RUSH HOUR-RELATED ROAD CRASHES: ASSESSING THE SOCIAL AND ENVIRONMENTAL DETERMINANTS OF FATAL AND NON-FATAL ROAD CRASH EVENTS

by

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DEDICATION

This dissertation is dedicated to my God, the Author, and Finisher of my faith.

He gave me the strength, wisdom, and courage to achieve this professional milestone.

Thank you, Jesus.

To my wife, Dr. Omotola Adeyemi, my support and encourager.

Thank you for becoming strong for us and for our family.

Ellen and David, I love you.

You are the best children any parent could ever pray for.

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ABSTRACT

OLUWASEUN JOHN ADEYEMI. Rush Hour-Related Road Crashes: Assessing the Socio-Environmental Determinants of Fatal and Non-Fatal Road Crash Events

(Under the direction of DR. AHMED ARIF and DR. RAJIB PAUL)

Road crashes remain a preventable cause of morbidity and mortality. The rush-hour period represents the time with the highest human and vehicular road densities. This dissertation aims to assess, during the rush and non-rush hour periods, the environmental factors associated with fatal crash injuries, the association of substance use and non-fatal crash injuries, and the association of crash response time and deaths at crash scenes. To address the first aim, data from the Fatality Analysis Reporting System was used. We limited the data to crashes during the rush hour period. The outcome variable was the fatal crash counts per county. The predictor variables were road design (intersection, driveway, ramp, work-zone), road type (interstate, highways, roads/streets), and inclement weather factors (rain, fog, snow). A nested spatial negative binomial regression model was used to estimate the incidence rate ratio of fatal crash injury during the rush hour period. To address the second aim, Crash data were extracted from the 2019 National Emergency Medical Services Information System data. The outcome variable was non-fatal crash injury, assessed on an ordinal scale – critical, emergent, and low acuity. The predictor variable was the presence of substance use (alcohol or illicit drugs). Age, gender, region of the body injured, and the revised trauma score was used as potential confounders. Partially proportional ordinal logistic regression was used to assess the unadjusted and adjusted odds of critical and emergent outcomes compared to low acuity patients. To address the third aim, data from the 2019 National Emergency Medical Services (EMS) Information System was used. The outcome variable was death-at-the-scene. The predictor variables were the crash response times – crash notification (EMS notification to departure from the base station) and EMS travel time (base station to crash scene). Age, gender, substance use, region of the body injured, the revised trauma score, and rurality/urbanicity of each injury location were used as potential confounders. Logistic regression was used to assess the unadjusted and adjusted odds of death-at-the-scene. During the rush-hour period, the median fatality rate per county was 7.30 per 100,000 population. Highways had the highest fatality risk, after adjusting for the interaction effect of intersection, driveway, ramp, and work-zone. Also, after adjusting for confounders, Substance use was associated with 2.09 (95% CI: 2.03 - 2.14) and 2.26 (95% CI: 2.14 – 2.38) odds of emergent and critical injury outcomes as compared to low acuity at all times of the day and during the rush hour period, respectively. After adjusting for confounders, a minute increase in the EMS travel time was associated with 0.4% (Adjusted OR: 1.004; 95% CI: 1.003 – 1.006) and 0.7% (Adjusted OR: 1.007; 95% CI: 1.005 – 1.009) increased odds of death-at-the-scene during all times of the day and the rush-hour period, respectively. This dissertation reports that certain environmental factors, substance use, and crash response times are significantly associated with fatal and non-fatal crash injuries. Also, the rate ratios and odds of fatal and non-fatal crash injuries are heightened during the rush hour period.

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CHAPTER 1
Introduction

Introduction

Within the last decade, an average of 100 persons dies daily from preventable crash injuries (National Highway Traffic Safety Administration, 2018). The pattern of deaths varies widely from death at the crash scene to deaths from complications, typically measured as occurring within 30 days post-crash (National Highway Traffic Safety Administration, 2016a). Between 2016 and 2019, the US experienced a subtle decline in fatal crash counts (National Center for Statistics and Analysis, 2020b; National Highway Traffic Safety Administration, 2020). These slow yet progressive successes were attributed to the multifaceted approach of the Federal Highway Administration's Zero Death vision, which aims to involve all states in strategic program and policy strengthening that will culminate in achieving zero fatal counts by 2050 (Ecola, Popper, Silberglitt, & Fraade-Blanar, 2018; Federal Highway Administration, 2020b). However, this gradual decline in deaths within recent years was interrupted by the 2020 COVID-19 pandemic. While the total vehicle miles traveled reduced during the COVID-19 pandemic, fatal crash counts slightly reduced and the fatality rate towered higher than reported counts for over a decade (National Center for Statistics and Analysis, 2020a).

Non-fatal crash injuries represent a significant and more frequent outcome of crash events. With non-fatal crash injuries occurring over 150 times the occurrence of fatal crash injuries (Ballesteros, Schieber, Gilchrist, Holmgreen, & Annest, 2003), non-fatal crash injuries represent a dominant source of disability. It is estimated that approximately 3.3 million persons, representing an age-adjusted rate of 1,013 per 100,000 US population are involved in all forms of non-fatal crash injuries (National Center for Injury Prevention and Control, 2020). As of 2010, non-fatal injuries cost US $23 billion in medical cost revenue, and $48 billion in work loss (National Center for Injury Prevention and Control, 2020). These estimates would have increased as non-fatal crashes have increased from 1.7 million crash events in 2015 to almost 2 million crash events in 2019 (National Highway Traffic Safety Administration, 2021).

The rush-hour period, also referred to as the period of peak traffic flow (Lee, Polak, Bell, & Wigan, 2012; Zheng, Wang, Zhu, & Jiang, 2020), is defined as the time of the day with the highest density of humans and automobiles on the road. It is a period that varies widely across geographical location, rural-urban delineation, days of the week, and the period of the year (Federal Highway Administration, 2017; Jaffe, 2014). In the US, the rush-hour period occurs in two phases: a morning phase ranging from 6 to 10 am, and an evening phase, from 3 to 8 pm (Lasley, 2019). Although the rush-hour period may capture about a third of the 24-hour duration in densely populated urban centers, and much less in rural areas (Congressional Research Service, 2018), roughly 40 percent of all crash events occur during this period (National Highway Traffic Safety Administration, 2019). It is estimated that about one in four fatal crashes occurs during the rush-hour period (Tippett, 2014). Also, between 1982 and 2017, the cost of traffic congestion had risen from $1.8 billion to $8.8 billion (Ellis & Glover, 2019; Lasley, 2019), excluding the cost of fatal and non-fatal crash injuries and property damage.

The social determinants of health are multivariable factors in the environment that influence daily functioning, quality of life, exposure to risk, and health outcomes (Healthy People.Gov, 2020). The neighborhood and built environment are one of the five domains of the social determinant of health. This domain captures the physical and social environmental characteristics that influence health outcomes (Healthy People.Gov, 2020). Moreover, the natural and built road environment plays a role in the occurrence of crash injuries. It is estimated that at least 300 fog-related fatal crashes occur annually in the U.S. (Hamilton, Tefft, Arnold, & Grabowski, 2014; Wu, Abdel-Aty, & Lee, 2018), with about one of every six weather-related crashes are associated with snow (Federal Highway Administration, 2020a). Also, approximately 40% of all crash events occur at intersections (National Highway Traffic Safety Administration, 2010), while driveways are associated with about three-fold increased risk of crash injuries (Anthikkat, Page, & Barker, 2013; Nadler, Courcoulas, Gardner, & Ford, 2001).

Substance use, an amorphous classification for alcohol, opioids, and other illicit drugs, are risk factors for impaired driving (Alcañiz, Santolino, & Ramon, 2016; Bondallaz et al., 2016; Clifasefi, Takarangi, & Bergman, 2006), crash-related morbidity and mortality (Allamani et al., 2013; Freeman, 2007; Kumar, Bansal, Singh, & Medhi, 2015). Alcohol is associated with an estimated 10,000 yearly crash deaths, a value representing more than a quarter of yearly crash counts (Centers for Disease Control Prevention, 2016; National Center for Statistics and Analysis, 2019b; Niederdeppe, Avery, & Miller, 2017). Cannabis is associated with two to three-fold increased risk of crash, two-fold increased risk of fatal collisions, and a significantly increased risk of non-fatal crash injury (Asbridge, Hayden, & Cartwright, 2012; G. Li, Brady, & Chen, 2013; M. C. Li et al., 2012; Santaella-Tenorio et al., 2020). Similarly, narcotics, stimulants, and depressants are associated with a three to five-fold increased risk of fatal crash involvement, with the odds further heightened when such drugs are combined with alcohol (G. Li et al., 2013; Martin, Gadegbeku, Wu, Viallon, & Laumon, 2017).

Central to the prevention of fatal crash injuries and worsened crash morbidity is a rapid crash response. Emergency medical services (EMS) represents the nation’s institution that provides pre-hospital care to crash and non-crash victims (EMS.Gov, 2020). Earlier studies have reported longer crash response times in rural areas compared to urban areas (Adeyemi, Paul, & Arif, 2020a; Byrne et al., 2019). Also, increased crash response time is associated with increased fatal crash risk (Byrne et al., 2019). Acute blood loss, a common diagnosis among crash injury victims (Stainsby, MacLennan, & Hamilton, 2000), is a predictor of hypovolemic shock, increased crash morbidity, and mortality. Thus, the prevention of fatal crash injuries requires timely intervention.

Significance

Approximately 1.25 million people die yearly from road-related crash injuries worldwide (Centers for Disease Control and Prevention, 2016). In the US, one person dies every 14 minutes from crash-related events (National Center for Statistics and Analysis, 2019d). Between 2016 and 2019, the US recorded three successive years of decline in fatal crash injury in over a decade (National Highway Traffic Safety Administration, 2020, 2021; National Safety Council, 2020). However, yearly fatal counts in 2019 still exceeded 37,000 (National Center for Statistics and Analysis, 2019a). Uncharacteristically, fatal deaths were in 2020, a year characterized by travel restrictions and stay-at-home order due to the COVID-19 pandemic, exceeded 42,000 (National Safety Council, 2021). Despite the declining fatal crash counts, crash-related morbidities have not substantially decreased (National Highway Traffic Safety Administration, 2017).

Elements within the natural and built road environment are associated with both fatal and non-fatal crash injuries. Road environmental characteristics such as traffic light and pedestrian walkways that were originally designed to prevent crash injuries are associated with yellow light speeding behavior and jaywalking behaviors, respectively (Marusek, 2014; Palat & Delhomme, 2012; Shaaban, Muley, & Mohammed, 2016). Work zone crash events across the US increased from 84,000 in 2009 to 123,000 in 2018 (American Road & Transportation Builders Association, 2018). It is estimated that one work zone fatal injury occurs for every four billion vehicle miles traveled (Federal Highway Administration, 2019). From 2007 to 2016, about 8% of fatal crash injuries were attributed to the presence of rain and about 2% were due to fog and snow (Federal Highway Administration, 2020a).

Alcohol and substance use are risk factors for risky driving behavior (Abayomi, Babalola, Olakulehin, & Ighoroje, 2016; Blows et al., 2005; Davey, Davies, French, Williams, & Lang, 2005). Within the last decade, an average of 29 people die daily from alcohol-impaired driving crashes (Centers for Disease Control Prevention, 2016; National Center for Statistics and Analysis, 2019b; Niederdeppe et al., 2017). In 2016, over a million drivers were arrested for driving under the influence of alcohol or narcotics (Centers for Disease Control Prevention, 2016). While nearly 15% percent of nighttime weekend drivers tested positive for marijuana (Centers for Disease Control Prevention, 2016).

Delays in crash response can occur at any point in the crash response chain. The crash response chain is typically segmented into phases such as crash notification, EMS departure from the base station, EMS arrival at the crash scene, transport to the hospital, and return to the base station (Byrne et al., 2019). Between 2017 and 2018, there were over two million ambulance responses across 2,268 US counties, with a median response time of 9 minutes (Byrne et al., 2019). Mortality rate ratio increased by 46% in areas with response times greater than 12 minutes compared to areas with less than 7 minutes (Byrne et al., 2019). Additionally, the mortality rate ratio increases by 1.9% for every minute increase in crash incident to notification time, and by 3% for every minute delay in crash notification and crash scene arrival time (Adeyemi et al., 2020a).

