel-Aty & Radwan, 2000). The zero-inflated negative binomial model has also been used to address the overdispersion problem caused by excessive zero counts (e.g., zero fatalities in a month at a location) (Abdulhafedh, 2017). Besides, geographically weighted regression (GWR) can better capture the inherent spatial autocorrelation and heterogeneity in the crash data (Arvin et al., 2019). Therefore, this study will adopt Poisson/negative binomial models (depending on the dispersion of the data) to analyze fatalities and crashes while using the linear model to analyze crash harm. The spatial aspects of crash data will be explored using GWR count and linear models.

The aforementioned studies are selected based on stay-at-home orders, congestion reduction, and road safety criteria. Research on these topics in the pandemic era is limited, and most of them are descriptive-based analyses, which may be a sign of a rush to publish the papers during the pandemic. As such, the outcome of those studies might influence their premature publication. However, several potential gaps are identified in the existing literature on road safety issues. Existing literature considered factors like VMT, speed, or lockdown dummy in their estimation. However, different types of driving violations during COVID-19 have not been explored in the literature. Also, whether the distance traveled from home during the pandemic has any impact on road safety or not needs to be investigated. In addition, analysis of the crash harm during COVID-19 needs to be explored. As the injury severity is high during the pandemic, it may provide a different level of estimations of the harm. As such, to fill the gaps in the literature, the study sought to investigate the impact of factors contributing to fatalities, crashes, and economic harm within the state of Tennessee before and during the pandemic by harnessing a unique database integrating crash and COVID-19 travel behavior data.

3. Conceptual framework

The study anticipates that an increase in the number of speeding-related crash cases increases the number of fatalities in crashes. It is believed that this assumption also holds for other types of violations, i.e., alcohol-drugs involved cases and other reckless driving cases. It is also expected that roadway factors like dark-lighted conditions and interstate crashes are suspected to increase fatalities. Vehicle-specific factors like more trucking activity during COVID-19 make roads vulnerable and can contribute to increasing fatalities in crashes. A higher number of short trips or long trips per population not staying at home is associated with higher exposure and crash risk. Regarding the economic losses, total crash harm could increase during COVID-19 compared to the pre-pandemic scenario. As the fatality rate increases, the crashes' economic loss could increase (Fig. 2).

4. Data: linking crashes and traveler behavior

County-level monthly data (cross-sectional time series) of the state of Tennessee covering the pre-pandemic and during the pandemic period is used in this study. A unique database is created by integrating two different sources, i.e., the Tennessee Integrated Traffic Analysis Network

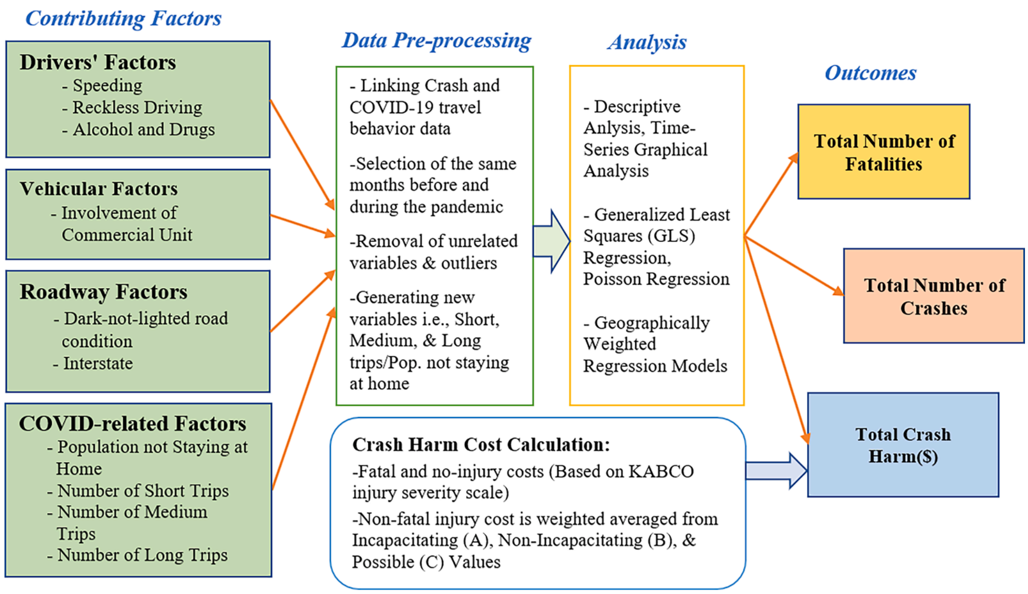


Fig. 2. Study Framework.

(TITAN) and the Bureau of Transportation Statistics (BTS) "Trips by Distance" (BTS, 2021). These datasets are linked at the county level. To make a consistent timeline, the study considers the same months pre-and-during the pandemic. In this study, ninety-five counties of Tennessee over 18 months (i.e., *pre-pandemic and during-pandemic periods)* constitute a sample of 1,710. The study's pre-pandemic refers to the periods in 2019 before the COVID-19 pandemic. In particular, January 1st to September 30th of 2019 is considered pre-pandemic. On the other hand, during-pandemic periods include the periods during the pandemic in 2020. The study uses a similar timeframe for the during-pandemic periods (January 1st to September 30th). The dates were chosen by following the COVID-19 timeline in the state of Tennessee. Specifically, the Tennessee state health operation center was activated in January 2020 with the declaration of COVID-19 as a public health emergency in the US. Tennessee started the state of emergency in March 2020 and continued through September 2020, which was initiated to encourage social distancing to help mitigate the spread of the virus (TN.GOV, 2021). In addition, the use of a similar timeframe for pre-and-during pandemic periods has already been documented in the literature (Doucette, Tucker, Auguste, Gates, et al., 2021; Doucette, Tucker, Auguste, Watkins, et al., 2021; Saladié et al., 2020). COVID-19-related information and travel information are collected from the BTS. Data on the number of people not staying at home is provided by the Maryland Transportation Institute and Center (MTIC) for the advanced transportation technology laboratory at the University of Maryland (BTS, 2021). MTIC collects travel information, such as the number of trips from anonymized "national panel of mobile device" data from multiple sources. The sample of mobile devices is representative of the entire population in a state or county. MTIC does not report data for counties having<50 devices in the sample on any given day to assure better data quality. MTIC defines trips as movements that last longer than 10 min at any location away from home.

The number of crashes and the number of fatalities per month are collected from the TITAN database, which is maintained by the Tennessee Department of Transportation (TDOT). TITAN includes information for all the police-reported crashes in Tennessee. TITAN also provides information regarding the number of injured and non-injured persons. An additional safety measure, crash harm, is adopted to account for the economic value of each injury level and the costs for each injury/property damage. For example, two fatalities in a crash will still be coded as a fatal crash, but crash harm captures this in terms of monetary cost. Comprehensive crash unit cost values (2016 dollars) of the federal highway administration (FHWA) are used to create this unique variable (Harmon et al., 2018). The dollar values are in the KABCO injury severity scale, whereas TITAN reports injury severity in three categories: fatal injury, non-fatal injury, & no injury. The study uses the economic values for fatal injury, non-fatal injury, & no injury types severity from the FHWA given values: $11.29 million for each fatal injury, an average value of $0.23 million for each non-fatal injury, and $0.012 million for each non-injured person involved in crashes. Crash harm is calculated at the county level by month and year. The following Equation (1) is applied to calculate the crash harm.

$$H_{mky} = \sum_{i=1}^{3} C_i{}^*N_i \tag{1}$$

where

H_{mky} = Crash harm of county "k" in month "m" and year "y"; (k = 1, 2, 3, ….., 95; m = 1, 2, ……, 9; y = 2019, 2020).

C_i = cost of each injury severity type i; (i = 1-Fatal injury, 2-Non-fatal injury, 3-No injury).

N_i = Number of persons involved in injury severity type i.

For example,

Crash harm of Carter County in March 2020 = $11.295 million * number of fatally injured persons + $0.23 million * number of non-fatal injured persons + $0.012 million * number of non-injured person involved in crashes = $11.295 * 2 + $0.23 * 34 + $0.012 * 185 = $31.61 million.

The dataset used in this study is error-checked through descriptive analysis, and the data is reasonable with no extreme outliers. Table 2 reports the descriptive statistics of the data. It is divided into pre-and post-COVID-19 scenarios. The mean values per ten thousand trips (i.e., Mean/Trips) are also generated to compare the pre-and-post COVID-19 values. There are three dependent variables: number of fatalities, number of crashes, and crash harm. As expected, it is found that fatalities have increased by 8.2 % during the pandemic compared to the pre-pandemic periods, whereas the number of crashes has decreased (15.3 %). Moreover, the total crash harm is lowered by $1.76 billion during COVID-19 in Tennessee. However, if per trip values are compared, it is found that the crash harm and the number of crashes are higher during COVID-19 than in pre-COVID-19 periods.

Regarding the independent variables, "*No. of Speeding Violations*" represents the number of speeding cases that resulted in crashes. It shows that such cases were higher in 2020 compared to 2019. The

Table 2
Descriptive Statistics (N = 1,710) *(Monthly, Per County)*.

Variable	Pre-pandemic (Jan-2019 to Sept-2019)						During-pandemic (Jan-2020 to Sept-2020)						Differences	
	Mean	SD	Min	Max	Total	Mean/Trips ('10,000)	Mean	SD	Min	Max	Total	Mean/Trips ('10,000)	"Mean" Diff (2020–2019)	"Mean/Trips" Diff (2020–2019)
No. of Fatalities*	1.01	2.03	0	19	867	0.044	1.06	2.63	0	29	938	0.052	0.05	0.01
No. of Crashes*	210.31	542.32	2	4048	179,811	4.93	178.15	447.66	1	3753	152,319	5.46	−32.15	0.53
Total Crash Harm ($Millions)*	28.92	66.95	0.02	554.33	24723.33	0.991	26.86	67.31	0.02	647.77	22966.45	1.032	−2.06	0.04
No. of Speeding Violations	1.37	6.27	0	59	1172	0.012	1.54	6.87	0	56	1313	0.017	0.17	0.01
No. of Reckless Driving Cases	7.65	22.97	0	256	6537	0.22	6.52	21.72	0	232	5577	0.23	−1.13	0.01
No. of Alcohol & Drugs Cases	6.47	10.05	0	93	5486	0.243	6.48	9.82	0	5	5541	0.329	0.01	0.09
No. of Cases Involving Commercial Units	4.16	8.07	0	59	3558	0.15	4	7.57	0	53	3417	0.171	−0.16	0.02
No. of Cases on Interstate Roadways	18.09	60.94	0	459	15,469	0.29	14.94	48.81	0	425	12,776	0.323	−3.15	0.03
No. of Cases on All Other Roadways	97.36	318.15	0	3030	164,342	1.84	84.64	278.1	0	2797	139,543	2.054	−12.72	0.21
No. of Day-Lighted Cases	146.04	12.89	1	2940	124,864	3.31	119	9.99	0	2475	101,749	3.62	−27.04	0.31
No. of Dark-not-Lighted Cases	17.77	0.89	0	212	15,191	0.76	17.13	25.04	0	239	14,643	0.87	−0.64	0.11
Short-length trips rate	2.85	0.53	1.62	5.13	2436.44	–	2.37	0.34	1.49	4.05	2022.4	–	−0.48	–
Mid-length trips rate	2.03	0.38	1.29	4.22	1735.35	–	4	0.39	2.95	6.53	1400.82	–	1.97	–
Long trips rate	0.15	0.06	0.06	0.47	129.61	–	0.16	0.05	0.04	0.4	138.22	–	0.01	–

* Dependent variables.

frequency of *alcohol and drug-related* cases and *reckless behavior cases* per trip also increased in 2020. Similarly, roadway and vehicular factors per trip are also reported to be increased during COVID-19. These variables are explored graphically in the next section. Three unique COVID-19-specific independent variables are generated from the collected BTS database by combining the information regarding the number of trips in terms of length and population not staying at home, which can reflect how far a person traveled when they did not stay at home during COVID-19. Since these unique variables on "trips per person not staying at home" will be added to the modeling, the crash/fatality per trip is not modeled, i.e., it is not used as a dependent variable. Trips are categorized by length: trips greater than zero to less than or equal to 5 miles are considered as short-length, trips greater than 5 miles, and less than or equal to 50 miles are considered as mid-length, and trips greater than 50 miles are considered as long trips. It is observed that the rate of mid-length and long trips were higher during the pandemic, whereas short-length trips showed a decline.