Problem Statement

Annually, more than 37,000 lives are lost and three million individuals are injured in crash events. Successes in the recent decline in fatal crash counts were eroded during the COVID-19 pandemic and fatal crash counts rose to heights not observed in the last two decades. There is compelling evidence on the effectiveness of interventions targeted at reducing substance use while driving (Centers for Disease Control and Prevention, 2011; Matsumura, Yamakoshi, & Ida, 2009; Smith et al., 2014), however recent trends in the spike in the death counts (National Safety Council, 2021) suggest a need for more focused interventions and policies. The rush-hour period, characterized by its increased density of automobiles and road users, may serve as the proxy of human and environmental interventions. However, the extent to which crash characteristics during the rush-hour period mirror the non-rush-hour period or the average crash characteristics at all times of the day remains unknown. Also, few studies have assessed the extent to which the natural and built road environment may influence fatal and non-fatal crash events. Current evidence suggests that substance use-related driving offenses are common at night. However, little is known about the impact of substance use on injury severity during the rush hour, non-rush-hour period, and at all times of the day. Moreover, while the rush-hour period is characterized by traffic congestion (Federal Highway Administration, 2017; Lasley, 2019), few studies have assessed crash response times during rush-hour and non-rush-hour periods and the effects of such variability on the occurrence of deaths at the scene of the crash event. Understanding these rush-hour crash characteristics will provide valuable insight on the design of future interventions, inform policy, and guide resource allocation.

Importance for Public Health

Understanding the similarity and the uniqueness of the rush-hour period may inform interventions and policies. The rush-hour period, with its dense population of road users, provides a period where human driving behavior may be assessed. The stress associated with driving in traffic congestion is associated with aggressive driving (Berdoulat, Vavassori, & Sastre, 2013), reduced use of seatbelt (Wong et al., 2016), engagement in phone-related distracted driving, and increased or reduced speeding depending on the road type. The rush-hour period may be used as a proxy in assessing crash risk exposure and a period where interventions may be conducted.

The influence of the built road environment on the proportion of crash events and fatal and non-fatal crash injury rates may be exacerbated during the rush hour. Research on this relationship may situate the rush-hour period as a proxy for environmental-based traffic interventions. Earlier studies that evaluated the association of crash injury and environmental characteristics had adjusted for the rush-hour period (Call, Medina, & Black, 2019; Jagerbrand & Sjobergh, 2016; Stevens, Schreck, Saha, Bell, & Kunkel, 2019). Using the rush-hour period as a proxy for temporal-based traffic interventions may be proficient if there is evidence that risks associated with the exposure of interest in the rush-hour period adequately mirror the exposure either at all times of the day or during the non-rush-hour period.

Alcohol and substance use and its relationship with fatal and non-fatal crash injuries is a well-established crash injury prevention domain (Allamani et al., 2013; Antonopoulos et al., 2011; Bachani et al., 2013; Blows et al., 2005; Bondallaz et al., 2016; Chen, Tsai, Fortin, & Cooper, 2012; Clifasefi et al., 2006; Kumar et al., 2015; Martin et al., 2017; Thomas et al., 2020). Interventions directed at preventing drunk driving such as ignition locks are one of the most effective crash injury prevention interventions aimed at mitigating injuries resulting from recidivism (Centers for Disease Control and Prevention, 2011; Matsumura et al., 2009; Smith et al., 2014). However, identifying first-time offenders, who are more likely to injure others at their first attempt, remains a challenge. (Dickson, Wasarhaley, & Webster, 2013). While earlier studies have reported increased cases of driving under the influence of alcohol and other substances during the night (Allamani et al., 2013), the occurrence of substance-use-related fatal and non-fatal injuries during the rush hour is not known.

Research on crash response time is not novel. Recent studies have estimated the disparity in crash response time in rural and urban areas and how these differences are associated with increased fatality (Adeyemi et al., 2020a; Byrne et al., 2019). Conceptually, crash response time may be longer during the rush-hour period due to traffic congestion. However, it is not known to what extent such delay associates with an increased fatality rate. The possibility exists that these deaths at the crash scene may be unsalvageable (Byrne et al., 2015; Calland et al., 2012). However, it is not known if a delay in crash response associates with the presence of deaths at the crash scene and how the odds of such events vary during the rush hour, non-rush hour, and at all times of the day.

Conceptualizing environmental determinants of crash injury using the socio-ecological framework

The environmental determinants of crash injuries can be modeled using the socio-ecological model (Center for Disease Control and Prevention, 2020). The socio-ecological model identifies the societal, community, relationship, and individual levels that identify areas where interventional efforts can prevent injury. This framework aptly depicts the nested relationship existing at each of the four levels with the individual factors nested in the relationship level factors, which in turn is nested within community and societal factors (Center for Disease Control and Prevention, 2020).

The individual factors associated with rush hour factors include age, education, income, history of substance use, engaging in risky driving behavior, and knowledge, attitude, and perception of safe driving. The relationship-level factors include peer pressure, family influences on driving behavior, and passenger effect on distracted driving. At the community level, the role of street and traffic lights, traffic signs, sidewalks, pedestrian bridges and crossings, appropriate road intersections, driveways, work zones, and ramps can accentuate or prevent the risk of crash injury. At the societal level, economic factors, unemployment, housing structure, road network, infrastructure, and the region's weather conditions play diverse roles in road crashes.

Environmental determinants of crash injury can be identified at the societal and community levels. Assessing the relationship of these multi-level nested factors to crash injury presents diverse options of statistical assessment. While hierarchical models have been used in previous studies in crash injury analysis (Ahmed, Huang, Abdel-Aty, & Guevara, 2011; Alarifi, Abdel-Aty, & Lee, 2018; Xu, Wang, Yang, Xie, & Chen, 2019; Yanmaz-Tuzel & Ozbay, 2010), the use of nested models may provide a novel statistical approach to assess crash injuries under the socio-ecological framework (Center for Disease Control and Prevention, 2020).

Theorizing Substance Use as a Determinant of Crash Injury using the Theory of Planned Behavior

Substance use-related impaired driving is risky driving behavior. Driving behaviors, similar to other actions, reflect knowledge, attitude, and perception (Bachani, Risko, Gnim, Coelho, & Hyder, 2017; Hassen, Godesso, Abebe, & Girma, 2011). Additionally, an individual's social network plays complex nonlinear role in the development of a behavior (Bartel et al., 2020; Chu, Hoeppner, Valente, & Rohrbach, 2015). Driving under the influence of alcohol or drugs (illegal, prescribed, or over-the-counter) represents an action that is not devoid of intent and may be a consequence of perceived behavioral control, attitude towards the use of alcohol or drugs, or perceived social norm (Ajzen, 2002; Bazargan-Hejazi et al., 2017). While addiction may influence the continued engagement in driving under the influence of drugs and alcohol, it rarely initiates the behavioral practice (Bondallaz et al., 2016; Sloan, Eldred, & Davis, 2014).

The Theory of Planned Behavior (TPB) explains how attitude, perceived behavioral control, perceived social norm, and intent influence behavioral outcomes (Ajzen, 2002). The TPB explains how behavior is influenced by intent, which is acted upon by attitude, perceived behavioral control, and social norm (Figure 2). Using the framework of TPB, a decision to drive under the influence of alcohol or other substances may be influenced by an individual's attitude towards substance use (attitude), the influence of peers, or observing close members of one's network engaging in such activities (perceived norm), or the individual's multitasking ability (perceived behavioral control). While the intention to drive after drinking may not always be a prior decision taken before using alcohol or drugs, the perception of being able to drive effectively under the influence of alcohol or drugs may overcome the inhibitory effect of attitude and perceived social norm if the individual holds such values.

Several studies have examined the relationship of alcohol and substance use with fatal and non-fatal crash injuries (Allamani et al., 2013; Chen et al., 2012; Compton & Berning, 2015; Degenhardt, Dillon, Duff, & Ross, 2006; Drummer et al., 2004; Freeman, 2007; Geller & Negussie, 2018). This study seeks to expand the substance use-related crash injury research by identifying the association of substance use with a fatal and non-fatal crash injury during the rush-hour period.

Conceptualizing Pre-Hospital Crash Response Delay

Preventing fatal road crash injuries is intrinsically hinged on rapid trauma care delivery to crash victims. Conceptually, crash responses can be categorized into three phases: duration from crash occurrence to notification of Emergency Medical Services (EMS), the period from EMS notification to EMS arrival, and the length from EMS arrival to hospital arrival. Any delay at any of the three phases can potentially increase the chance of unfavorable health outcomes.

Identifying the points of delay can give insights into where interventions can be focused on. With the rush-hour period identified as the period with the highest traffic densities, it is expected that crash response may be prolonged compared to other times of the day. Additionally, rural and urban discrepancies in the population and vehicle densities may play a role in the crash response times. It is unknown how crash response times during the rush-hour period associates with fatal crash injuries in rural and urban areas.

Research Focus

This dissertation aims to assess the social and environmental determinants of fatal and non-fatal crash injuries during the rush-hour period. The rush-hour period is an area with sparse literature. This dissertation seeks to provide crash injury characteristics within the rush-hour period and offer comparable information on the pattern of assessed exposures during the non-rush-hour period and across all times of the day.

This dissertation will assess three domains of crash exposures – the road environment, human risky behavior, and crash response time. Within the domain of the road environment, this dissertation will assess the relationship between fatal crash injury and the natural elements – rain, fog, and snow, and elements within the built environment such as intersections, driveways, work zones, interstates, and highways. Substance use is a risky behavior driving behavior. Also, crash victims with substance use are at increased risk of worse health outcomes. Rapid crash response provides the opportunity to identify salvageable crash injuries and reduce morbidity and mortality. Directing research across these three related yet distinct crash domains will provide information useful for formulating community-based policies and identify areas in need of targeted public health intervention.

Research Questions

This dissertation focuses on three distinct research areas – the environmental determinants of fatal crash injuries during the rush-hour period, the association of substance use on non-fatal crash injuries, and how crash response time associates with the presence of deaths at the crash scene. The research questions guiding these three research domains are as follows:

1. What are the association of road types (interstates, highways, local roads, and streets), road designs (intersections, driveways, ramps, work zones), and inclement weather (rain, fog, snow) with fatal crash injuries during the rush-hour period, and how do these factors affect the spatial distribution of fatal crash injuries?
2. What is the association of substance use on the critical, emergent, and low acuity crash injuries during the rush-hour, non-rush-hour period, and at all times of the day, and what are the probabilities of each of these injury severities occurring?
3. What are the durations of crash response times during the rush-hour, non-rush-hour, and at all times of the day, and how do the crash response times associate with the presence of deaths at the crash scene during the rush-hour and non-rush-hour period?

Aims and Hypotheses

This dissertation has three aims. Firstly, this dissertation aims to assess the environmental determinants of road crash injury during the rush-hour period and its association with fatal road crashes. It is hypothesized that road types (such as highways, interstate, local streets), road characteristics (such as intersections, ramps, and work zones), and the natural environment (such as rain, fog, and snow) will be associated with increased risk of fatal road crashes during the rush-hour period.

Secondly, this dissertation aims to assess the association between substance use and non-fatal crash injury. It is hypothesized that substance use will be associated with increased odds of critical and emergent injury severity compared to low acuity injury. It is hypothesized the odds of critical and emergent injuries will be higher in the rush-hour and non-rush-hour periods and at all times of the day.

Thirdly, this dissertation aims to assess the association between crash response times and the occurrence of deaths at the crash scene. It is hypothesized that the increased duration of crash notification to EMS departure from the base station and an increased duration in the travel time from the base station to the crash scene will be associated with increased odds of deaths at the crash scene. It is hypothesized that the odds of deaths at the crash scene will be elevated during the rush-hour and non-rush-hour periods and at all times of the day.

Originality of the research

Though anecdotally acknowledged as the period with the highest human and road environmental interactions, the rush-hour period is a minimally explored domain of crash injury prevention research. While some risky driving behaviors, such as drunk driving, are known to occur more during nighttime than daytime driving (National Highway Traffic Safety Administration, 2018a), little is known on how substance use associates with injury severity and how the substance use-related injury severities vary during the rush and non-rush-hour periods. Deaths at the crash scene is a sparsely researched crash outcome. It is unknown what proportion of deaths at the crash scene occur during the rush-hour period and how crash response times associates with deaths at the crash scene. occurrences.

Assumptions

This dissertation assumes that the rush-hour period is a fixed period. In reality, the rush-hour period is a dynamic and highly fluctuant period (Federal Highway Administration, 2017), that varies by days of the week, rurality and urbanicity, US regions and division, and across seasons.

However, the decision to characterize the rush-hour period as a fixed and unvarying allows for dichotomous categorization in epidemiological studies.

CHAPTER 2: MANUSCRIPT 1

An assessment of the relationship between road environment characteristics and county-level fatal crash injury patterns in the United States

Abstract

Background: A substantial proportion of crash injuries occur during the rush-hour period. This study aims to assess the relationship between county-level road environmental characteristics and fatal road crash counts during the rush-hour period.

Method: We merged eight-year (2010 - 2017) data from the Fatality Analysis Reporting System. We limited the data to crashes during the rush hour period (6–10 am; 3– 8 pm). The outcome variable was the counts of fatal crashes per county. The predictor variables were road design (intersection, driveway, ramp, work-zone), road type (interstate, highways, roads/streets), and inclement weather factors (rain, fog, snow). A nested spatial negative binomial regression model was used to estimate the rate ratio of fatal crash injury during the rush-hour period, with estimated county population sizes used as the offset variable. Small area estimates, adjusted crash fatality rates, clusters, and outliers were visualized using choropleths maps.

Results: The median prevalence of rush-hour-related fatal crashes was 7.3 per 100,000 population. Case-specific fatality rates from interstates, highways, roads, streets, intersections, rain, fog, and snow were higher than the median fatality rates. Also, the median crash fatality rates were significantly higher in rural counties as compared to urban counties. During the rush-hour period, fatal crash injury rates were significantly elevated on interstates, highways, roads and streets, intersections, driveways, and work zones. Further, rain and fog were significantly associated with elevated fatal crash rates during the rush-hour period.

Conclusion: Certain built, and natural road environment factors may influence crash injury rates during the rush-hour period.

Keyword: Rush hour, Fatal Crash Injury, Road Environment, Nested Spatial Regression, Cluster and Hotspot Analysis, Fatality Rates

Introduction

Road crashes are preventable causes of morbidity and mortality in the United States (U.S.). In 2017, there were 6.5 million crashes, which accounts for the death of over 37,000 individuals and about 2.8 million injuries. One person dies every 14 minutes from crash-related events each day in the U.S. (National Center for Statistics and Analysis, 2019a). In 2016, over 2.5 million individuals were treated for crash-related injuries in the emergency departments across the US (National Center for Statistics and Analysis, 2017a). The cost of health care and loss from productivity exceeded 75 billion dollars in 2015 (Center for Disease Control and Prevention, 2020a). Fatal and non-fatal crashes are disproportionately distributed across the day, with crash injuries predominantly occurring around the rush-hour period (Varghese & Shankar, 2007).

The rush-hour period represents the time of the day in which the roads have the highest densities of human and automobile activities (Call, Medina, & Black, 2019; Norros, Kuusela, Innamaa, Pilli-Sihvola, & Rajamaki, 2016). In the U.S., the rush hour is between 6 to 10 am and 3 and 8 pm (Call, Wilson, & Shourd, 2018; Paleti, Eluru, & Bhat, 2010; Xu & Xu, 2020). This period varies by county and rurality (Jaffe, 2014), with urban communities in North Carolina, for example, having one of every four road crashes occurring during the rush hour (Tippett, 2014). The evening rush hour witnesses more crash events than the morning rush hour period (HG.org, 2020; Tippett, 2014; Varghese & Shankar, 2007).

Background

An individual's geographical location is an important social determinant of health (González, Wilson-Frederick Wilson, & Thorpe, 2015; Healthy People, 2020), and the road environment has long been associated with fatal and non-fatal crashes injuries (National Highway Traffic Safety Administration, 2010). In the U.S., over 1.2 million fatal and non-fatal crash injuries occur at or near intersections (Federal Highway Administration, 2020b; National Highway Traffic Safety

Administration, 2010). Factors reported to be associated with intersection-related crash injuries include driving inattention, misjudgment of the speed of another vehicle, distracted driving, and aggressive driving (Federal Highway Administration, 2020b; National Highway Traffic Safety Administration, 2010). Inadequate surveillance is associated with a six-fold increased crash risk at intersections compared to non-intersections, while misjudgment of another vehicle's speed is associated with four-fold increased risk of intersection-related crash events (National Highway Traffic Safety Administration, 2010).

While intersections represent an area where two or more roadways meet, driveways represent road stretches that lead into public or commercial roads (Liu, 2007; Nadler, Courcoulas, Gardner, & Ford, 2001). Driveways crash injuries commonly involve slow-moving vehicles, backup driving, crashes from making a left or right turn into a major road (Liu, 2007; Nadler et al., 2001). Child pedestrians are commonly involved in drive-way-related crash injuries (Anthikkat, Page, & Barker, 2013; Nadler et al., 2001). A systematic review reported that residential driveways are associated with over three-fold crash injury (Anthikkat et al., 2013). Also, driveways that exit into a local road have longer lengths and run along property boundaries are associated with a three-to-five-fold increased risk of crash injury (Anthikkat et al., 2013; Shepherd, Austin, & Chambers, 2010).

Work zones represent non-permanent road characteristics that have been associated with property damage and crash injury (American Road & Transportation Builders Association, 2018; Federal Highway Administration, 2019). In the U.S., about five percent of all fatal crashes occur at work zones (American Road & Transportation Builders Association, 2018). Work zone-related crash events increased from 84,000 in 2009 to 123,000 across the U.S., with the associated injuries rising from 19,000 to 31,000 (American Road & Transportation Builders

Association, 2018). It is estimated that one work zone fatal injury occurs every four billion vehicle miles traveled (VMT) (Federal Highway Administration, 2019). Also, the work zone area's length and the frequency of work zone regions are associated with increased crash injury and property damage (Chen & Tarko, 2012; Ozturk, Ozbay, & Yang, 2014; Athanasios Theofilatos, Ziakopoulos, Papadimitriou, Yannis, & Diamandouros, 2017).

Earlier studies have identified an increased risk of crash injuries during the rain (Andrey & Yagar, 1993; Jung, Jang, Yoon, & Kang, 2014; Qiu & Nixon, 2008; A. Theofilatos & Yannis, 2014), snow (El-Basyouny, Barua, & Islam, 2014; Fridstrøm, Ifver, Ingebrigtsen, Kulmala, & Thomsen, 1995; A. Theofilatos & Yannis, 2014), and fog (A. Theofilatos & Yannis, 2014; Wu, Abdel-Aty, & Lee, 2018). Between 2007 and 2016, about 8% of fatal crash injuries were associated with rain, while fog and snow were each related to 2% of all fatal crash injuries across the U.S. (Federal Highway Administration, 2020a). Rain, fog, and snow each accounted for 46%, 9%, and 10%, respectively, of weather-related fatal crash counts (Federal Highway Administration, 2020a). About 300 - 400 fog-related fatal crashes occur yearly in the U.S. (Hamilton, Tefft, Arnold, & Grabowski, 2014; Wu et al., 2018), and snow accounts for 16% of all weather-related crashes (Federal Highway Administration, 2020a). The conceptual link between these inclement weather factors and fatal crash events is related to driving visibility and road surface friction. Rain, fog, and snow are associated with low visibility, while rain and snow limit skid-resistance due to reduced surface friction (El-Basyouny et al., 2014; Li et al., 2019).

Central to the built and natural environmental characteristics of the crash scene is the rural-urban status. The U.S. rural community is home to about 20 percent of the U.S. population (United States Census Bureau, 2019a), and less than a third of vehicle miles traveled in the U.S. occurs in the rural areas (Federal Highway Administration, 2018; Insurance Institute for Highway Safety, 2019). However, rural counties have about half of all fatal crashes (Insurance Institute for Highway Safety, 2019; National Center for Statistics and Analysis, 2019b). Earlier studies have reported speeding as a major risky driving behavior that contributes to fatal crash injuries in rural communities (Federal Highway Administration, 2000b; Insurance Institute for Highway Safety, 2019). However, the rural areas have poorer road qualities, evidenced by an increased proportion of structurally deficient bridges and poor pavement conditions (Congressional Research Service, 2018). Additionally, rural communities have fewer hospitals and health-related infrastructures (Center for Disease Control and Prevention, 2020c; Pink, Osgood, & Sana, 2020) and longer response time (Byrne et al., 2019; King, Pigman, Huling, & Hanson, 2018; K. E. M. Miller, James, Holmes, & Van Houtven, 2020). With a larger proportion of the older population living in the rural community (Smith & Trevelyan, 2019; United States Department of Agriculture, 2019), the risk of fatal injury is further heightened with the increased prevalence of co-morbid conditions and disabilities (Garcia et al., 2019; Zhao, Okoro, Hsia, Garvin, & Town, 2019).

In predicting crash occurrence at the county level, there is a need to establish the independence of observations to reduce analytical errors (Sainani, 2010). The possibility exists that the occurrence of crash events in a county may increase (positive autocorrelation) or reduce (negative autocorrelation) the likelihood of its occurrence in neighboring counties, especially, if such counties share similar exposures – a concept defined as spatial autocorrelation (Kirby, Delmelle, & Eberth, 2017). Spatial autocorrelation techniques, commonly with the use of global Moran’s I (Anselin, 1988) or general Getis-Ord (Getis & Ord, 2010), presents ways for adjustings for spatial autocorrelation. Additionally, crash events share unobserved roadway characteristics (Carson & Mannering, 2001), and these spatial estimators adjust for the unobserved environmental elements (Jonathan, Wu, & Donnell, 2016). Earlier studies have suggested including spatial estimators in crash injury risk modeling (Jonathan et al., 2016; Lord, Cloutier, Garnier, & Christoforou, 2018). According to Tobler's first law of geography (Sui, 2004), all things are related, but close things are more related than far things. With increasing distance, the global Moran's I value tends to reduce (Epperson, 2005). Detecting spatial clusters, therefore, rely on using local estimators of spatial autocorrelation (Waller & Gotway, 2004) such as local Moran's I (Anselin, 1995) and Getis-Ord GI* (Getis & Ord, 2010; Ord & Getis, 1995). Additionally, county-level estimates may be better predicted using small area estimation techniques, and the spatial structure of counties provides more accurate estimation compared to national or state-level estimates (Kirby et al., 2017).

Identifying the environmental factors associated with fatal road crashes and their spatial distribution is important to create focused intervention and resource allocation. It is unknown to what extent road types, road designs, and inclement weather conditions associates with fatal crash events within the rush hour period. To our knowledge, no publicly available study reported fatal crash injury rates during the rush hour period. The literature on rush hour-related crash injury is sparse, and this study seeks to provide substantial information on the environmental factors associated with fatal crash events during the rush hour period. Therefore, this study aims to assess the relationship between county-level road environmental characteristics and fatal road crash rates. It is hypothesized that county-level measures of road types (such as interstate, highways, roads, and local streets), road designs (such as intersections, driveways, ramps, and work zones), and the natural environment (such as rain, snow, and fog) will be associated with increased rates of fatal crash events. Additionally, this study aims to identify clusters of fatal crash injuries during the rush-hour period. It is hypothesized that homogenous clusters of fatal crash events will emerge from predicted estimates of the county-level fatal crash rates.

Methods

Study Design

This ecological study pooled eight years of data (2010 – 2017) from the Fatality Analysis Reporting System (FARS). The FARS dataset is a repository of fatal road crash events hosted by the National Highway Traffic Safety Agency (NHTSA). It provides a nationwide census of all crash injuries involving at least a fatality across counties in the U.S. and the District of Columbia (National Highway Traffic Safety Administration, 2017). Data are released every year in multiple linkable files across domains representing the crash scene, person-related, and vehicle-related information (National Highway Traffic Safety Administration, 2016a). For this study, the variables were extracted from the accident file.

Inclusion and Exclusion Criteria

This study's inclusion criterion was that the crash event must have occurred during the rush hour period. We defined the rush hour crashes as road accidents that occurred between 6 to 10 am and 3 to 8 pm (Federal Highway Administration, 2017). We restricted the data to counties within the conterminous U.S., excluding counties in Alaska, Hawaii, Northern Mariana Islands, U.S. Virgin Islands, American Samoa, Guam, and Puerto Rico. Each county was classified as either urban or rural using the Rural-Urban Commuting Area (RUCA) code (Economic Research Services, 2019). Counties that were classified within the range of metropolitan to high commuting micropolitan were classified as urban, while low commuting micropolitan to rural areas were classified as rural. The final data consisted of 3,102 counties, with 1,691 classified as urban while 1,411 classified as rural (Figure 1-1).