5. Exploratory analysis

Fig. 3 illustrates the monthly trend of road crashes, fatalities, and total crash harm in Tennessee. The time-series graphs capture several noteworthy facts. All the values have plummeted in the beginning phase of the pandemic (Feb'20 to Apr'20). After that, the values begin to catch up and eventually return to the pre-pandemic scenarios. However, the number of fatalities rises higher than in the pre-pandemic era, suggesting a serious concern over road safety during the COVID-19 pandemic.

5.1. Drivers' Factors:

Drivers generally make different types of violations while driving. Literature suggests that speeding-involved crashes are common during COVID-19. Drug and alcohol use and reckless behaviors are also other top-ranked causes of car crashes. Reckless behaviors include tailgating, failing to stop at red lights or stop signs, braking abruptly, not using turn signals when changing lanes or turning, failing to use headlights at night or in extreme weather, making illegal turns, or lane changes. Fig. 4 suggests that reckless driving contributed to a 50 % increase in fatal crashes in Tennessee, while the total number of crashes decreased by 15 %. The increase is spotted during the beginning phase of the pandemic (i.e., March 2020) and in the latter part of 2020. Speeding-related crashes and fatalities have both increased during COVID-19. There was an overall increase of 15 speeding-related fatal crashes in 2020 compared to 2019. The cases remain high for almost all of 2020.

5.2. Roadway Factors:

Roadway factors include the lighting condition of the roads and the speed limits of interstates, among others. It is difficult to detect a pedestrian walking or an object at night, even on a lighted road, due to a lack of good visual acuity and contrast sensitivity. Crashes and fatalities in the dark (not lighted) conditions are higher than in the day-light conditions, according to the literature (Adegbite et al., 2019). Roads such as interstates with higher speed limits can be vulnerable to fatal crashes, especially with the presence of reckless drivers. In Fig. 5, it can be observed that crashes on the interstate decreased by 17 % in 2020; however, fatal crashes surged by 21 % in 2020 compared to 2019.

5.3. Vehicular Factors:

Fig. 6 presents the trends of crashes and fatalities involving commercial units in Tennessee during 2019–2020. It is observed that the total number of crashes involving commercial vehicles decreased by 7 %, while fatal crashes increased by 11 % in 2020 compared to 2019. Fatal crashes were 17 at the start of the pandemic, while 24 in August

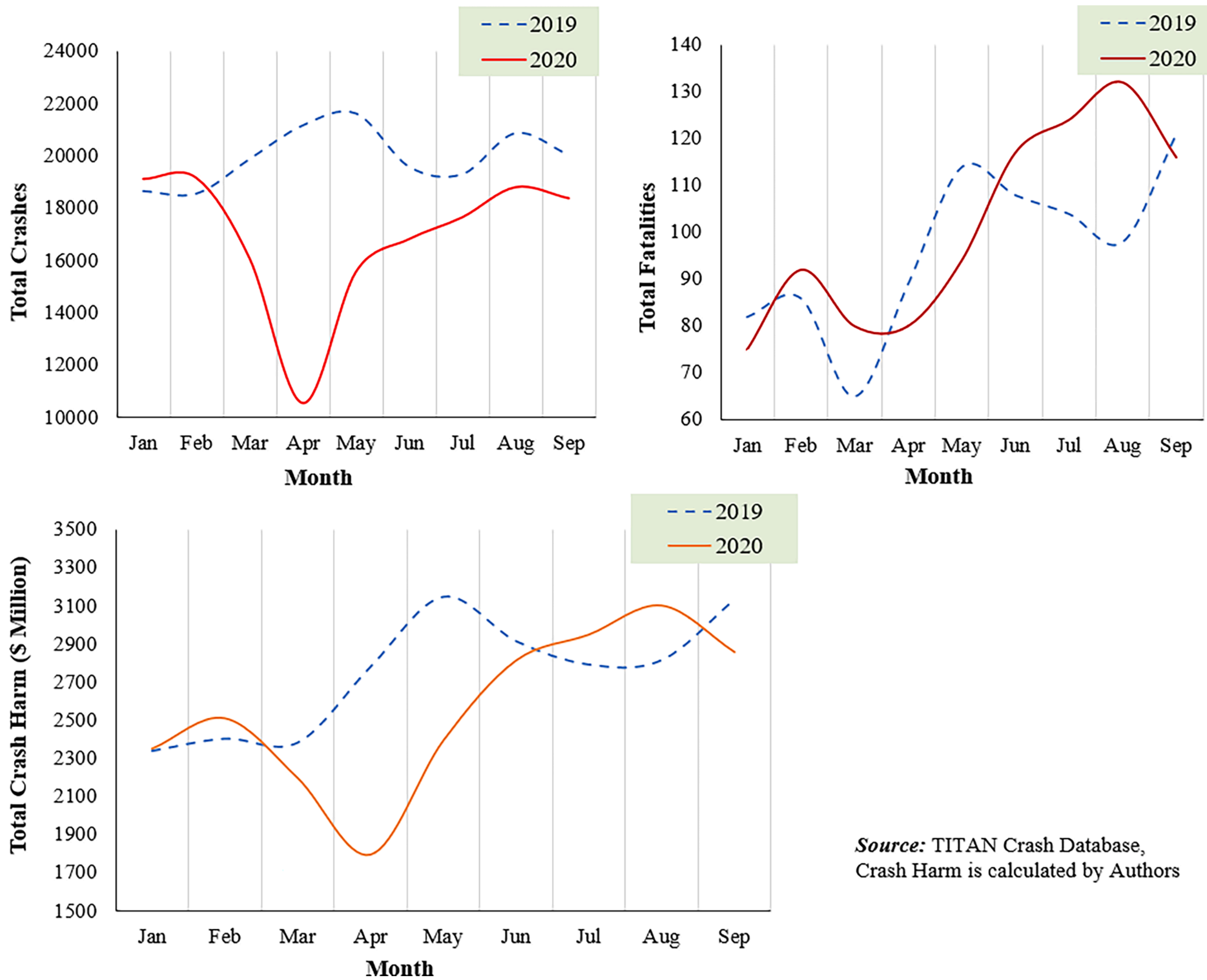


Fig. 3. Monthly Trends of Crashes, Fatalities, and Crash Harm in Tennessee, 2019 (pre-pandemic) – 2020 (during pandemic).

2020 and 10 in September 2020.

6. Modeling

In this study, the number of fatalities, the number of crashes, and crash harm are modeled as the dependent variables. To show the COVID-19 impacts solely, the first differences are calculated using the monthly county-level data for 2019 and 2020. The first differences are the values found by subtracting 2019 values from 2020, as shown in *Equations (2) and (3)*. These monthly differences account for the variation across counties and months and provide a better measure of the correlates of fatalities, crashes, and crash harm. The differences can have both positive and negative values. Positive difference values show that 2020 values are higher than 2019, and vice-versa. In the analysis, county and month are indexed to confirm the panel structure of the data.

$$Y = \Delta y_i = y_{i,2020} - y_{i,2019} \tag{2}$$

$$X = \Delta x_i = x_{i,2020} - x_{i,2019} \tag{3}$$

where Δy_i is the difference between 2020 and 2019 in the dependent variable i and Δx_i is the difference between 2020 and 2019 in the independent variable i.

6.1. *Generalized least squares linear regression Model:*

The difference in crash harm is a continuous variable that can be modeled using the generalized least squares (GLS) linear regression model. Previously, linear models are applied to estimate the coefficients for total crash harm in work zone crashes (Khattak & Targa, 2004). GLS extends the ordinary least squares estimation by addressing the possible unequal error variances and correlations between different errors in the time-series data (Greene, 2003). Therefore, GLS can efficiently estimate regression coefficients, as shown in *Equation (4)*.

$$Y = X\beta + \varepsilon,\ E(\varepsilon) = 0, Cov\,(\varepsilon) = \omega \tag{4}$$

where Y is the dependent variable, and X are the independent variables for a set of units, i.e., TN counties over time. β denotes the unknown regression coefficients. ε is the vector of random errors, and ω is the variance–covariance matrix. GLS involves minimizing $(Y - X\beta)'\omega^{-1}(Y - X\beta)$ with respect to β. The resultant estimator b of the regression coefficients β can be expressed in *Equation (5)*.