Data Processing

The data extracted from the accident file included the state and county codes, the year and hour of the crash, the route the collision occurred (route-related accidents), the relationship of the crash to a junction or a specific location (junction-related accidents), the relationship of the accident to the boundaries of work zones (work zone accident), atmospheric conditions (weather-related accidents), and the number of fatalities that occurred with each crash. The raw data file reported route-related crashes as a single variable with multiple categories comprising interstate roads, U.S. highway, state highway, county road, local streets in townships, municipality, and frontage other roads, and unknown. Three dummy road type variables were generated from this variable: interstate, highways (U.S. highway + state highway), and roads and streets (county road + local streets in townships, municipality, and frontage roads).

Similarly, junction-related crashes were coded originally as a multi-categorical nominal variable comprising of non-junction, intersection and intersection-related, driveway and driveway-related, ramp and ramp-related, railway grade crossing, crossover-related, shared-use path crossing, acceleration/deceleration lane, through the roadway, other location, unknown and not reported. Three road design dummy variables were generated from this variable: intersection (intersection + intersection-related), driveway (driveway + driveway-related), and ramp (ramp + ramp-related). Additionally, weather-related crashes were coded as multi-categorical nominal variables. These variables were weather (first weather condition that affects visibility), weather1 (second weather condition that affects visibility), and weather2 (any other weather condition that affects visibility). Each of these variables was reported in multiple categories: clear weather, no additional atmospheric condition, rain, sleet, snow, fog/smog/smoke, severe crosswinds, blowing sand/soil/dirt, blowing snow, freezing rain/drizzle, others, unknown, or not reported. Three inclement weather-related crashes dummy variables were generated across the weather variables:

rain (rain + freezing rain/drizzle), snow (snow + blowing snow + sleet), and fog (fog/smog/smoke). Work zone-related crashes were reported as a multi-categorical nominal variable: None, construction, maintenance, utility, work zone type unknown, and not reported. This variable was re-categorized into a dummy variable: work zone (construction, maintenance, utility, type unknown). The number of fatalities per crash was measured as a continuous variable.

Data files across 2010 and 2017 were appended. A five-digit county Federal Information Processing Standard (FIPS) code was generated by concatenating the two-digit state code and the three-digit county codes.

Variable Definition

The outcome variable was the median fatal counts per county. The choice of using the median was based on the finding that the yearly distribution of the fatal counts per county was not normally distributed. To obtain the median fatal counts, the fatal counts for each county were aggregated by year to generate the yearly counts. Then, the median count across the years was computed. The average of the 2010 to 2017 county population estimates was used as the offset variable. The dummy variables were aggregated per county across the years. Counts of 0 represented an absence of the category of interest, while values of 1 and higher represented the presence of the category of interest in the county. The recoded dummy variables served as the predictor variables.

For this study, the county characteristics of interest that served as the control variables were the percentage of the White and male population, county rates of hospital utilization, unemployment, vehicle density, county gross domestic product (GDP), and median household income. Data on the county population, the percentage of the white and male population, median household income, and vehicle estimate per county were computed as the average of 2010 to 2017 estimate from the American Community Survey (United States Census Bureau, 2019b). The hospital utilization rate per county was obtained from the mean emergency department utilization per 1000 by Medicare beneficiaries per county (Center for Medicare and Medicaid Services, 2019). The mean unemployment rate per county was obtained from the 2010-2017 local area unemployment statistics of the U.S. Bureau of Labor (U.S. Bureau of Labor Statistics, 2019).

We created a spatial weight matrix of all the eligible county and county equivalents in the dataset using the queen contiguity setting. The spatial weight matrix essentially maps the spatial relationship between the location, to establish the occurrence of spatial autocorrelation (Zhou & Lin, 2008). Spatial autocorrelation of the residuals provides information on the independence of the residuals. The presence of significant spatial autocorrelation suggests that there is a lack of independence of the residuals. We used the Euclidean distance with the k nearest neighbor set at 4.

Analysis

Descriptive Statistics

We visualized the distribution of fatal counts per county. Further, we computed the rush hour-related raw and predicted median fatality rate by dividing the fatal counts per county by the county's population estimates. Also, we reported the fatality rate specific to the road types (interstate, highway, road, and streets), road types (intersections, driveway, ramps, work zone), and inclement weather (rain, snow, fog). Differences in the crash-specific rates against their dummy variables were measured using the Mann-Whitney U test. We reported the distribution of rush hour fatality rate and the county characteristics across the urban and rural counties. Differences in the fatality rates and county characteristics were measured using independent T-tests and the Mann-Whitney U tests as appropriate.

Regression Models

We used univariate negative binomial regression analysis to assess the relationship of all the predictor variables and county characteristics with fatal crash events. Variance inflation factor was used to assess multicollinearity.

We reported the adjusted incidence rate ratio for each of the ten variables in the road type, road design, and inclement weather group, adjusting for county characteristics. We then estimated a nested regression model using all determinants. Specifically, with road designs (intersection, driveway, ramp, and work zone) nested in road types (interstate, highways, and road/streets), interaction variables were generated for road design and road types, and these interaction variables were added to the model. After establishing evidence of spatial autocorrelation on all the regression models using the global Moran's I, a corresponding nested spatial regression model was designed, and incidence rate ratios and the 95% confidence intervals (CI) were estimated. Spatial and non-spatial models were compared using the Akaike Information criteria (AIC) (Lee & Bell, 2009). Using Matérn covariance as a kernel function in the Gaussian process (Kammann & Wand, 2003), the final nested spatial regression models for each of the individual and all-determinant models are stated below:

<u>Model 1: Interstate with nested road designs</u>

$$Y = \beta 0_1 + \beta 1 Interstate + \beta 2 Interstate * Intersection + \beta 3 Interstate * Driveway +$$

$$\beta 4 Interstate * Ramp + \beta 5 Interstate * WorkZone + \beta \gamma_1 Covariates +$$

$$\text{Matérn}(1 \mid longitude + latitude) + offset(log(popestimate)$$

<u>Model 2: Highway with nested road designs</u>

$Y = \beta 0_2 + \beta 6 Highway + \beta 7 Highway * Intersection + \beta 8 Highway * Driveway + \beta 9 Highway * Ramp + \beta 10 Highway * WorkZone + \beta \gamma_2 Covariates +$ Matérn(1 | $longitude + latitude) + offset(log(popestimate)$)

<u>Model 3: Road and Streets with nested road designs</u>

$Y = \beta 0_3 + \beta 11 Road + \beta 12 Road * Intersection + \beta 13 Road * Driveway + \beta 14 Road * Ramp + \beta 15 Road * WorkZone + \beta \gamma_3 Covariates +$ Matérn(1 | $longitude + latitude) + offset(log(popestimate)$)

<u>Model 4: Inclement Weather</u>

$Y = \beta 0_4 + \beta 16 Rain + \beta 17 Fog + \beta 18 Snow + \beta \gamma_4 Covariates +$Matérn(1 | $longitude + latitude) + offset(log(popestimate)$)

<u>Model 5: All-determinants model</u>

$Y = \beta 0_5 + \beta 1 Interstate + \beta 2 Interstate * Intersection + \beta 3 Interstate * Driveway + \beta 4 Interstate * Ramp + \beta 5 Interstate * WorkZone + \beta 6 Highway + \beta 7 Highway * Intersection + \beta 8 Highway * Driveway + \beta 9 Highway * Ramp + \beta 10 Highway * WorkZone + \beta 11 Road + \beta 12 Road * Intersection + \beta 13 Road * Driveway + \beta 14 Road * Ramp + \beta 15 Road * WorkZone + \beta 16 Rain + \beta 17 Fog + \beta 18 Snow + \beta \gamma_5 Covariates +$ Matérn(1 | $longitude + latitude) + offset(log(population\ estimate)$)

The all-determinant spatial model was the most parsimonious, and this model was used to generate small area estimates and the adjusted fatality rates per county. Cluster and outlier analysis was performed using Anselin's local Moran's to identify fatal crash events spatial clusters (Anselin, 1995). Also, a hotspot analysis was performed using the Getis-ORD star (Getis & Ord, 2010) to assess the spatial distribution of significant crash rates across neighboring counties.

Data analysis was performed using Stata version 16 (StataCorp, 2020) and R version 3.6.2 /R Studio version 1.2.5033 (R Core Team, 2019; RStudio Team, 2019). Specifically, the R-packages used for this study were the Spatial Dependence package (SPDEP) (Bivand et al., 2019), Modern Applied Statistics with S (MASS) (Ripley et al., 2019), and the Mixed-Effect Models, Particularly Spatial Models (spaMM) (Rousset, Ferdy, Courtiol, & GSL authors, 2020). Spatial weights and choropleths were created with ArcGIS Pro version 10.8 (Environmental Systems Research Institute, 2020).

Results

Fatal Injury Rates

Across the eight years, fatal road crashes were reported in 2,550 of the 3,102 counties. The median rush hour-related fatality rate per county was 7.30 (IQR: 11.1) per 100,000 population (Table 1-1). Across road types, the median (IQR) rush hour-related fatal crash injuries were highest on the highways (9.4 (10.8) per 100,000 population), followed by roads and streets (8.4 (9.7) per 100,000 population) and interstate (7.4 (9.9) per 100,000 population). Intersection-specific and driveway-specific median (IQR) fatal crash injuries were 7.8 (9.1) and 7.1 (7.8) per 100,000 population, respectively, during the rush hour period. The median (IQR) fog and rain-related fatal crash injuries during the rush hour period were 9.3 (10.5) and 7.8 (8.9) per 100,000 population, respectively, during rush hour period. There were significant differences in the median fatal crash injuries that occurred on the interstate ($p<0.001$), highways ($p<0.001$), roads, and streets ($p<0.001$), compared to the other road types during the rush hour period. Similarly, the median rates of fatal crashes that occurred on intersections ($p<0.001$) and ramps ($p<0.001$)

were significantly different from non-junctions during the rush hour period. Additionally, rain (p<0.001), fog (p<0.001), and snow-related (p=0.042) fatal crash rates were significantly different from those that occurred in normal weather during the rush hour period.

There were significant differences in the median fatal crash injury rates by rural and urban status (p<0.001) (Table 1-2). The median (IQR) rush hour-related fatal crash injury rate in rural and urban counties was 9.5 (18.7) 6.3 (7.7) per 100,000 population. Other county characteristics that demonstrated significant rural-urban differences were the county-level hospital utilization (higher urban rates), unemployment rates (higher urban rates), household income (higher urban rates), the proportion of Whites (higher rural rates), males (higher rural rates), gross domestic product (higher urban rates), and vehicle density (higher rural rates).

Risk of Fatal Injuries

In the univariate models, intersections, driveways, and ramps were associated with reduced rates of fatal crash injury across all counties during the rush hour period (Table 1-3). However, among rural counties, intersections (RR: 1.44; 95% CI: 1.30 - 1.60) and driveways (RR: 1.35; 95% CI: 1.13 - 1.62) were associated with 44% and 35% increased rates of fatal crash injuries, respectively. Also, across all counties, highways and roads and streets were associated with a two-fold (RR: 2.07; 95% CI: 1.89 - 2.28) and 9% (RR: 1.09; 95% CI: 1.02 - 1.17) increased rate of fatal crash injuries during the rush hour period. There was significantly elevated fatal crash injury in urban (RR: 1.86; 95% CI: 1.64 - 2.11) and rural highways (RR: 2.99; 95% CI: 2.65 - 3.38), in urban (RR: 1.11; 95% CI: 1.02 - 1.22) and rural (RR: 1.56; 95% CI: 1.41 - 1.73) roads and streets, and in rural interstate roads (RR: 1.85; 95% CI: 1.61 - 2.13). Across the rural counties, rain (RR: 1.41; 95% CI: 1.24 - 1.62), fog (RR: 1.52; 95% CI: 1.15 - 1.99), and snow

(RR: 1.31; 95% CI: 1.07 - 1.59) were associated with significantly elevated fatal crash injury during the rush hour period.