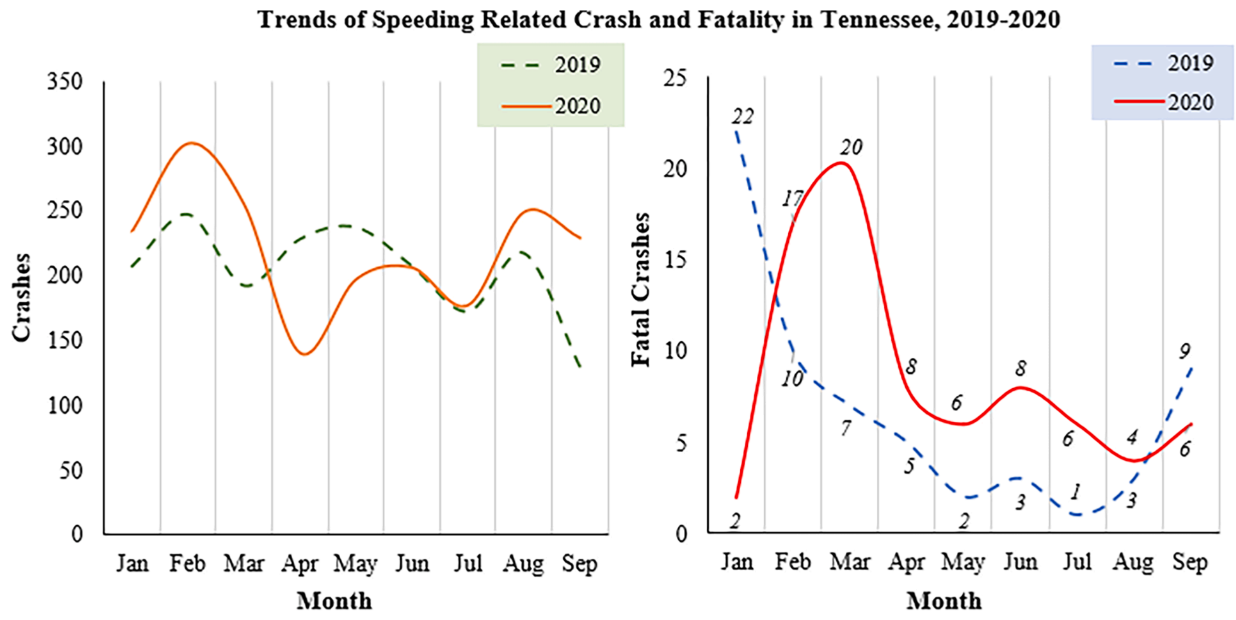
$$\mathrm{b} = \left(\mathrm{X}'\omega^{-1}X\right)^{-1}X'\omega^{-1}Y \tag{5}$$

Equation (6) denotes the estimated covariance matrix V of b.

$$V = \widehat{Cov}(b) = \left(X'\omega^{-1}X\right)^{-1} \tag{6}$$

A notable property of GLS is that its estimate of β is unbiased (*E(b)* = β).

Under the assumption of normality distributed random errors, the log-likelihood function (ℓ) can be written as follows in *Equation (7)*:



Year	Crashes	Fatal Crashes
2019	1,836	62
2020	1,989 (+8%)	77 (+24%)

Year	Crashes	Fatal Crashes
2019	6,561	38
2020	5,598 (-15%)	57 (+50%)

Fig. 4. Speeding and Reckless Driving- related Crashes & Fatalities in Tennessee, 2019 (pre-pandemic) – 2020 (during-pandemic).

$$\ell = -\frac{n}{2}\log(2\pi) - \frac{1}{2}\log|\omega| - \frac{1}{2}\left[(Y - X\beta)'\omega^{-1}(Y - X\beta\right. \quad (7)$$

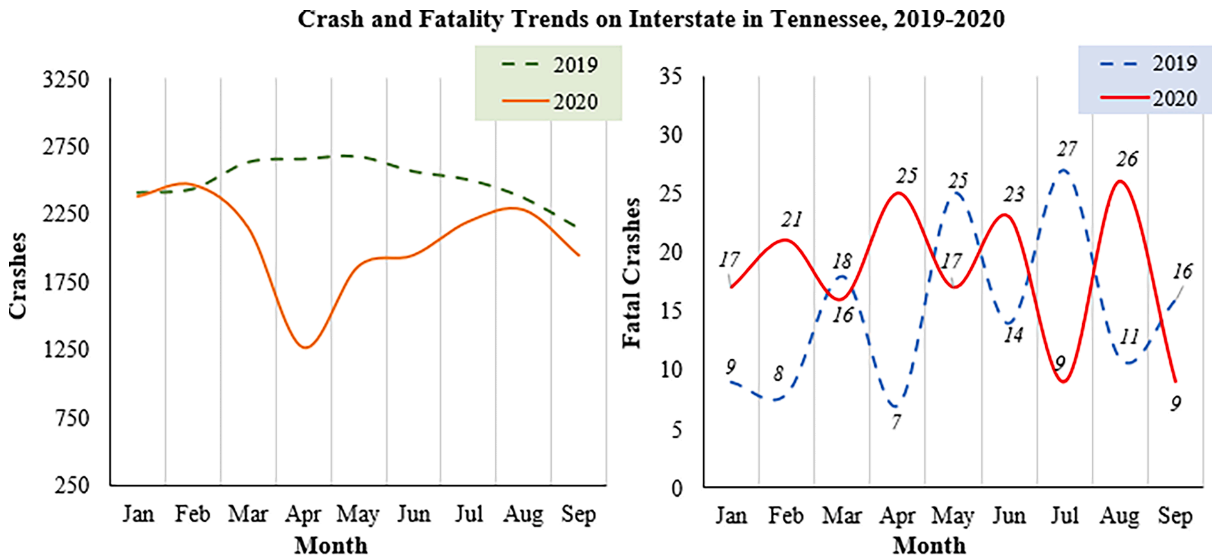
6.2. Poisson regression

The difference in the number of fatalities and the difference in the number of crashes are count variables. However, the variables contain both positive and negative count values. Since count models cannot handle negative values, a constant value (minimum of the difference in the count outcome variable) is added to the differences. Then, the transformed differences would be greater than or equal to zero. This transformation makes the outcome variables eligible to use the count models (Atkinson, 1985; Woo et al., 2019). Count models, e.g., Poisson and negative binomial regression, are powerful predictive tools applied in crash frequency analysis (Abdulhafedh, 2017; Shankar et al., 1995). The Poisson regression model can be employed to analyze count data when there is no overdispersion in the data.

The Poisson distribution of a random variable Y follows the following probability density function in *Equation (8)* for a given value Y = y:

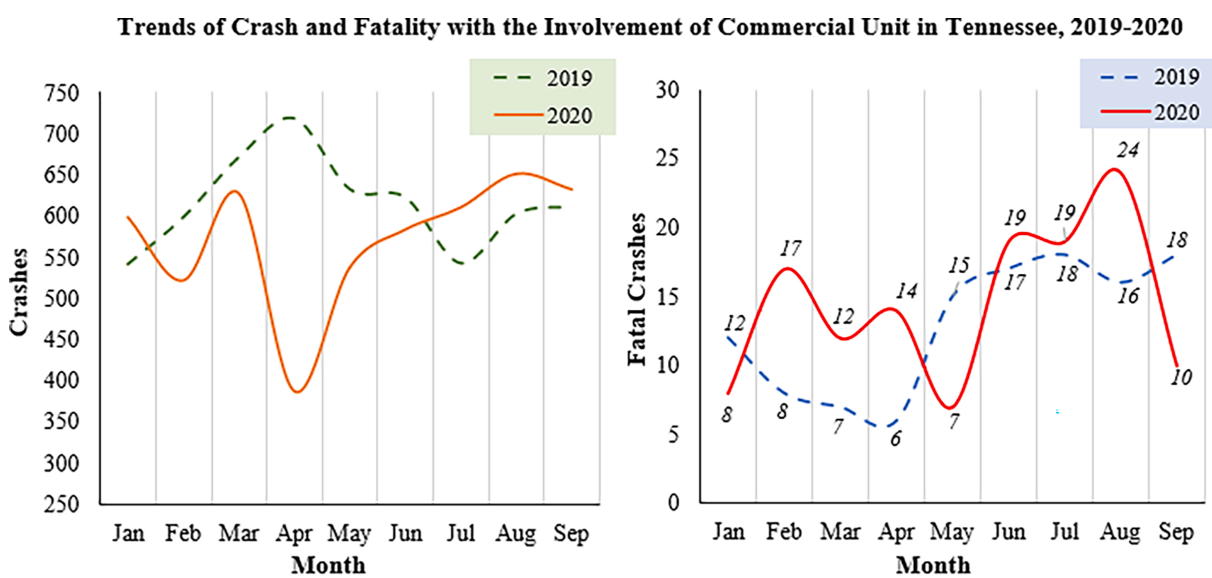
$$P(Y = y|\varphi) = \frac{e^{-\varphi}\varphi^{y}}{y!} \quad (8)$$

where φ is the mean rate of occurrence. This rate is determined by a set



Year	Crashes	Fatal Crashes
2019	22,389	135
2020	18,522 (-17%)	163 (+21%)

Fig. 5. Roadway Factors' Related Crashes and Fatalities in Tennessee, 2019 (pre-pandemic) – 2020 (during-pandemic).



Year	Crashes	Fatal Crashes
2019	5,537	117
2020	5,154 (-7%)	130 (+11%)

Fig. 6. Involvement of Commercial Vehicle in Crashes & Fatalities in Tennessee, 2019 (pre-pandemic) – 2020 (during-pandemic).

of k predictors, $X = (X_1, X_2, \ldots\ldots, X_k)$. It can be expressed by *Equation (9)*:

$$\varphi = \exp(X\beta) \tag{9}$$

Then, the Poisson regression model for observation *i* can be defined by *Equation (10)* below:

$$P(Y_i = y_i | X_i, \beta) = \frac{e^{-\exp(X_i\beta)}\exp(X_i\beta)^{y_i}}{y_i!} \tag{10}$$

The likelihood function for a sample size n is given by *Equation (11)* below:

$$L(\beta; y, X) = \prod_{i=1}^{n} \frac{e^{-\exp(X_i\beta)}\exp(X_i\beta)^{y_i}}{y_i!} \tag{11}$$

Then, the log-likelihood function is generated, as shown in *Equation (12)*.

$$\ell(\beta) = \sum_{i=1}^{n} y_i X_i \beta - \sum_{i=1}^{n} \exp(X_i\beta) - \sum_{i=1}^{n} \log(y_i!) \tag{12}$$

An overdispersion test on *Equation (13)* can be performed to reflect how much the sample fluctuates around a mean value.

$$Var(Y) = \mu + \alpha\mu^2 \tag{13}$$

Where α reflects the amount of overdispersion, which is non-negative and implies the variance Var(Y) can exceed the mean (μ). When α approaches zero, there is no overdispersion in the data (i.e., expected mean = variance). A likelihood ratio test is performed in STATA (statistical software) to test for the significance of the overdispersion parameter (α). When α is statistically not significant (5 % level), the Poisson distribution can appropriately model the data.

6.3. Geographically weighted regression Models:

Geographically Weighted Regression (GWR) models are also adopted in this study to explore further the existence of spatial non-stationarity or heterogeneity in the correlates of the difference in crash fatalities, crashes, and crash harm. Spatial heterogeneity shows different mean and variance values at each location, if there exists any (Haque et al., 2022). The GWR model allows the parameters to vary over space; hence, it is believed to be applicable for the current analysis. GWR models were applied in the literature to analyze the spatial heterogeneity of related factors in road crashes (Mohammadnazar et al., 2021, 2022; Wali et al., 2018). Geographically weighted Poisson regression models are estimated for analyzing the difference in the number of fatalities and the difference in the number of crashes. Also, a conventional geographically weighted linear regression is estimated for the differences in crash harm. Fixed Gaussian kernel functions have been used to determine the GWR weights that estimate the geographical changes in local extent.

The equations for the GWR models are given in *Equations (14) and (15)*. *Equation (14)* describes the geographically weighted Poisson regression model and *Equation (15)* shows the geographically weighted linear regression model.

$$Y_i = \sum_k \beta_k(u_i, v_i) X_{k,i} + \varepsilon_i \tag{14}$$

$$Y_i \ Poisson\left[N_i \exp\left(\sum_k \beta_k(u_i, v_i) Y_{k,i}\right)\right] \tag{15}$$

Here,

Y_i = dependent variable at location i;

$X_{k,i}$ = k^{th} independent variable at location i;

ε_i = Gaussian error at location i;

(u_i, v_i) = x-y coordinate of the i^{th} location;

$\beta_k(u_i, v_i)$ = coefficients that are varying conditionals on the locations.

The equation to estimate $\beta_k(u_i, v_i)$ is as follows, i.e., *Equation (16)*:

$$\beta^{'}\ (\mathrm{i}) = \left(X^T W(i) X\right)^{-1} X^T W(i) Y \tag{16}$$

Here, W(i) represents a matrix of weights specific to location i such that observations nearer location i are given more weight than observations that are located far away from i. The form of the matrix W(i) is as follows, i.e., *Equation (17)*:

$$\mathrm{W}(i) = \begin{bmatrix} w_{i1} & 0 & 0 \\ 0 & w_{i2} & 0 \\ 0 & \cdots & w_{in} \end{bmatrix} \tag{17}$$

Here, w_{in} is the weight given to the observation n for the estimate of the local parameters at i location. *Equation (18)* denotes the adopted fixed Gaussian kernel of GWR model.

$$w_{ij} = \exp\left(\frac{-d_{ij}^2}{\theta^2}\right) \tag{18}$$

Here,

i = regression point index;

j = locational index;

w_{ij} = the weight value of observation at location j for estimating the coefficient at location i;

d_{ij} = Euclidean distance between i and j;

θ = A fixed bandwidth size defined by a distance metric;

7. Results

7.1. Results of the Preliminary Models:

Results of the Poisson regression models and the GLS linear regression model are presented in Table 3. Columns (1), (2), and (3) denote the results for the three dependent variables: difference in the number of fatalities (model 1), number of crashes (model 2), and crash harm (model 3). Model significance tests show that the models fit the data well. The pseudo-R^2 values of models (1) and (2) are 8 % and 54 %, and the R^2 value of the crash harm model is 44 %. The correlation among the independent variables is checked, and the values are less than or equal to 0.5 or −0.5, referring to no multicollinearity issues. The distributions of all the dependent variables are shown in Fig. 7. In model (1), the Poisson distribution is shifted to 7 units to the right after adding the minimum difference of fatalities (which is −7) between 2020 and 2019 (Fig. 7a). Similarly, model (2) has shifted by 233 units to the right (Fig. 7b). The general relationships between the independent variables and dependent variable (i.e., direction) do not change when a constant is added to the dependent variable, except everything is shifted to the same constant units to the right (Woo et al., 2019). In Table 3, the Poisson coefficient sign of the independent variables indicates the direction of their effects on the dependent variable. The generated average marginal effect explains the probability of the association. The coefficient of each variable can be interpreted one by one for all three models.

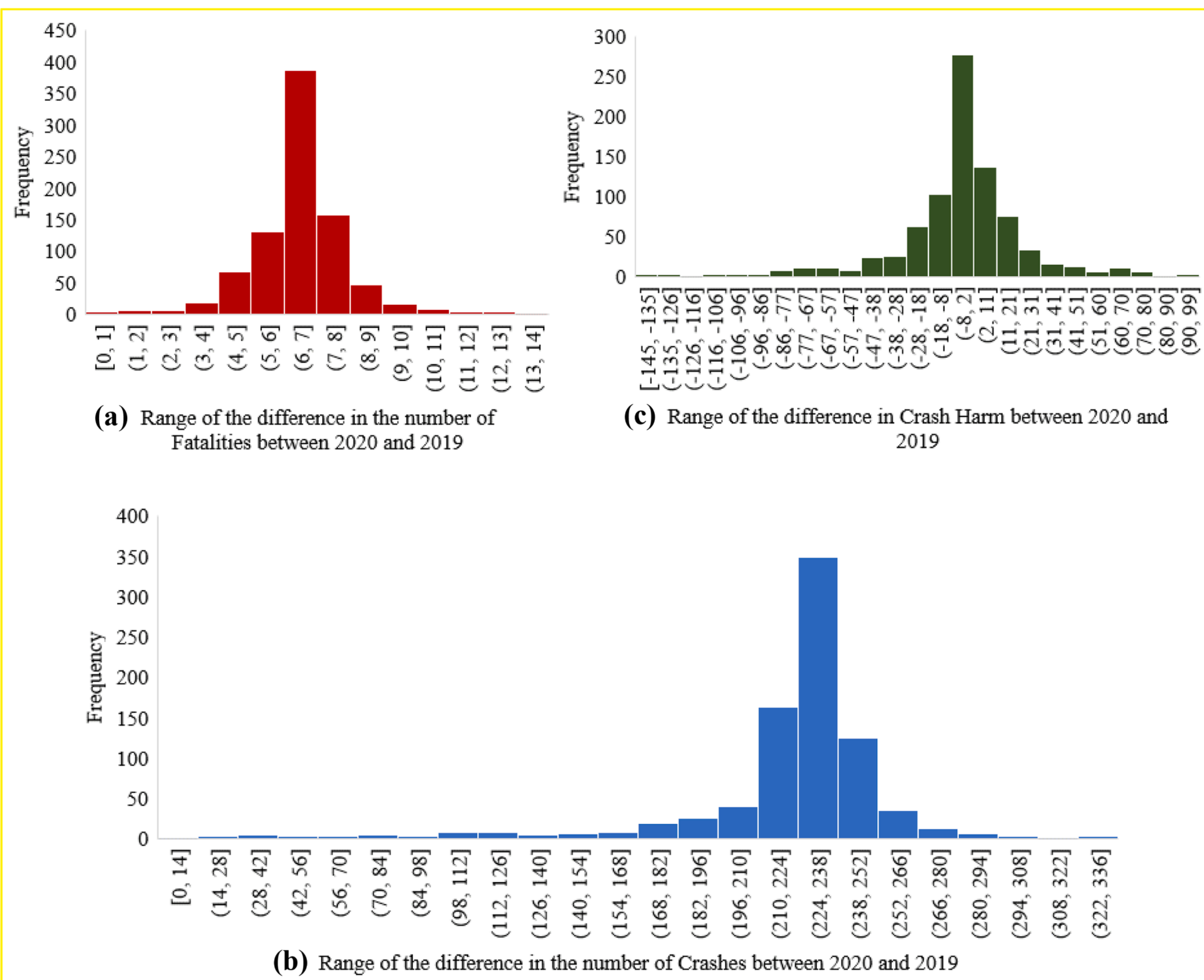
The first one is the "*Diff. in the No. of Speeding Violations*", which is positive and significant for the three models. It indicates that one unit increase in the differences of *speeding* violation cases is associated with an increase of the difference in crash harm between 2020 and 2019 by $0.87 million. Also, an increase in the differences of *speeding*-related cases is associated with increased probabilities of crash fatalities and crashes by 0.07 % and 2.39 %, respectively, in 2020 during COVID-19. The findings are consistent with the earlier assumption. Speeding-related crashes are dangerous and fatal. Speeding makes the vehicles more difficult to control, especially when driving around a curve or encountering a road hazard or other cars. Since speeding exerts the most force upon impact and involves a larger mass or higher acceleration, it causes the most severe injuries and fatalities (Mahdinia et al., 2022b,a), and eventually generates more economic harm. Less traffic during COVID-19 encouraged drivers to speed, eventually leading to fatalities. "*Diff. in the No. of Reckless Driving Cases*" is also positive and statistically significant in models (2) & (3). Difference in the reckless driving behaviors is found to be associated with an increase in the probability of crashes by 0.89 % during COVID-19. Whereas crash harm is associated with an increase of $0.31 million from a one-unit increase in such cases. Reckless behavior, e.g., failing to yield to traffic and running stop signs and red lights, make roads more vulnerable to fatal crashes. "*Diff. in the No. of Alcohol & Drugs Cases*" is associated with an increase in the probability of the number of fatalities in crashes by 0.46 %. This variable was excluded from model (2) as it was highly correlated with the number of crashes. Nonetheless, the increase of one alcohol & drugs related crash is associated with an increase in crash harm differences by $7.42 million, indicating much greater damage during COVID-19 as a result of increased *Alcohol & Drugs* related cases.

An increase in *"Diff. in the No. of Cases on Interstate Roadways"* is associated with a 0.02 % increase in the probabilities of crash fatalities and a 0.91 % increase in the probabilities of the number of crashes during COVID-19. Whereas on other roads, excluding interstates, the coefficient appears to be negative for fatalities. Interstates expose drivers to a higher speed limit than highways, which became deadly during COVID-19. An increase in *"Diff. in the No. of Dark-not-Lighted Cases"* is associated with an increase in total crash harm by $0.64 million. The chance of crash occurrence is also associated to be increased by 1.7 % due to an increase in the *dark-not-lighted* cases.

Table 3
Estimation Results of the Preliminary Models.

	(1) Diff. in the No. of Fatalities (Poisson Regression Model)			(2) Diff. in the No. of Crashes (Poisson Regression Model)			(3) Diff. in Crash Harm (Millions) (Generalized Least Squares Linear Regression Model)	
Variables (County Level)	Coef.	*P*-value	Marginal Effect	Coef.	*P*-value	Marginal Effect	Coef.	*P*-value
Diff. in the No. of Speeding Violations	0.074	0.022**	0.075	2.322	0.003***	2.386	0.866	0.001***
Diff. in the No. of Reckless Driving Cases	0.026	0.144	0.027	0.917	0.011**	0.898	0.313	0.021**
Diff. in the No. of Alcohol & Drugs Cases	0.465	0.025**	0.468	na	na	na	7.42	0.000***
Diff. in the No. of Cases Involving Commercial Units	0.041	0.164	0.041	1.030	0.064*	1.037	0.515	0.015**
Diff. in the No. of Cases on Interstate Roadways	0.021	0.052*	0.022	0.934	0.000***	0.913	0.052	0.522
Diff. in the No. of Cases on All Other Roadways	−0.008	0.002***	−0.008	−0.185	0.010**	−0.189	−0.114	0.000***
Diff. in the No. of Day-Lighted Cases	−0.001	0.700	−0.001	1.705	0.000***	1.682	0.054	0.001***
Diff. in the No. of Dark-not-Lighted Cases	0.004	0.781	0.004	1.729	0.000***	1.700	0.641	0.000***
Diff. in Short-length trips rate	−0.651	0.091*	−0.656	−17.979	0.075*	−7.059	−0.703	0.728
Diff. in Mid-length trips rate	0.500	0.678	0.503	−3.125	0.887	−3.070	−0.731	0.781
Diff. in Long trips rate	15.237	0.233	15.347	15.061	0.100*	15.420	30.559	0.064*
Constant	13.516	0.000***		17.711	0.000***		−0.977	0.319
Model Fit Statistics								
χ^2	128.62			7401.12			588.45	
Model Significance Test (Prob > χ^2)	0			0			0	
Overdispersion (α)	0			0			na	
Log-likelihood	−1771.25			−5008.04			−3722.45	
AIC	3568.51			10040.08			7470.71	
BIC	3630.27			10097.10			7527.72	
Pseudo-R^2/ R^2	0.08			0.54			0.44	

Note: * $p < 0.1$; ** $p < .05$; *** $p < .01$.
"na" = not applicable.