After adjusting for county characteristics, intersections, interstate, highway, roads, and street, rain and fog were associated with significantly elevated fatal crash injuries during the rush hour period (Table 1-4). The adjusted spatial model showed that while intersection was associated with a 21% increased rate of fatal crash injuries (RR: 1.21; 95% CI: 1.13-1.28), ramps were associated with a 14% decreased rate of fatal crash injuries (RR: 0.84; 95% CI: 0.78-0.95). Also, the interstate (RR: 1.45; 95% CI: 1.32-1.59), highway (RR: 2.48; 95% CI: 2.25-2.72), and road/street (RR: 1.48; 95% CI: 1.37-1.60) were associated with increased rates of fatal crash injuries in the rush hour period. Rain (RR: 1.15; 95% CI: 1.08-1.23), fog (RR: 1.29; 95% CI: 1.15-1.47) and snow (RR: 1.15; 95% CI: 1.06-1.25) were each associated with increased fatal rates.

In this study, the all-determinant spatial nested model performed better than the individual and non-spatial all-determinant models. The AIC of the all-determinant spatial model was lower than each of the individual determinant models (result not shown) and lower than the non-spatial all-determinant model (result not shown). Additionally, the significant Global Moran's I of the residuals of the model suggested the presence of spatial autocorrelation (p=0.011) and further strengthened the need for a spatial model. Contrary to the earlier results, the spatial model showed that ramps were not protective against fatal crash injury, and the snow was not associated with increased fatal crash injury. Intersection (RR: 2.59; 95% CI: 2.11-3.18), driveway (RR: 1.70; 95% CI: 1.18-2.43), work zone (RR: 1.94; 95% CI: 1.26-2.93), interstate (RR: 1.62; 95% CI: 1.47-1.80), highway (RR: 2.79; 95% CI: 2.51-3.10), roads and streets (RR:

1.67; 95% CI: 1.53-1.83), rain (RR: 1.08; 95% CI: 1.02-1.14), and fog (RR: 1.20; 95% CI: 1.09-1.32) were associated with increased rate of fatal crash injury during the rush hour period.

Spatial Distribution

The crude fatal counts and small area estimates from the all-determinant spatial model for all the U.S. counties were displayed using choropleths maps (Figure 1-2A). Twenty-two counties, located in California, Nevada, Arizona, Texas, Florida, Michigan, Illinois, and New York, had elevated crude and predicted rush hour-related fatal counts (>50 fatalities) (Figure 1-2B).

We generated the crude and adjusted fatality rates using the average county population as the denominator (Figure 1-3). A total of 64 counties located in 22 states had crude fatality rates above 50 deaths per 100,000 population during the rush hour period (Figure 1-3A). However, after adjusting for county characteristics and the environmental determinants, only three counties, located in Kansas and Wyoming, had fatality rates in excess of 50 deaths per 100,000 population during the rush hour period (Figure 1-3B).

A cluster and outlier analysis showed that "high-high" clusters of rush hour-related fatal events in counties located in Idaho, Montana, Nevada, California, Wyoming, Utah, and across a few states in the Southeast (Figure 1-4A). Similarly, a hotspot analysis identified several counties in California, Nevada, Idaho, Montana, North Dakota, South Dakota, Wyoming, New Mexico, Colorado, and states in the Southeast as significant hotspots for rush hour-related fatal crash events (Figure 1-4B).

Discussion

In this study, the prevalence of rush hour-related fatal crashes was 7.3 per 100,000 population. Case-specific fatality rates from interstates, highways, roads, streets, intersections, rain, fog, and snow were higher than the median fatality rates. Also, the median crash fatality rates were significantly higher in rural counties as compared to urban counties. During the rush hour period, fatal crash injury rates were significantly elevated on interstates, highways, roads and streets, intersections, driveways, and work zones. Further, rain and fog were significantly associated with fatal crash rates during the rush hour period. Rush hour-related fatal crash injuries disproportionately affected counties located in Idaho, Montana, Nevada, California, Wyoming, Utah, New Mexico, Texas, Colorado, Arkansas, Kentucky, Tennessee, and Alabama.

For over three decades, nationally representative crash reports have consistently reported elevated fatal crash counts in rural communities compared to urban communities (Insurance Institute for Highway Safety, 2019; National Center for Statistics and Analysis, 2017b; TRIP, 2020). It was not until 2016 that a reversal of trend showed an increasing crash count in urban communities with a subtle decline in rural communities (Insurance Institute for Highway Safety, 2019; National Center for Statistics and Analysis, 2017b). Earlier studies have attributed elevated rural fatal crash injuries to speeding (Insurance Institute for Highway Safety, 2019) and poor road conditions (Congressional Research Service, 2018; TRIP, 2020). Additionally, we report that some rural-urban socioeconomic differences exhibit significant associations with fatal crash injuries. In rural counties, increased White population proportion, vehicle density, median household income, and decreased male proportion are associated with reduced fatal crash injury during the rush hour period. Conversely, in urban counties, increased hospital utilization, unemployment rate, the proportion of Whites and males, county GDP, and decreased median household income were associated with increased fatal crash injury rates. These non-causal observatory findings identify how the social determinants of health differentially influence the fatal crash injury patterns in rural and urban environments (Healthy People, 2020).

In decreasing order of prevalence rates, road type-specific crash fatality rates were highest on the highways, followed by road and streets, and on interstates during the rush-hour period. The fatality rates pattern follows a similar pattern with the rates higher on highways, followed by roads and streets and interstates. The contrast in the prevalence rates on highways and on the interstate may be a reflection of the rush hour period. During the rush-hour period, highway road users are more likely to be residents within the state going from their homes to their workplaces in the morning and vice-versa in the evening. Contrastingly, interstate road users may be traversing different counties and states, although some workers engage in long commutes to work (Di Milia, Rogers, & Åkerstedt, 2012). Further, the interstate accounts for less than 2% of the total road mileage on all U.S. roads, but about 24% of all travel occurs on the interstate (Federal Highway Administration, 2000a). Irrespective of the road type, travel duration, and mileage are associated with increased fatality rate (Rolison & Moutari, 2018).

We report an elevated rate of fatal crash injuries at intersections, driveways, and work zones during the rush hour period. With more than 50% of fatal and non-fatal crashes occurring at intersections (Federal Highway Administration, 2020b), it was expected that the intersection-specific fatality rate would be higher than driveway, ramp, and work zone-specific fatality rates. Speeding and driving inattention might be some of the reasons associated with increased fatal crash rate at intersections, driveways, and work zones. Liu et al. (2007) reported that rush-hour driving was associated with the speed at which drivers approach the intersections. NHTSA reported that misjudgment of another vehicle's speed and inadequate surveillance was associated with four to six-fold increased odds of fatal crash injuries (National Highway Traffic Safety Administration, 2010). A recent meta-analysis reported that increasing work zone driving duration increases crash rates by approximately three folds, and for every kilometer increase in the length of the work zone region, the crash rate increases by two folds (Athanasios Theofilatos et al., 2017).

Earlier studies have reported that rain-related fatal crash injuries account for 8-10% of all fatal crash counts (Black, Villarini, & Mote, 2017; S. Saha, Schramm, Nolan, & Hess, 2016). In addition, we report elevated rates of fatal crash injuries from rain, with the rates significantly higher in rural counties during the rush hour period. However, fog-specific fatal crash rates were higher than rain and snow-specific fatal crash rates during the rush hour. Additionally, the rate of fog-related fatal crashes was higher than the rate associated with rain during the rush hour period. The increased fatality rate from these adverse weather events may be associated with decreased visibility (El-Basyouny et al., 2014; Li et al., 2019). Earlier studies have reported reduced speeding when driving in the rain, snow, and fog (Federal Highway Administration, 2020a; Y. N. Miller, Hilpert, Klein, Tyler, & Brooks, 2007; Wu et al., 2018).

Despite the increased rate of fatal events at different road types and road designs, the rates are disproportionately distributed across the U.S. This study and earlier studies (Byrne et al., 2019; National Center for Statistics and Analysis, 2019a; National Highway Traffic Safety Administration, 2016b) have reported worse crash rates and increased rate of fatal crash injuries in rural counties as compared to urban counties. However, identifying counties in need of focused crash interventions, especially during the rush hour, may hold the solution to achieving zero fatality rates. We demonstrated that counties located in states identified in this study serve as clusters and hotspots for fatal crash events during the rush hour after adjusting for environmental and county characteristics. Earlier studies have reported increased crash fatality rates in similar states (Ecola et al., 2018; National Highway Traffic Safety Administration, 2018). Prioritizing intervention by states is not a novel approach to reducing fatal crash injury.

There have been reports urging state-specific interventions towards specific risk factors associated with fatal crash events (Ecola et al., 2015; Ecola et al., 2018). Since each state within the U.S. is responsible for enacting policies and implementing crash prevention programs (Ecola et al., 2015), the need for tools that will guide decisions and policymakers on prioritization is needed. The Motor Vehicle Prioritizing Interventions and Cost Calculator for States (Center for Disease Control and Prevention, 2020b) represent one of those decision tools, which focuses primarily on risky driving behavioral intervention. This study demonstrates the need for a complementary tool that will help each state improve the road environmental network.

This study compared estimates from the nested spatial negative binomial model and the non-spatial model. The spatial model performed better, evidenced by the model diagnostic information. Further, this study highlights the benefits of perfunctorily assessing spatial autocorrelation as the use of spatial estimators influences the results of the study. An argument may be made on how much improvement the spatial model provides. The small value of the global Moran's I may be a reflection of long-range dependencies and the decay with increasing distance (Epperson, 2005). We demonstrate that the spatial model improved the model and produced marginally better estimates with narrower confidence intervals. For example, the nested spatial model showed that there was no significant relationship between snow and fatal crash injury while the non-spatial model would have been falsely interpreted as snow being associated with reduced odds of fatal crash injury during the rush hour period.

Predicting crash injury rate ratios from environmental characteristics requires establishing a hierarchical modeling approach (Alarifi, Abdel-Aty, & Lee, 2018; D. Saha, Alluri, Gan, & Wu, 2018) or nested (Abdel-Aty & Abdelwahab, 2004; Patil, Geedipally, & Lord, 2012). For this study, a nested model was intuitive as road designs are contained within each road type. Earlier studies have adopted other spatial modeling methodologies such as geographically weighted Poisson regression models (Bao, Liu, & Ukkusuri, 2019; Goldstick, Carter, Almani, Brines, & Shope, 2019; Hezaveh, Arvin, & Cherry, 2019), ordered probit model (Castro, Paleti, & Bhat, 2013), spatial autoregressive model (Dezman et al., 2016), multiple additive Poisson regression models (Ding, Chen, & Jiao, 2018), and multivariate Poisson lognormal spatial model (Jonathan et al., 2016). These models were influenced mainly by how crash injury was defined and the choice of predictor variables. This study, which used a nested model, adds to the crash injury literature an additional prediction model. We demonstrate its parsimonious use in assessing environmental characteristics, using the lens of social determinants of health.

This study has its limitations. Because of its ecological nature, causal inferences cannot be established. FARS dataset relies on crash reporting across all states. Therefore, data entry and processing errors cannot be eliminated. The rush-hour period varies widely across states and counties. Therefore, our definition of the rush-hour period may overestimate the rush-hour period in some counties and underestimate others. Due to the non-static traffic pattern across counties, there is a possibility of misclassification bias. However, such misclassification is likely to be non-differential. Despite these limitations, this study is one of the few studies that identify regions requiring crash injury-related interventions. The national, rural, and urban estimates of the average median fatal crash injury rates fill the gap in the crash injury prevention literature; there is no recent study that quantified rush hour-specific crash prevalence and fatality risks. Additionally, this study provides information that can inform policy and resource allocation in the presence of other competing public health issues.

Conclusion

As the U.S. journeys toward achieving a zero-fatal crash injury rate, identifying the built and natural environmental elements associated with fatal crash injuries can inform policy and practice. Also, understanding the rural and urban differences in fatal crash injury patterns during the rush hour period and counties and clusters where significant injuries occur will help identify areas needing focused intervention. This study identifies road environmental characteristics associated with fatal crash injury during the rush hour period and demonstrates, through spatial modeling tools, areas that may need focused intervention. While this study provides information on the rush hour-related crashed, an understudied domain in crash injury prevention, it provides a useful tool that can guide policy, public health practice, and resource allocation at the national, state, and county levels.