(a) Range of the difference in the number of Fatalities between 2020 and 2019

(c) Range of the difference in Crash Harm between 2020 and 2019

(b) Range of the difference in the number of Crashes between 2020 and 2019

Fig. 7. Histograms of the differences between 2020 and 2019 in (a) the number of Fatalities, (b) the number of Crashes, and (c) Crash Harm.

Fatalities appeared to decrease in day-lighted cases. It was not significant in the fatality model. On the other hand, it is found that if the "*Diff. in the No. of Cases Involving Commercial Units*" increases by one, the chance of crash differences increases by 1.03 %. Besides, crash harm increases by $0.51 million. Long-haul drivers undergo significant changes during the pandemic that may affect their health and safety. Traveling at higher speeds and risky behaviors could lead to vulnerability to crash fatalities.

The difference in the number of *Short-length trips* per person not staying at home is negative and statistically significant in models (1) and (2). Besides, the "*Diff. in Long trips rate*" is significant and positive in models (2) and (3); however, the "*Diff. in Mid-length trips rate*" is not statistically significant. These results suggest that the increase in short trips per population not staying at home was associated with a fewer number of fatalities and crashes. However, the longer trip lengths are associated with the increase in probability of the differences in crashes, as shown by the increasing likelihood of crash frequency for the *long trips rate*. Specifically, an increase in the differences of long trips per person not staying at home is associated with an increase in the chance of the differences in crashes by 15.42 % during the pandemic. Similarly, crash harm showed increased association with the increase of long trips per person not staying at home during COVID-19. Overall, it is observed that the increase in trip length increases the fatality risk in crashes during COVID-19.

7.2. Results of the spatial Models:

Table 4 presents the results of the GWR global models with the coefficients and significance level. The *t*-value > 1.96 or <-1.96 indicates that the variables are significant at 95 % confidence level and indicates a p-value of <0.05. The GWR local models' results are similar to the results of the discussed GLS regression models. Moreover, the pseudo-R^2/R^2 values of the model (1), (2), & (3) have slightly been improved, which are 8 %, 85 %, and 45 %, respectively.

The GWR local models' results are illustrated in Table 5. The table contains various distribution parameters such as mean, minimum, maximum, and difference of criterion (i.e., a test of spatial variability) for the estimates. These values help to see the distribution of parameters and their range of variation across space. Variables with a negative difference of criterion values indicate the presence of spatial variability in those variables. The local model fits the data better than the global and first difference regression models. The pseudo-R^2/R^2, AIC, and BIC are better than the previously analyzed models (i.e., Poisson, GLS, and GWR global models). The pseudo-R^2 values for models (1) and (2) are now 10 %, and 90 %, respectively. Similarly, the increased R^2 value for model (3) is 59 %. In addition, the sign of the estimates in local models is the same as observed in the global models. The range of variation can be explored by looking at each variable's minimum and maximum values. It appears that for most of the variables, the mean values of the coefficients of the local model are closer to their global values. For instance, the range of model (1) correlates for the "*Diff. in the No. of Cases Involving Commercial Units*" variable is between 0.039 and 0.042 with a mean of 0.041, which is closer to its global coefficient value of 0.040.

The maps showing the spatial variation of local parameter estimates of Tennessee counties are illustrated in Figs. 8–10. The average value of the local parameter estimates is calculated for each county using the Geographic Information System (GIS) software. The higher values of the coefficients are presented by a darker shade, and lower values are presented by a lighter shade. The maps show that the local parameter estimates vary across the counties of Tennessee. Figs. 8–10 show that correlates can be partially stationary in some counties but change across jurisdictions. For example, Fig. 8(a), 9(a), & 10(a) show the correlates of "*Diff. in the No. of Speeding Violations*" for the differences in fatalities, crashes, and crash harm that varies across Tennessee. This indicates the impact of speeding, as a positively correlated variable for crash frequency, fatalities, and crash harm, is higher in West Tennessee. Going from west to east, except for a few counties, the effect of speeding differences decreases significantly. One thing can be presumed that lack of enforcement in the counties with higher estimates could play a role. However, an inverse relationship between speeding and the outcome variables is observed in some counties. One explanation could be that speeding and other violations do not result in fatalities necessarily in some counties, partly because they may not have high-speed roads (e.g., freeways) or differing levels of traffic enforcement (which cannot be captured in these data). Several studies have found similar findings (Baruya, 1998; Imprialou et al., 2016; Lave, 1985). According to Imprialou et al. (2016), the increased design standards of some roadways and the longer available distances between vehicles at high-speed conditions (i.e., lower traffic volume) may contribute to the inverse relationship between speeding and crashes in some regions. In Fig. 10 (b), the difference in *Alcohol & Drugs Cases* shows high variability in the south-western regions, e.g., Shelby County, where the difference in crash harm increases with the increase in the differences of *Alcohol &*

Table 4
Estimation Results of the GWR Global Models.

Variables (County Level)	(1) Diff. in the No. of Fatalities (Poisson Regression Model) Estimate	*t* (Est/Standard Error)	(2) Diff. in the No. of Crashes (Poisson Regression Model) Estimate	*t* (Est/Standard Error)	(3) Diff in Crash Harm (Linear Model) Estimate	*t* (Est/Standard Error)
Diff. in the No. of Speeding Violations	0.010	1.57*	2.421	3.573***	1.334	4.754***
Diff. in the No. of Reckless Driving Cases	0.000	0.019	0.912	2.535***	0.452	3.108***
Diff. in the No. of Alcohol & Drugs Cases	0.583	2.128***	na	na	5.041	2.977***
Diff. in the No. of Cases Involving Commercial Units	0.040	1.318	1.051	1.919*	0.631	2.757***
Diff. in the No. of Cases on Interstate Roadways	0.004	2.096**	0.925	4.087***	0.205	2.349**
Diff. in the No. of Cases on All Other Roadways	−0.005	−1.953*	−0.191	−2.864***	−0.135	−6.368***
Diff. in the No. of Day-Lighted Cases	0.002	1.710*	1.707	36.001***	0.107	6.676***
Diff. in the No. of Dark-not-Lighted Cases	0.008	0.154	1.725	6.246***	0.26	2.265**
Diff. in Short-length trips rate	−0.409	−0.765	−17.308	−1.794*	0.78	0.359
Diff. in Mid-length trips rate	−0.065	−0.054	−3.120	−0.144	−4.395	−1.549
Diff. in Long trips rate	3.046	0.247	15.644	0.684	40.664	2.280**
Constant	13.539	9.821***	17.335	74.500***	−1.339	−1.266
Model Fit Statistics						
AIC	281.74		1892.88		7590.9	
BIC	355.71		1944.83		7652.66	
Pseudo-R^2/ R^2	0.08		0.85		0.45	

Note: * p < 0.1; ** p <.05; *** p <.01; "na" = not applicable.

Table 5
Estimation Results of the GWR Local Models.

Variables (County Level)	(1) Diff. in the No. of Fatalities (Poisson Regression Model)				(2) Diff. in the No. of Crashes (Poisson Regression Model)				(3) Diff. in Crash Harm (Linear Model)			
	Mean β	Min β	Max β	*Test of Spatial Variability	Mean β	Min β	Max β	*Test of Spatial Variability	Mean β	Min β	Max β	*Test of Spatial Variability
Diff. in the No. of Speeding Violations	0.007	−0.034	0.050	−1.580	0.413	−14.424	15.967	−46.525	0.927	−1.126	5.120	−35.686
Diff. in the No. of Reckless Driving Cases	−0.009	−0.015	0.001	0.189	−0.467	−2.268	1.062	10.314	−0.038	−0.468	0.800	3.015
Diff. in the No. of Alcohol & Drugs Cases	0.579	0.440	0.706	0.039	na	na	na	na	8.786	−1.835	46.291	−86.870
Diff. in the No. of Cases Involving Commercial Units	0.041	0.039	0.042	0.727	0.382	−1.399	7.333	−3.515	0.682	0.152	1.350	8.377
Diff. in the No. of Cases on Interstate Roadways	0.004	−0.004	0.010	−0.093	1.783	−0.157	5.485	−26.151	0.195	−0.239	1.463	−39.380
Diff. in the No. of Cases on All Other Roadways	−0.002	−0.006	0.001	−2.563	0.600	−0.600	2.046	−36.973	0.089	−0.161	0.980	−169.921
Diff. in the No. of Day-Lighted Cases	0.001	−0.001	0.002	−0.509	1.103	0.022	1.830	−30.830	0.004	−1.160	0.170	−271.109
Diff. in the No. of Dark-not-Lighted Cases	0.004	−0.002	0.011	0.075	0.586	−1.213	1.247	7.255	0.066	−0.480	0.525	2.008
Diff. in Short-length trips rate	−0.403	−0.485	−0.318	0.725	−13.584	−87.024	2.882	5.330	−0.783	−5.235	6.236	8.189
Diff. in Mid-length trips rate	0.004	−0.198	0.193	0.689	−0.710	−40.482	48.073	10.940	−1.468	−9.177	15.604	5.801
Diff. in Long trips rate	3.105	2.029	4.327	0.308	14.661	−5.762	17.555	8.596	16.179	−35.52	71.928	5.546
Constant	13.537	13.497	13.580	0.536	17.332	17.324	17.340	11.041	−1.387	−4.400	2.016	4.725
Model Fit Statistics												
AIC	279.05				1339.34				7058.71			
BIC	338.31				1708.73				7270.12			
Pseudo-R^2/ R^2	0.10				0.90				0.59			

* Geographical variability tests of local coefficients. A negative value suggests spatial variability. “na” = not applicable.

Drugs induced cases between 2020 and 2019. Difference in the interstate-related fatalities, crashes, and economic harm, in Fig. 8(c), 9 (b), and 10(d), are also higher in the western counties of Tennessee. Similarly, all the remaining variables in Figs. 8–10 support these assertions. Overall, these spatial variations can be due to the deviations in traffic, roadway conditions, socio-economics, and some other unobserved factors that can relate to spatial contexts.

8. Discussion

The increase in the number of crashes and fatalities during the pandemic are associated with the increased differences in the number of violations, including speeding, reckless driving, and alcohol & drugs cases, between 2020 and 2019. With more people staying at home during COVID-19, motorists have opportunities to drive on the near-empty streets. The combination of risky drivers and less congested roads may increase the chance of fatalities in a crash. Tefft et al. (2022) indicated that risky driving behaviors might be attributable to a small subset of young drivers who have an increased propensity to drive during COVID-19, whereas safer drivers lowered their driving. The finding of this study is aligned with Hughes et al. (2022) and Inada et al. (2021), who found the number of fatalities is positively associated with the increased frequency of speed-related violations during COVID-19 in Japan and California, U.S.A., respectively. Speeds were found to increase substantially compared to the forecasted evolution (Katrakazas et al., 2021). Dark-not-lighted roads bring greater danger during COVID-19, which is consistent with Adegbite et al. (2019), who found that dark-not-lighted roads are responsible for about 31 % of intersection crashes and fatalities. Moreover, during COVID-19, crashes and fatalities happened more on interstates and with the involvement of commercial trucks (Patwary and Khattak, 2022a). The surge in online delivery during COVID-19 increased commercial trucks’ mileage compared to other vehicles (Patwary and Khattak, 2022b). Fatigue and the urgency of delivering goods and services accompanied by the reckless behaviors of drivers may contribute to their increased involvement in road crashes and fatalities during COVID-19. The results further show that more mid-length and long trips per population not staying at home induces fatalities in crashes. This is relatable to Zhang et al. (2021a), who found the average person miles traveled to be positively associated with the person involved in crashes during COVID-19. It may be because traveling longer distances might urge the drivers to speed up and go to the desired places in a short time, given the less congested roads during COVID-19. Total crash harm was reduced during COVID-19 in 2020; however, crash harm per trip went up in 2020 compared to 2019. Fatalities constitute the majority of the crash harm costs. Since the fatalities soared during COVID-19, the economic harm per trip has increased as expected. Moreover, the difference in crash harm is associated with the increased differences in violations, interstate and commercial trucks involved crashes, dark-not-lighted road crashes, and the increased number of long trips per population not staying at home. In addition, GWR models found

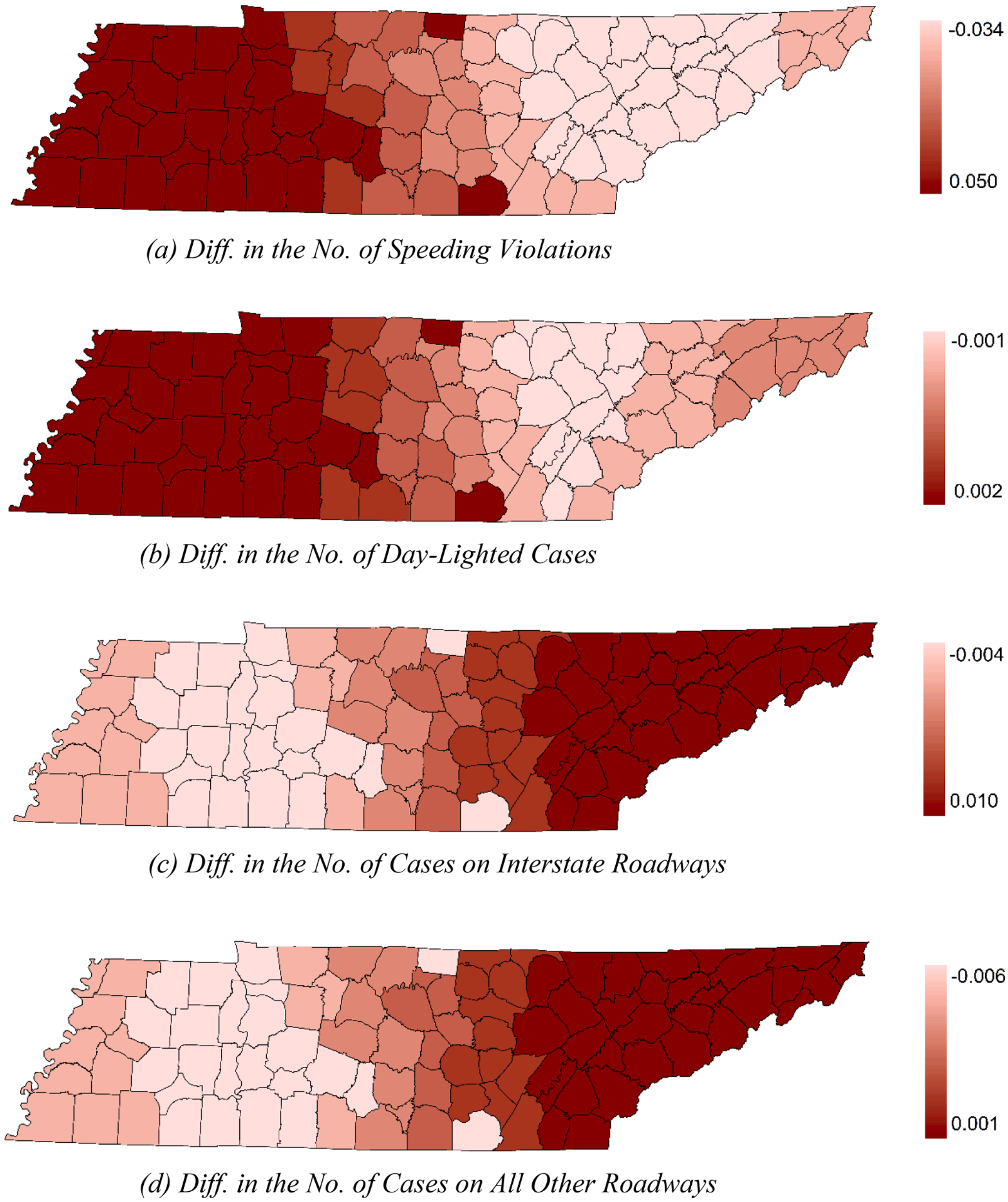


Fig. 8. Spatial variation of local parameter estimates for the difference in the number of fatalities in Tennessee at the county level.

spatial variation in several parameter estimates, including the differences in speeding violations, alcohol & drugs cases, and the cases on interstate roadways, in Tennessee at the county level. The correlates of these variables are mostly found to be higher in the western regions than the eastern regions of Tennessee, suggesting different levels of enforcement, roadway conditions, other built-in environment, and some other unobserved factors, e.g., cultural diversities (Mohammadnazar et al., 2021).

9. Limitations

This research is not without limitations. Estimates in the Bureau of Transportation Statistics' "Trips by Distance" database are relatively new and scantly peer-reviewed, which may potentially serve as a source of bias. Also, these data are experimental and may not undergo the highest quality standards. However, recent reports and studies are starting to cite this source. The inclusion of pre-existing regional characteristics such as weather and terrain information could have added more insights into the analysis. Although this study applied a framework for spatial heterogeneity or non-stationarity estimation, the results of the study may not be applicable to other states because of differences in geography, roadway network, and socio-economics.

10. Conclusions

The COVID-19 pandemic has impacted the whole world, including the transportation sector. The number of fatalities in crashes has increased in the US despite a significant reduction in traffic flow. The emphasis of this study is to use a comprehensive set of safety measures and assess what happened to road safety in Tennessee during COVID-19 by exploring the contributing factors. The findings are based on a unique dataset linking crash data and COVID-19 travel behavior data. The results show that while fatalities and crash harm per trip increased on roadways, there was still a reduction in total crashes and total monetary harm. Additionally, several models, including generalized least squares linear, Poisson, and geographically weighted regression models using the differences between 2020 and 2019 values, are adopted to rigorously quantify correlates of fatalities, crashes, and crash harm.

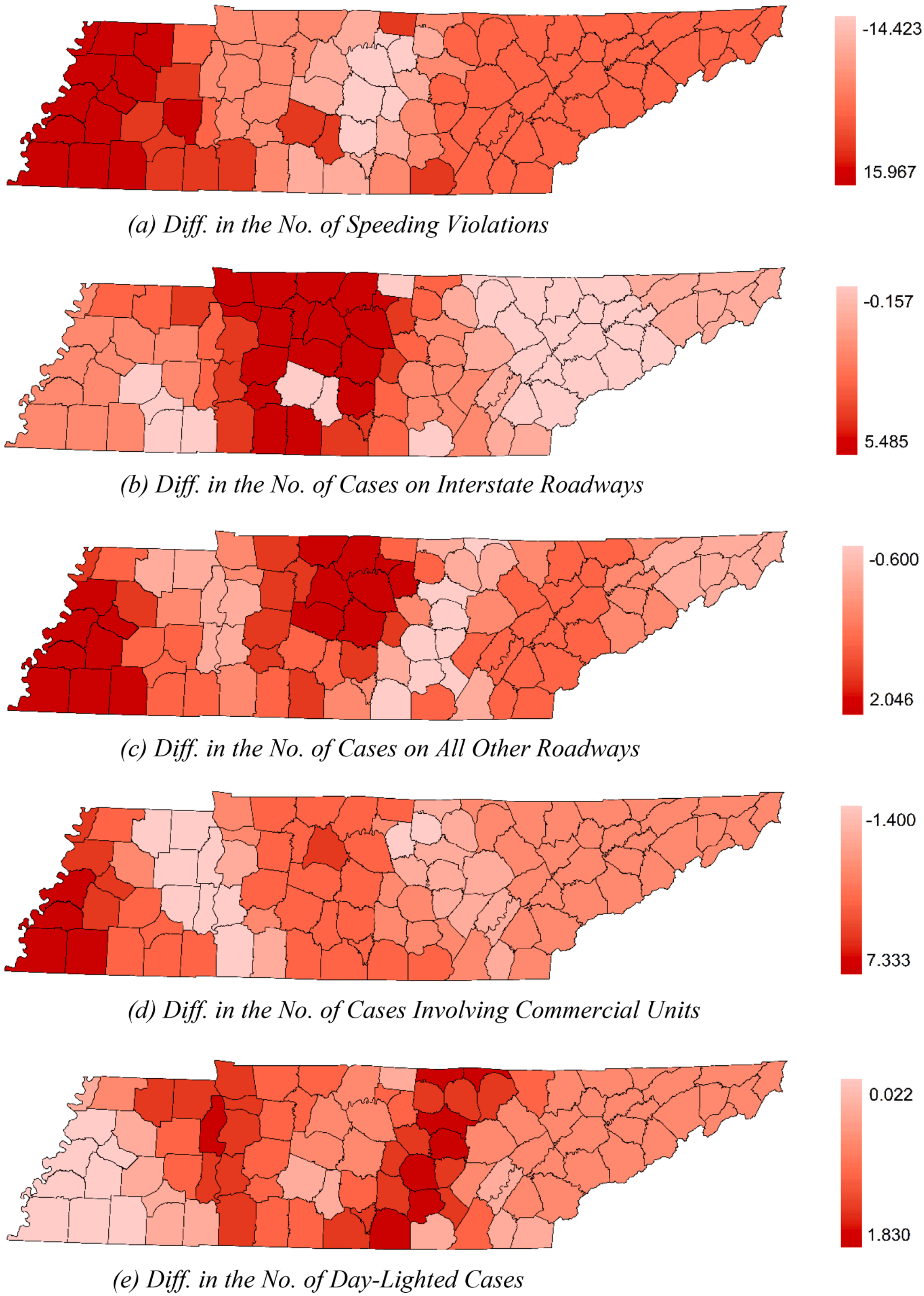


Fig. 9. Illustration of the spatial variation of local parameter estimates for the difference in the number of crashes in Tennessee at the county level.