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Tables and Figures: Manuscript 1

Table 1- 1: Case-specific fatality rates from road environmental characteristics during the rush hour period between 2010-2017

Categorical Variable	Median Fatal Rate (IQR) (/100,000 population)	p-value*
Road Type		
Interstate-specific death	7.4 (9.9)	<0.001
Highway-specific death	9.4 (10.8)	<0.001
Roads and Streets- specific deaths	8.4 (9.7)	<0.001
Road Design		
Intersection- specific deaths	7.8 (9.1)	<0.001
Driveway-specific deaths	7.1 (7.8)	0.187
Ramp-specific deaths	4.6 (3.4)	<0.001
Work Zone-specific deaths	6.7 (8.2)	0.288
Inclement *		
Rain-specific deaths	7.8 (8.9)	<0.001
Fog-specific deaths	9.3 (10.5)	<0.001
Snow-specific deaths	7.5 (9.0)	0.042

*Mann-Whitney U test; Association measured between the variable and its dummy variable e.g. interstate-related fatality rates vs non-interstate-related fatality rates

Table 1- 2: County characteristics and rush hour-related fatal crash injuries stratified by rural-urban status

Variable (N=3102)	All counties N=3,102	Urban Counties n=1,691	Rural Counties n=1,411	p-value
Median fatality rate (/100,000)	7.3 (11.1)	6.3 (7.7)	9.5 (18.7)	<0.001[b]
Mean Hospital utilization per county	702.8 (149.8)	719.1 (132.1)	683.5 (166.3)	<0.001[a]
Median Unemployment rate	4.3 (1.8)	4.4 (1.5)	4.2 (2.3)	0.001[b]
Median Household Income (/1000)	48.7 (14.3)	51.5 (16.7)	46.2 (11.8)	<0.001[b]
Median % white population	92.4 (15.2)	89.0 (17.9)	95.4 (8.1)	<0.001[b]
Mean % male population	50.0 (2.2)	49.6 (1.9)	50.4 (2.4)	<0.001[b]
Median Average GDP (/100,000)	7.9 (21.7)	8.6 (24.8)	7.0 (16.8)	0.005[b]
Mean Vehicle density	361.5 (38.3)	357.3 (31.7)	371.1 (43.0)	<0.001[a]

a: Independent sample t-test b: Mann-Whitney U test; GDP: Gross Domestic Product

Table 1- 3: Negative binomial regression (non-nested) models assessing the unadjusted relationship between rush hour-related fatal road accidents and road environmental and county-level characteristics stratified by rural-urban status

Variables	Univariate Models			VIF*
	All counties	Urban Counties	Rural Counties	
Road Design				
Intersections	**0.94 (0.88 – 0.99)**	0.96 (0.89 – 1.04)	**1.44 (1.30 – 1.60)**	1.57
Driveways	**0.86 (0.80 – 0.94)**	0.93 (0.85 – 1.01)	**1.35 (1.13 – 1.62)**	1.23
Ramps	**0.56 (0.50 – 0.63)**	**0.67 (0.60 – 0.75)**	1.21 (0.40 – 3.85)	1.31
Work Zones	0.94 (0.84 – 1.06)	0.97 (0.86 – 1.10)	**1.69 (1.28 – 2.24)**	1.10
Road Type				
Interstate	0.96 (0.89 – 1.03)	0.95 (0.88 – 1.03)	**1.85 (1.61 – 2.13)**	1.31
Highway	**2.07 (1.89 – 2.28)**	**1.86 (1.64 – 2.11)**	**2.99 (2.65 – 3.38)**	1.36
Roads and Streets	**1.09 (1.02 – 1.17)**	**1.11 (1.02 – 1.22)**	**1.56 (1.41 – 1.73)**	1.33
Inclement Weather				
Rain	0.95 (0.88 – 1.02)	0.97 (0.89 – 1.05)	**1.41 (1.24 – 1.62)**	1.29
Fog	1.23 (1.07 – 1.43)	1.24 (1.07 – 1.46)	**1.52 (1.15 – 1.99)**	1.03
Snow	0.89 (0.80 – 0.99)	0.86 (0.78 – 0.96)	**1.31 (1.07 – 1.59)**	1.08
Hospital utilization	**1.00 (1.00 – 1.00)**	**1.00 (1.00 – 1.00)**	0.99 (0.99 – 1.00)	1.46
Unemployment rate	**1.08 (1.05 – 1.10)**	**1.10 (1.07 – 1.13)**	1.02 (0.99 – 1.05)	1.48
Household Income	**0.99 (0.99 – 0.99)**	**0.99 (0.99 – 0.99)**	**0.99 (0.99 – 0.99)**	1.61
% White population	**1.00 (1.00 – 1.00)**	**1.00 (1.00 – 1.00)**	**0.99 (0.99 – 0.99)**	1.53
% male population	**1.07 (1.05 – 1.09)**	**1.07 (1.04 – 1.09)**	**1.02 (1.00 – 1.05)**	1.27
Average GDP	**1.00 (1.00 – 1.00)**	**1.00 (1.00 – 1.00)**	0.99 (0.99 – 1.00)	1.01
Vehicle density	0.99 (0.99 – 1.00)	0.99 (0.99 – 1.00)	**0.99 (0.99 – 0.99)**	1.77

VIF: Variance Inflation Factor: values $\leq$3 is accepted as this suggests no multicollinearity; Metropolitan status (VIF=1.48) was added to the final model as the model final model evidenced by a reduced AIC

Table 1- 4: Negative binomial regression models predicting rush hour-related fatal road accidents occurring at road environmental and county-level characteristics.

Variables	Individual Determinants		All Determinants: Nested Models	
	Non-spatial	Spatial Model	Non-spatial [a]	Spatial Model [b]
Road Design*				
Intersection*	**1.14 (1.07-1.21)**	**1.21 (1.13-1.28)**	**2.71 (2.19-3.34)**	**2.59 (2.11-3.18)**
Driveway*	1.00 (0.94-1.08)	1.04 (0.97-1.11)	**1.69 (1.16-2.46)**	**1.70 (1.18-2.43)**
Ramp-related*	**0.76 (0.69-0.85)**	**0.86 (0.78-0.95)**	0.63 (0.14-2.12)	0.82 (0.18-2.58)
Work Zone*	1.05 (0.95-1.16)	1.04 (0.94-1.14)	**2.09 (1.34-3.20)**	**1.94 (1.26-2.93)**
Road Type				
Interstate**	**1.55 (1.41-1.71)**	**1.45 (1.32-1.59)**	**1.76 (1.58-1.96)**	**1.62 (1.47-1.80)**
Highway**	**2.51 (2.29-2.76)**	**2.48 (2.25-2.72)**	**2.91 (2.62-3.24)**	**2.79 (2.51-3.10)**
Roads and Streets**	**1.45 (1.33-1.57)**	**1.48 (1.37-1.60)**	**1.64 (1.50-1.79)**	**1.67 (1.53-1.83)**
Weather*				
Rain*	**1.09 (1.02-1.16)**	**1.15 (1.08-1.23)**	1.05 (0.99-1.11)	**1.08 (1.02-1.14)**
Fog*	**1.28 (1.13-1.45)**	**1.29 (1.15-1.47)**	**1.21 (1.09-1.35)**	**1.20 (1.09-1.32)**
Snow*	1.01 (0.92-1.10)	**1.15 (1.06-1.25)**	**0.92 (0.85-0.99)**	1.04 (0.97-1.12)
Mode Diagnostics				
AIC			12534.0	12344.7
Global Moran's I			0.04	
Z-score/p-value			3.29 / 0.011	
Local Moran's I				p<0.05(675 counties)

*Each model adjusted for hospital utilization, unemployment rate, household income, % white population, % male population, average GDP, vehicle density, rurality, and metropolitan status; **Each model created as with an interaction effect of intersection, driveway, ramp, and work zone, adjusted for hospital utilization, unemployment rate, household income, % white population, % male population, average GDP, vehicle density, and metropolitan status; a: Model equation for unified non-spatial model: $Y = \beta 0_5 + \beta 1 Interstate + \beta 2 Interstate * Intersection + \beta 3 Interstate * Driveway + \beta 4 Interstate * Ramp + \beta 5 Interstate * WorkZone + \beta 6 Highway + \beta 7 Highway * Intersection + \beta 8 Highway * Driveway + \beta 9 Highway * Ramp + \beta 10 Highway * WorkZone + \beta 11 Road + \beta 12 Road * Intersection + \beta 13 Road * Driveway + \beta 14 Road * Ramp + \beta 15 Road * WorkZone + \beta 16 Rain + \beta 17 Fog + \beta 18 Snow + Offset\ (\log(Population\ Estimate)) + \beta\gamma_5 Covariates$ b: Model equation for unified spatial model: $Y = \beta 0_5 + \beta 1 Interstate + \beta 2 Interstate * Intersection + \beta 3 Interstate * Driveway + \beta 4 Interstate * Ramp + \beta 5 Interstate * WorkZone + \beta 6 Highway + \beta 7 Highway * Intersection + \beta 8 Highway * Driveway + \beta 9 Highway * Ramp + \beta 10 Highway * WorkZone + \beta 11 Road + \beta 12 Road * Intersection + \beta 13 Road * Driveway + \beta 14 Road * Ramp + \beta 15 Road * WorkZone + \beta 16 Rain + \beta 17 Fog + \beta 18 Snow + Matern\ (1 | Longitude + Latitude) + Offset\ (\log(Population\ Estimate)) + \beta\gamma_5 Covariates$

Figure 1- 1: Data selection and aggregation steps

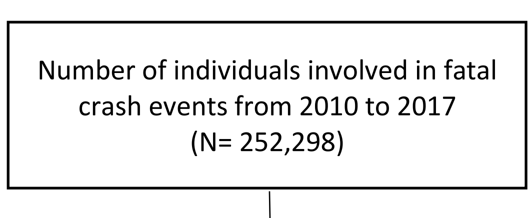
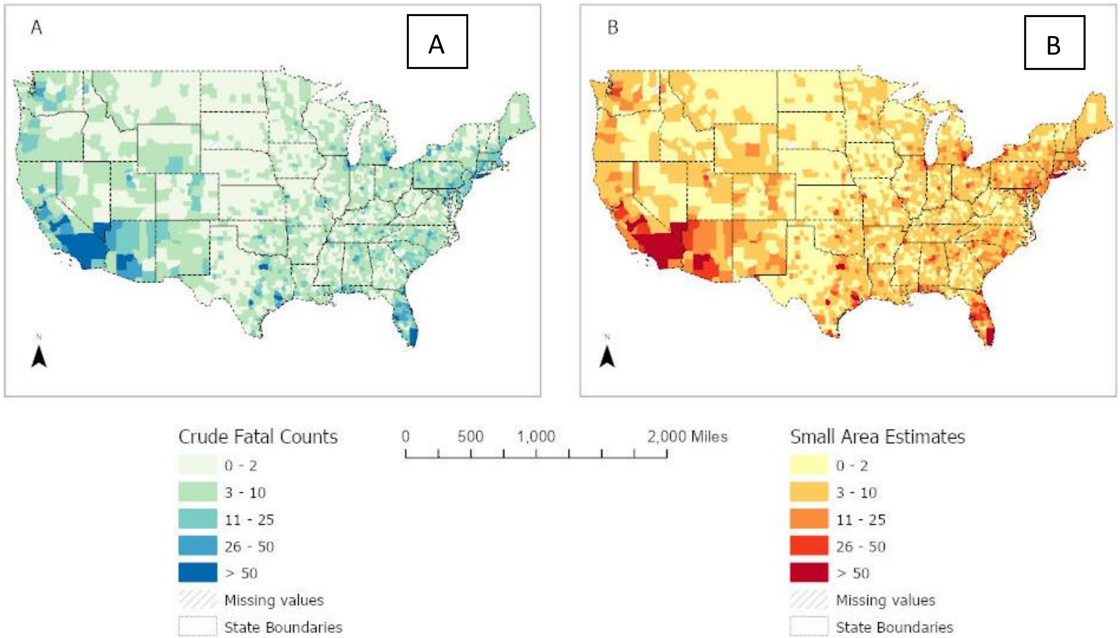
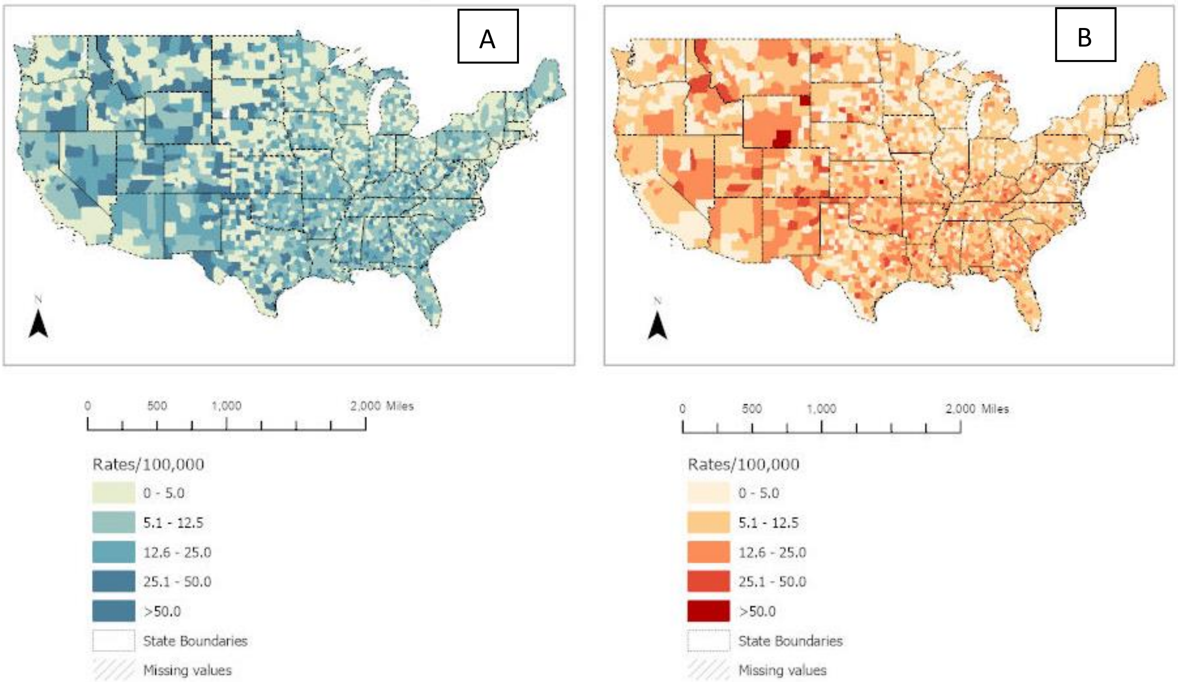