The modeling results show that the difference in the number of crash fatalities between 2020 and 2019 is associated with the increased differences in violations, including speeding, reckless driving, and alcohol & drugs cases. Fatal crashes are more likely to occur on interstates and dark-not-lighted roads and involve commercial trucks with the surge of online delivery during COVID-19. Importantly, these similar factors largely contribute to the overall crash harm. In addition, more long trips per person not staying at home during COVID-19 are associated with more crashes and more crash harm at the county level. GWR models show that several correlates of fatalities, crashes, and crash harm are spatially varied across the counties of Tennessee. Especially, the parameter estimates for the difference in speeding cases are found to be higher in the western regions of Tennessee while being lower in the eastern regions. This variation suggests different levels of traffic

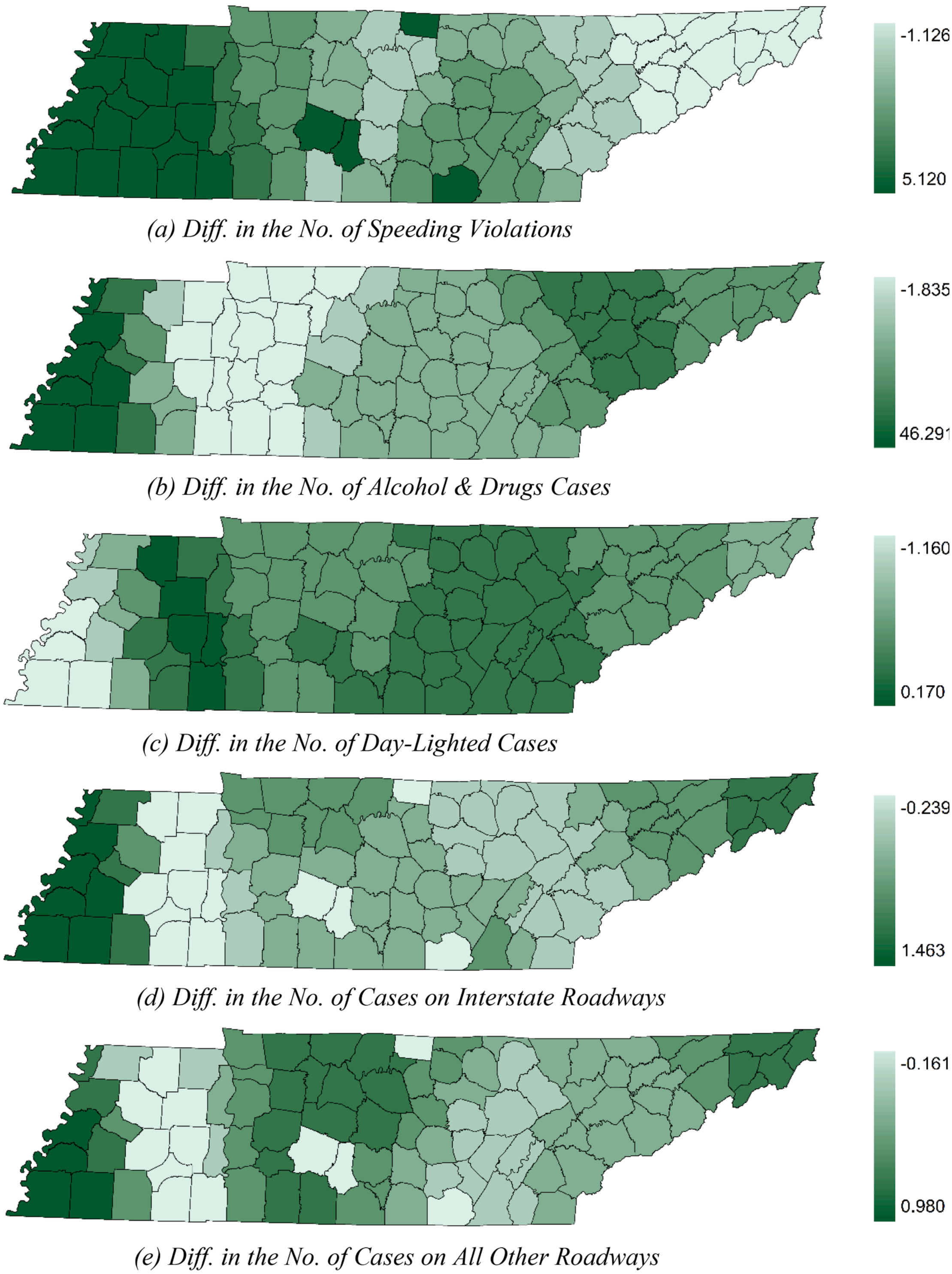


Fig. 10. Spatial Variation of Local Parameter Estimates for the difference in crash harm across the State of Tennessee.

enforcement, socio-economics, roadway, traffic, and other built-in environmental factors.

The study findings may help safety practitioners to better understand the factors contributing to crashes and fatalities, even during a safety–critical event like the COVID-19 pandemic. Reducing the violations identified in this study may lower the number of crashes, fatalities, and, eventually, the overall crash harm. Regarding traffic enforcement, more effort should be given to preventing risky driving behaviors, including speeding, reckless driving, and night driving, especially during a global emergency like COVID-19 when the traffic volume is lower, and these behaviors are more commonplace. Proper countermeasures may help to improve road safety. Speeding-related violations may be reduced through speed camera enforcement, the reduction of the speed limit in hotspots, placement of more warning signs, and the use of vehicular technology, e.g., intelligent speed adaptation (ISA) (Oei & Polak, 2002; Warner & Åberg, 2008). Furthermore, as suggested in the literature, automated vehicles (AVs) and big data applications have the potential to improve road safety in these aspects (Haque et al., 2021; Lee et al., 2021; Lian et al., 2020). For example, the Cincinnati crash analysis reduction strategy (CARS) is a big data-oriented approach designed to identify dangerous crash hotspot locations, unravel the persistent crash contributing factors, and provide flexibility to explore strategies to reduce traffic crash harms (Corsaro et al., 2012).

Future researchers may investigate whether mobility to a specific location or for a certain activity is related to the increase in fatalities or not. The research can be extended with the inclusion of some key spatial variables, e.g., roadway traffic, weather information, terrain, etc., that may effectively reveal the role of the regional built environment (pre-existing characteristics) in the occurrence of crashes and fatalities. In addition, the use of daily time-series data for all the state counties of the US may provide more insights with the consideration of the weekend and weekday aspects. Collective efforts by researchers and public and private sectors are required to gather more related data and develop road safety strategies concerning the new reality of the COVID-19 pandemic. Finally, future researchers could analyze the safety effects of the travel reduction, changes in travel mode, or time of travel while considering the rebound effect phenomenon since research previously showed rebound effect has the potential to offset the benefits of less travel (Hughes et al., 2022; Patwary et al., 2020, 2021; Patwary, 2021).

CRediT authorship contribution statement

A. Latif Patwary: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **Asad J. Khattak:** Conceptualization, Formal analysis, Writing – review & editing, Supervision, Funding acquisition, Project administration.

Declaration of Competing Interest

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

Data availability

The authors do not have permission to share data.

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References

Abdel-Aty, M.A., Radwan, A.E., 2000. Modeling traffic accident occurrence and involvement. Accid. Anal. Prev. 32 (5), 633–642.

Abdulhafedh, A., 2017. Road crash prediction models: Different statistical modeling approaches. J. Transp. Technol. 7 (02), 190.

Adegbite, Q., Billah, K., Sharif, H., Dessouky, S., 2019. Urban Intersections and Traffic Safety in the City of San Antonio. (Ed.),ˆ(Eds.). MATEC Web of Conferences.

Arvin, R., Kamrani, M., & Khattak, A. J. (2019). How instantaneous driving behavior contributes to crashes at intersections: Extracting useful information from connected vehicle message data. Accident Analysis & Prevention, 127, 118-133. doi: 10.1016/j.aap.2019.01.014.

Atkinson, A.C., 1985. Plots, transformations and regression; an introduction to graphical methods of diagnostic regression analysis.

Baruya, A., 1998. Speed-accident relationships on European roads. (Ed.),ˆ(Eds.). 9th International Conference on Road Safety in Europe.

Blincoe, L., Miller, T. R., Zaloshnja, E., Lawrence, B. A., 2015. The economic and societal impact of motor vehicle crashes, 2010.

Brodeur, A., Cook, N., Wright, T., 2021. On the effects of COVID-19 safer-at-home policies on social distancing, car crashes and pollution. J. Environ. Econ. Manag. 106, 102427.

BTS. (2021). *Trips by Distance*. US Bureau of Transportation Statistics. Retrieved October 27, 2021 from https://data.bts.gov/Research-and-Statistics/Trips-by-Distance/w96p-f2qv.

Carter, D. (2020). Effects of COVID-19 Shutdown on Crashes and Travel in NC. North Carolina. Department of Transportation, Transportation Research Board (TRB) Webinar.

CCSA. (2020). COVID-19 and Increased Alcohol Consumption: NANOS Poll Summary Report. Retrieved July 20, 2020 from https://www.ccsa.ca/covid-19-and-increased-alcohol-consumption-nanos-poll-summary-report.

Clark, D.E., Cushing, B.M., 2004. Rural and urban traffic fatalities, vehicle miles, and population density. Accid. Anal. Prev. 36 (6), 967–972.

Corsaro, N., Gerard, D.W., Engel, R.S., Eck, J.E., 2012. Not by accident: An analytical approach to traffic crash harm reduction. J Crim Just 40 (6), 502–514.

Doucette, M.L., Tucker, A., Auguste, M.E., Gates, J.D., Shapiro, D., Ehsani, J.P., Borrup, K.T., 2021a. Evaluation of motor vehicle crash rates during and after the COVID-19-associated stay-at-home order in Connecticut. Accid. Anal. Prev. 162, 106399.

Doucette, M.L., Tucker, A., Auguste, M.E., Watkins, A., Green, C., Pereira, F.E., Borrup, K. T., Shapiro, D., Lapidus, G., 2021b. Initial impact of COVID-19′s stay-at-home order on motor vehicle traffic and crash patterns in Connecticut: an interrupted time series analysis. Inj. Prev. 27 (1), 3–9.

FHWA. (2020). 2020 Traffic Volume Trends. Retrieved November 27, 2021 from https://www.fhwa.dot.gov/policyinformation/travel_monitoring/20martvt/#:~:text=The%20seasonally%20adjusted%20vehicle%20miles,miles)%20compared%20with%20February%202020.

Gao, J., Wang, J., Bian, Z., Bernardes, S. D., Chen, Y., Bhattacharyya, A., Thambiran, S. S. M., Ozbay, K., Iyer, S., 2020. The Effects of the COVID-19 Pandemic on Transportation Systems in New York City and Seattle, USA. arXiv preprint arXiv:2010.01170.