Figure 1- 2: Raw (A) and Predicted (B) Median Rush-Hour Fatality Crash Counts per County: 2010 – 2017



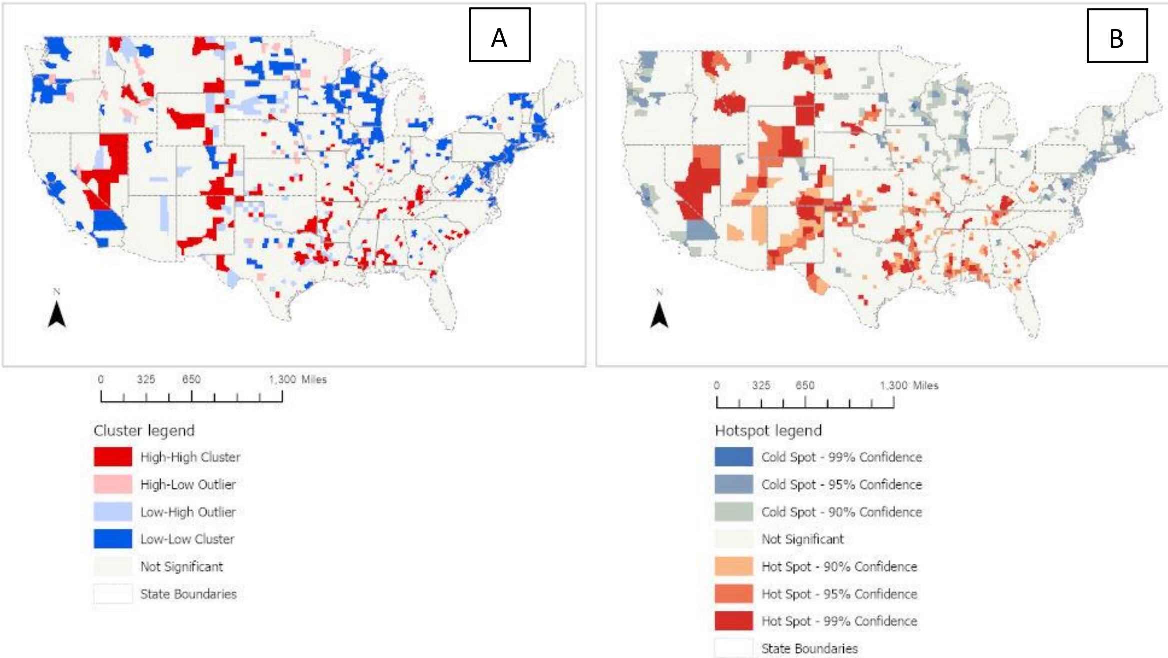
A: Raw fatal crash counts generated from the median fatal crash counts that occurred during the rush hour period between 2010 and 2017. B: Predicted crash counts generated from small area estimates of the nested spatial negative binomial regression model

Figure 1- 3: Crude (A) and Adjusted (B) Fatality Rate of Rush Hour related Fatal Crash Injury per County: 2010 – 2017



A: County-level crude fatality rates per 100,000 population computed as by the median fatal counts divided by 2018 county population estimates. B: County-level adjusted fatality rates per 100,000 population adjusted for road environmental determinants (road design, road type, inclement weather) , and county-level hospital utilization, unemployment rate, household Income, percent white population, percent male population, average gross domestic product, vehicle density, metropolitan status, and rurality

Figure 1- 4: Cluster and Outlier analysis (A) and Hotspot Analysis (B) of Rush Hour-Related Fatal Crash Injuries per County: 2010 – 2017



A: Cluster and outlier analysis estimated using Anselin Local Moran's I, showing areas of significant high-high and low-low clusters of fatal crash injuries across the United States. B: Hotspot analysis estimated using Getis ORD* showing regions with significant hotspots of fatal crash injuries.

Appendix 1: R Codes

```
library(MASS)
library("spaMM", lib.loc = "~/R/x86_64-pc-linux-gnu-library/3.6")
library("sp", lib.loc = "~/R/x86_64-pc-linux-gnu-library/3.6")
library("spdep", lib.loc = "~/R/x86_64-pc-linux-gnu-library/3.6")
setwd("/users/oadeyemi")
wt2 = read.gal("3102counties_wt.gal",override.id = TRUE)
wt2.listw = nb2listw(wt2, style = "W", zero.policy = TRUE)
class(wt2.listw)
summary(wt2.listw, zero.policy = TRUE)
rta.data14 = read.csv("model11cdata.csv", header = T)

#variables
Y <- as.matrix(rta.data14$fatalpc)
Y2 <- as.matrix(rta.data14$fatalcount)
X1 <- as.factor(rta.data14$interstate)
X2 <- as.factor(rta.data14$ushighway)
X3 <- as.factor(rta.data14$statehighway)
X4 <- as.factor(rta.data14$countyroad)
X5 <- as.factor(rta.data14$localstreet)
X6 <- as.matrix(rta.data14$frontcollision)
X7 <- as.matrix(rta.data14$sidecollision)
X8 <- as.matrix(rta.data14$rearcollision)
X9 <- as.factor(rta.data14$intersect)
X10 <- as.factor(rta.data14$driveway)
X11 <- as.factor(rta.data14$ramp)
X12 <- as.factor(rta.data14$rain2)
X13 <- as.factor(rta.data14$fog2)
```

```
X14 <- as.factor(rta.data14$snow2)
X15 <- as.factor(rta.data14$workz)
X16 <- as.matrix(rta.data14$schb)
X17 <- as.matrix(rta.data14$popestimate)
X18 <- as.matrix(as.integer(rta.data14$ed_util))
X19 <- as.matrix(as.integer(rta.data14$unemployment_rate))
X20 <- as.factor(rta.data14$ruca2gp)
X20B <- as.factor(rta.data14$metro)
X21 <- as.matrix(as.integer(rta.data14$median_household_income_2017))
X22 <- as.matrix(as.integer(rta.data14$percent_white))
X23 <- as.matrix(as.integer(rta.data14$male_percent))
X24 <- as.matrix(as.integer(rta.data14$gdp_avrg))
X25 <- as.matrix(as.integer(rta.data14$vehpc))
X26 <- as.matrix(as.integer(rta.data14$meanvtotal))
X27 <- as.factor(as.integer(rta.data14$hway))
X28 <- as.factor(as.integer(rta.data14$road))
X301 <-as.factor(rta.data14$interinter)
X302 <-as.factor(rta.data14$interdriveway)
X303 <-as.factor(rta.data14$interramp)
X304 <-as.factor(rta.data14$interwzone)
X305 <-as.factor(rta.data14$hwayintersect)
X306 <-as.factor(rta.data14$hwaydriveway)
X307 <-as.factor(rta.data14$hwayramp)
X308 <-as.factor(rta.data14$hwaywzone)
X309 <-as.factor(rta.data14$roadintersect)
X310 <-as.factor(rta.data14$roaddriveway)
X311 <-as.factor(rta.data14$roadramp)
X312 <-as.factor(rta.data14$roadwzone)
```

```
#Analysis

Mod14h = fitme(fatalcount ~ interstate + interinter + interdriveway + interramp + interwzone
                  + hway + hwayintersect + hwaydriveway + hwayramp + hwaywzone
                  + road + roadintersect + roaddriveway + roadramp + roadwzone
                  + intersect + driveway + ramp + workz + rain2 + fog2 + snow2
                  + ed_util + unemployment_rate + ruca2gp + metro +
median_household_income_2017 + percent_white + male_percent + gdp_avrg + vehpc +
Matern(1|longitude + latitude) + offset(log(popestimate)), data=rta.data14,
          family = negbin(stop(4.23)), method = "ML")

summary(Mod14h)

extractAIC(Mod14h)


est_Mod14h <- cbind(Estimate = coef(Mod14h), confint(Mod14h, "snow2"))

summary (est_Mod14h)
```

CHAPTER 3: MANUSCRIPT 2

An assessment of the nonfatal crash risks associated with substance use during rush and non-rush hour periods

Abstract

Background: Understanding how substance use is associated with severe crash injuries may inform traffic safety planning and enhance emergency care preparedness. Little is known on how the rush hour period influences the relationship between substance use and crash injury severity.

Objectives: This study aims to ascertain the association of substance use and crash injury severity at all times of the day and during rush (6-9 AM; 3-7 PM) and non-rush-hours. Further, this study assesses the probabilities of occurrence of low acuity, emergent, and critical injuries associated with substance use.

Methods: Crash data were extracted from the 2019 National Emergency Medical Services Information System. The outcome variable was non-fatal crash injury, assessed on an ordinal scale: critical, emergent, low acuity. The predictor variable was the presence of substance use (alcohol or illicit drugs). Age, gender, region of the body injured, and the revised trauma score were included as potential confounders. Partially proportional ordinal logistic regression was used to assess the unadjusted and adjusted odds of critical and emergent outcomes compared to low acuity patients, during rush-hour and all-time periods.

Results: Substance use was associated with two-fold adjusted odds of critical and emergent injuries as compared to low acuity injury. Although the proportion of substance use was higher during the non-rush hour period, substance use was associated with increased adjusted odds of critical and emergent injuries during rush hours. The interaction effect of rush hour and substance use results in an elevated odds of worse injury outcome. The probability of encountering low acuity, emergent, and critical injuries was approximately equal during rush and non-rush hours.

Conclusion: Substance use is associated with critical and emergent injury severity, with the odds heightened during the rush hour period.

Keyword: Rush hour, Non-fatal Crash Injury, Substance Use, Non-proportional ordinal logistic regression, Emergency Medical Response, Injury severity

Introduction

The incidence of nonfatal crash injuries remains high in the United States. As of 2017, an estimated 2.8 million crashes involving at least one passenger vehicle occurred, resulting in approximately 1.7 million injuries (National Center for Statistics and Analysis, 2019b). Crash injury rates had increased from 711 per 100,000 in 2011 to 761 per 100,000 U.S. population in 2015 (National Highway Traffic Safety Administration, 2016b). Non-fatal crash counts ranged from 1.7 million in 2015 to 1.9 million in 2019, except in 2016 when nonfatal crash counts exceeded 2 million (National Highway Traffic Safety Administration, 2021). Between 2015 and 2019, the age-adjusted rates of nonfatal crash injuries reduced from 1,284 to 1,013 per 100,000 population (National Center for Injury Prevention and Control, 2020). While the declining trend is an acknowledgment of the myriads of crash prevention strategies, current estimates suggest that about 5,000 to 6,000 persons sustain crash injuries every day (National Highway Traffic Safety Administration, 2021).