Greene, W.H., 2003. Econometric Analysis. Pearson Education India.

Haque, A.M., Arvin, R. and Khattak, A., 2021. *Harnessing Basic Safety Messages to Identify High-Risk Hotspots for Transit Buses* (No. TRBAM-21-03606).

Haque, A.M., Mahdinia, I., Patwary, A.L., Khattak, A.J., 2022. Are damages to remainder parcels in right-of-way acquisitions stationary? A spatial analysis of appraisal report data. Transp. Res. Rec. 03611981221105073.

Harmon, T., Bahar, G.B. and Gross, F.B., 2018. *Crash costs for highway safety analysis* (No. FHWA-SA-17-071). United States. Federal Highway Administration. Office of Safety.

Harris, A., 2020. Traffic deaths rise in Tennessee during COVID-19 pandemic. Retrieved November 27, 2021 from https://www.wvlt.tv/2020/09/23/traffic-deaths-rise-in-tennessee-during-covid-19-pandemic/.

Hughes, J.E., Kaffine, D., Kaffine, L., 2022. Decline in Traffic Congestion Increased Crash Severity in the Wake of COVID-19. Transportation Research Record 03611981221103239.

Imprialou, M.-I.-M., Quddus, M., Pitfield, D.E., Lord, D., 2016. Re-visiting crash–speed relationships: a new perspective in crash modelling. Accid. Anal. Prev. 86, 173–185.

Inada, H., Ashraf, L., Campbell, S., 2021. COVID-19 lockdown and fatal motor vehicle collisions due to speed-related traffic violations in Japan: a time-series study. Inj. Prev. 27 (1), 98–100.

Katrakazas, C., Michelaraki, E., Sekadakis, M., Ziakopoulos, A., Kontaxi, A., Yannis, G., 2021. Identifying the impact of the COVID-19 pandemic on driving behavior using naturalistic driving data and time series forecasting. J. Saf. Res. 78, 189–202.

Khattak, A., Mohammadnazar, A., Patwary, A.L., Ahmad, N., Haque, A. and Mahdinia, I., 2022. *A Localized Safety Performance Functions Approach Accounting for "Within" Tennessee Variations on Freeways & Interchanges* (No. RES2020-04).

Khan, M.M., Odoi, E.W., 2023. Geographic disparities in COVID-19 testing and outcomes in Florida. BMC Public Health 23 (1), 1–13.

Khattak, A., Targa, F., 2004. Injury severity and total harm in truck-involved work zone crashes. Transp. Res. Rec. 1877 (1), 106–116.

Kononov, J., Bailey, B., Allery, B.K., 2008. Relationships between safety and both congestion and number of lanes on urban freeways. Transp. Res. Rec. 2083 (1), 26–39.

Lave, C.A., 1985. Speeding, coordination, and the 55 mph limit. Am. Econ. Rev. 75 (5), 1159–1164.

Lee, J., Baig, F., Li, X., 2021. Media influence, trust, and the public adoption of automated vehicles. IEEE Intell. Transp. Syst. Mag.

Lian, Y., Zhang, G., Lee, J., Huang, H., 2020. Review on big data applications in safety research of intelligent transportation systems and connected/automated vehicles. Accid. Anal. Prev. 146, 105711.

Lin, L., Shi, F., & Li, W. (2020). Assessing Road Traffic Safety Under COVID-19: Inequality, Irregularity, and Severity. arXiv preprint arXiv:2011.02289.

Liu, N., Zhang, F., Wei, C., Jia, Y., Shang, Z., Sun, L., Wu, L., Sun, Z., Zhou, Y., Wang, Y., 2020. Prevalence and predictors of PTSS during COVID-19 outbreak in China hardest-hit areas: Gender differences matter. Psychiatry Res. 287, 112921.

Mahdinia, I., Khattak, A.J., Haque, A.M., 2022. How effective are pedestrian crash prevention systems in improving pedestrian safety? Harnessing large-scale experimental data. Accident Analysis & Prevention 171, 106669.

Mahdinia, I., Mohammadnazar, A., Khattak, A.J., 2022. Understanding the role of faster emergency medical service response in the survival time of pedestrians. Accident Analysis & Prevention 177, 106829.

Mohammadnazar, A., Mahdinia, I., Ahmad, N., Khattak, A.J., Liu, J., 2021. Understanding how relationships between crash frequency and correlates vary for multilane rural highways: Estimating geographically and temporally weighted regression models. Accid. Anal. Prev. 157, 106146.

Mohammadnazar, A., Patwary, A.L., Moradloo, N., Arvin, R., Khattak, A.J., 2022. Incorporating driving volatility measures in safety performance functions: Improving safety at signalized intersections. Accident Analysis & Prevention 178, 106872.

Noland, R.B., Quddus, M.A., 2005. Congestion and safety: a spatial analysis of London. Transp. Res. A Policy Pract. 39 (7–9), 737–754.

NSC. (2021). Preliminary Semiannual Estimates. Retrieved May 1, 2021 from https://injuryfacts.nsc.org/motor-vehicle/overview/preliminary-estimates/.

Oei, H.-L., Polak, P., 2002. Intelligent speed adaptation (ISA) and road safety. IATSS Res. 26 (2), 45–51.

OHS. (2020). Motor Vehicle Fatality Rates up 14% in March, Despite COVID-19. Occupational Health and Safety. Retrieved February 13, 2021 from https://ohsonline.com/articles/2020/05/22/motor-vehicle-fatality-rates-up-14-percent-in-march-despite-covid19.aspx.

Palazzo, J. (2021). Historic rise in traffic deaths due to pandemic. Retrieved November 20, 2021 from https://www.wkrn.com/news/local-news/historic-rise-in-traffic-deaths-due-to-pandemic/.

Patwary, A. L., & Khattak, A. (2022a). A Study of Truck-Involved Crashes and Fatalities Before and During the COVID-19 Pandemic: Evidence of Traffic Safety from Tennessee. (Ed.),ˆ(Eds.). 101st Annual Meeting of Transportation Research Board (TRB).

Patwary, A. L., & Khattak, A. J. (2022b). Interaction Between Information and Communication Technologies and Travel Behavior: Using Behavioral Data to Explore Correlates of the COVID-19 Pandemic. Transportation Research Record, 0(0), 03611981221116626. doi: 10.1177/03611981221116626.

Patwary, A.L., Yu, E., English, B., Hughes, D., 2020. Efficiency Studies of the US Transportation Sector. Master's thesis. University of Tennessee, Knoxville.

Patwary, A.L., Yu, T.E., English, B.C., Hughes, D.W., Cho, S.H., 2021. Estimating the rebound effect of the US road freight transport. Transportation Research Record 2675 (6), 165–174.

Quddus, M.A., Wang, C., Ison, S.G., 2010. Road traffic congestion and crash severity: econometric analysis using ordered response models. J. Transp. Eng. 136 (5), 424–435.

Saladié, Ò., Bustamante, E., Gutiérrez, A., 2020. COVID-19 lockdown and reduction of traffic accidents in Tarragona province, Spain. Transp. Res. Interdisciplinary Perspectives 8, 100218.

Sebego, M., Naumann, R.B., Rudd, R.A., Voetsch, K., Dellinger, A.M., Ndlovu, C., 2014. The impact of alcohol and road traffic policies on crash rates in Botswana, 2004–2011: a time-series analysis. Accid. Anal. Prev. 70, 33–39.

Shankar, V., Mannering, F., Barfield, W., 1995. Effect of roadway geometrics and environmental factors on rural freeway accident frequencies. Accid. Anal. Prev. 27 (3), 371–389.

Sutherland, M., McKenney, M., Elkbuli, A., 2020. Vehicle related injury patterns during the COVID-19 pandemic: what has changed? Am. J. Emerg. Med. 38 (9), 1710–1714.

Tefft, B. C., Villavicencio, L., Benson, A., Arnold, L., Kim, W., Añorve, V., & Horrey, W. J. (2022). Self-Reported Risky Driving in Relation to Changes in Amount of Driving During the COVID-19 Pandemic [Research Brief]. AAA Foundation for Traffic Safety. https://aaafoundation.org/self-reported-risky-driving-in-relation-to-changes-in-amount-of-driving-during-the-covid-19-pandemic/.

TN.GOV. (2021). COVID-19 Timeline. Retrieved September 2, 2022 from https://www.tn.gov/governor/covid-19/covid19timeline.html.

Van Benthem, A., 2015. What is the optimal speed limit on freeways? J. Public Econ. 124, 44–62.

Vingilis, E., Beirness, D., Boase, P., Byrne, P., Johnson, J., Jonah, B., Mann, R.E., Rapoport, M.J., Seeley, J., Wickens, C.M., 2020. Coronavirus disease 2019: What could be the effects on Road safety? Accid. Anal. Prev. 144, 105687.

Wali, B., Khattak, A.J., Waters, J., Chimba, D., Li, X., 2018. Development of safety performance functions: incorporating unobserved heterogeneity and functional form analysis. Transp. Res. Rec. 2672 (30), 9–20.

Walker, A. (2020). This Spring, We All Drove Much Less. Yet Traffic Deaths Went Up. Why? Retrieved November 1, 2021 from https://www.curbed.com/2020/10/covid-traffic-deaths-up-speeding.html.

Wang, C., Quddus, M., Ison, S., 2013. A spatio-temporal analysis of the impact of congestion on traffic safety on major roads in the UK. Transportmetrica A: Transport Science 9 (2), 124–148.

Warner, H.W., Åberg, L., 2008. The long-term effects of an ISA speed-warning device on drivers' speeding behaviour. Transport. Res. F: Traffic Psychol. Behav. 11 (2), 96–107.

Wickens, C.M., Smart, R.G., Mann, R.E., 2014. The impact of depression on driver performance. Int. J. Ment. Heal. Addict. 12 (4), 524–537.

Woo, H., Eskelson, B.N., Monleon, V.J., 2019. Tree height increment models for national forest inventory data in the Pacific Northwest, USA. Forests 11 (1), 2.

Yeo, J., Park, S., Jang, K., 2015. Effects of urban sprawl and vehicle miles traveled on traffic fatalities. Traffic Inj. Prev. 16 (4), 397–403.

Zhang, J., Feng, B., Wu, Y., Xu, P., Ke, R., Dong, N., 2021a. The effect of human mobility and control measures on traffic safety during COVID-19 pandemic. PLoS One 16 (3), e0243263.

Zhang, J., Hayashi, Y., Frank, L.D., 2021b. COVID-19 and transport: findings from a world-wide expert survey. Transp. Policy 103, 68–85.

Patwary, A., 2021. Estimating the Rebound Effect of the US Road Freight Transport Background Method and Data, United States Association for Energy Economics. Retrieved from https://policycommons.net/artifacts/1818323/estimating-the-rebound-effect-of-the-us-road-freight-transport-background-method-and-data/2555784/ on 28 Jan 2023. CID: 20.500.12592/2k7jvg.