The rush-hour period represents the time of the day with the highest traffic density. This period commonly occurs between 6 and 10 am and 3 and 8 pm, although the exact duration varies widely across states and rural-urban areas (Jaffe, 2014). About 25% of fatal crashes occur during the rush hour period (National Highway Traffic Safety Administration, 2019a, 2019b). Contrastingly, approximately 37 percent of nonfatal crashes occur during the rush hour period, with a greater proportion of these crashes occurring during the evening rush hour period (National Highway Traffic Safety Administration, 2019a). Crash injuries that occur during the rush hour period are associated with increased injury severity, reduced crash response time, and increased odds of mortality (Chen, Zhang, Xing, & Lu, 2020).

Alcohol and illicit drugs, collectively referred to as substance use, is a major cause of road crash events (Alcañiz, Santolino, & Ramon, 2016; Bondallaz et al., 2016; Clifasefi, Takarangi, & Bergman, 2006), and crash-related morbidity and mortality (Allamani et al., 2013; Freeman, 2007; Kumar, Bansal, Singh, & Medhi, 2015). Drunk driving, defined as a driver's blood-alcohol level of 0.08 gram per deciliter (Freeman, 2007), is associated with about five times the odds of moderate injury (Niederdeppe, Avery, & Miller, 2017; Penmetsa & Pulugurtha, 2017). Drug-impaired driving occurs when drugs such as marijuana, opioids, cocaine, methamphetamine, and some prescribed and over-the-counter (OTC) medications alter a driver's attention (Berning, Compton, & Wochinger, 2015; National Highway Traffic Safety Administration, 2016a). Between 2016 and 2019, drunk driving accounted for more than 10,000 deaths yearly in the United States (Centers for Disease Control Prevention, 2016; National Center for Statistics and Analysis, 2019a; Niederdeppe et al., 2017). In 2016, over a million drivers were arrested for driving under the influence of alcohol or narcotics (Centers for Disease Control Prevention, 2016), and about 13 percent of nighttime weekend drivers have marijuana in their system (Centers for Disease Control Prevention, 2016).

Despite having a substantial proportion of fatal and nonfatal crash events, the rush hour period has received less attention in the literature. It is unknown if the prevalence and the odds of nonfatal injury from substance use are comparable during the rush hour and the all-time periods. Additionally, little is known about how substance use is associated with adverse clinical outcomes during rush hour and the all-time period. An exploration of the temporal and geographical distribution of nonfatal crash outcomes may inform policies and targeted intervention as the U.S. journeys to zero fatal count (Ecola, Popper, Silberglitt, & Fraade-Blanar, 2018). This study evaluates the relationship between substance use and crash injury severity patterns during the rush and non-rush-hour periods. It is hypothesized that substance use will be associated with worse injury severity during the rush hour than the non-rush-hour period. Also, this study aims to assess the predicted probabilities of critical, emergent, and low acuity crash injuries during the rush hour and non-rush hour periods. It is hypothesized that there will be no difference in the probabilities of occurrence of the crash injury severities during the rush and non-rush-hour periods.

Methods

Study Design

This study was a cross-sectional analytical study using the 2019 data from the National Emergency Medical Services Information System (NEMSIS). The NEMSIS is a national database of all trauma and non-trauma emergency cases, which standardize data obtained from all regional EMS agencies (Mann, Kane, Dai, & Jacobson, 2015; National Emergency Medical Services Information System, 2019). Cases reported in the NEMSIS are from emergency 911 calls across 46 out of the 50 states and the District of Columbia (National Emergency Medical Services Information System, 2019). As stated in the NEMSIS documentation (NEMSIS, 2020), data from Idaho, Missouri, Massachusetts, and Ohio were not captured in the NEMSIS dataset.

Inclusion and Exclusion Criteria

The inclusion criteria were car crashes occurring during the rush and non-rush hour period. A total of 34,248,324 persons were involved in all events resulting from the EMS activations in 2019 (Figure 2-1). A total of 33,063,246 were excluded for not being crash-related activations. Car crashes, identified using the ICD-10 codes V40 to V49, were selected (n=795,371). Values in the outcome (n=354,012) and the predictor variables (n=74,948) coded as “not reported” were excluded. Additionally, cases that died before the EMS arrival at the crash scene (n=1,236) were excluded. Covariates with cases coded as "not reported" less than 1% (n=26,829) were excluded listwise. Not reported categories over 1% were coded into a separate category as "unknown". The final analytical sample consists of 338,346 persons involved in car crashes across all times of the day, with 140,360 cases (41.5%) occurring during the rush hour period.

Injury Outcomes

The main outcome variable was the injury severity post-EMS evaluation. Injury severity was defined as a three-point categorical variable: critical, emergent, and lower priority. Critical patients represent individuals with life-threatening injuries with high mortality risk if intervention is not commenced immediately. Emergent cases represent individuals with injuries and symptoms that have the potentials of worsening, resulting in morbidity if intervention was not commenced quickly. Lower acuity patients are individuals with injuries that have a low probability of worsening or developing complications (National Highway Traffic Safety Administration, 2005).

Substance Use

The primary predictor variable was substance use. Substance use was defined as car crash injuries with evidence of alcohol or drugs either from a self-report, reported from the smell of the patient's breath, or the presence of alcohol or drug containers or paraphernalia at the crash scene. Positive cases of substance use were defined in the NEMSIS in six categories: alcohol containers/paraphernalia at the scene, drug paraphernalia at the scene, patients admit to alcohol use, the patient admits to drug use, substance use level known from law enforcement or hospital records, and smell of alcohol on breath (Emergency Medical Services, 2020). These positive indicators were recoded as positive cases of substance use, while cases that were classified as none reported were recoded as negative substance use.

Confounding

For this study, age, gender, injured areas, the revised trauma scores were selected as potential confounders. Age, originally reported as a continuous variable, was grouped into five categories: less than 16 years, 16 to 25 years, 26 to 35 years, 36 to 55 years, 56 to 75 years, and greater than 75 years. Gender was grouped as male and female. The body parts injured were recoded into six categories: head and neck, abdomen and genitals, chest and back, extremities, general body, and unknown.

The revised trauma score (RTS) of each patient was computed based on the patient's Glasgow Coma Scale score, respiratory rate, and systolic blood pressure. RTS represents a clinical outcome score calculatable at the crash scene, and a higher score suggests higher odds of survival. The RTS is a useful triaging tool, and it is recommended as the first criteria to assess prehospital physiological trauma severity (American College of Surgeons Committee on Trauma, Rotondo, Cribari, & Smith, 2014). RTS correlated poorly with parts of the body injured in this study, and it was added as a variable without concerns for autocorrelation. An earlier study has reported a similar poor correlation with injury severity scores (Galvagno et al., 2019).

The calculation of the RTS was based on the computed variables as defined originally by Champion and colleagues (Champion et al., 1989). In brief, GCS, SBP, and RR values were classified into five categories ranging from 0 to 4. RTS represents the sum of (0.9368*GCS category) + (0.7326 * SBP category) + (0.2908 * RR category). The ranges of the GCS, SBP, and RR are tabulated in Appendix 2.

Stratification

All cases were stratified as occurring during the rush hour or non-rush hour. Rush hour period was defined as crash injuries between 6 am and 9 am and 3 pm and 7 pm (Federal Highway

Administration, 2017). Although the rush hour period varies across regions, states, and rurality/urbanicity, a meta-analytical study identified these time intervals as the widest range of rush hour traffic occurrence in the U.S. (Adeyemi, Arif, & Paul, 2021).

Analysis

The frequency distribution of the categorical variables during all-time, rush, and non-rush hours periods were summarized. The differences in the crash injury characteristics were assessed using the chi-square statistics. The mean and median revised trauma scores of all the patients were computed, and the differences in these scores during the rush and non-rush hours were measured using the independent sample t-test and the Mann-Whitney U test.

The unadjusted and adjusted odds ratios and the 95% confidence intervals of emergent and critical injury from substance use were estimated using partially proportional ordinal logistic regression (Richard Williams, 2016) . The decision to use a partially proportional ordinal logistic regression was because the parallel lines assumption, tested for using the Brant test, was violated (Brant test was positive) (Richard Williams, 2005). Non-proportional ordinal logistic essentially represents multinominal variable characteristics (Fujimoto, 2003). However, in the setting of trauma, low priority, emergent, and critical state represent a dynamic assessment that is not mutually exclusive. The partially proportional ordinal logistics was selected for this study. Specifically, the syntax, gologit2, was used to estimate the odds ratio. By default, the gologit2 produces the estimates of critical and emergent cases compared to low acuity (base category), and the critical and low categories compared to the emergent cases (base category) (Richard Williams, 2005). The predicted probabilities of each of the outcome categories were estimated using the “margins” syntax (R Williams, 2019). Data were analyzed using SAS version 9.4 (SAS Institute Inc, 2019) and Stata version 16.0 (StataCorp, 2020).

Results

In this study, a total of 337,750 persons sustained car crash injuries; about 76% were of lower acuity, 20% were emergent, and 3.7% were critical (Table 2-1). A larger proportion of the car crash victims were females (55.8%) and between the ages of 36 and 55 years (27.3%). Multiple body injuries (23.2%) and injuries to the head and neck (18.3%) were the two commonly injured body parts, and the median RTS was 7.84. Substance use-related car crashes formed about 10.5% of all the cases.

There were significant differences in the crash characteristics that occur during rush and non-rush hours. A higher proportion of individuals aged 36 to 55 were involved in car crashes during rush hours (28.3%) as compared to non-rush hours (26.6%; $p<0.001$). Also, more females were involved in rush hour-related car crashes (58.1%) compared to the non-rush hour period (54.2%). Injuries to the head and neck (Rush Hour (RH):19.2% vs. non-Rush Hour (NRH): 17.7%), abdomen and genitals (RH:2.8% vs. NRH: 2.4%), chest and back (RH:16.3% vs. 14.2%), and the extremities (RH:16.1 vs. NRH:15.5) were significantly more during the rush hour period compared to the non-rush hour period ($p<0.001$). The mean RTS was significantly higher during rush hour crashes than in non-rush hour crashes. A significantly lower proportion of substance use-related car crashes occurred during the rush hour period (RH:6.2% vs. NRH: 13.5%; $p<0.001$). Similarly, a significantly lower proportion of emergent and critical cases occurred during the rush hour (21.5%) compared to the non-rush hour period (25.8%; $p<0.001$)

Compared to crash injury victims less than 16 years old, all age categories were associated with significantly elevated odds of critical and emergent injury severity compared to low acuity during the all-time period (Table 2-2). Males were associated with 40% (Odds Ratio (OR): 1.40; 95% CI: 1.37 - 1.42) increased odds of critical and emergent injury severity with reference to low acuity when compared to females. When compared to general body injuries, injuries to the abdomen and genitals were associated with 14% increased odds of critical and emergent injury severity compared to low acuity while injuries to the head and neck (OR: 0.78; 95% CI: 0.76 - 0.80), chest and back (OR: 0.75; 95% CI: 0.73 - 0.76), and extremities (OR: 0.65; 95% CI: 0.63 - 0.66) were less likely to be associated with critical and emergent injury severity. A unit increase in RTS was associated with 96% reduced odds (0.04; 95% CI: 0.04 - 0.04) of critical and emergent injury severity as compared to low acuity. Substance use was significantly associated with progressively worsening injury severity. In the unadjusted model, substance use was associated with 2.73 (95% CI: 2.66 – 2.79) increased odds of critical and emergent injury severity. Rush hour was significantly associated with 21% reduced odds of critical and emergent injury severity as compared to low acuity injury.

After adjusting for age, gender, injury region, and RTS, substance use was associated with two times the odds (Adj OR: 2.08; 95%CI= 2.02 - 2.14) of critical and emergent injury outcome as compared to low acuity across the all-time period (Table 2-3). During the rush hour, substance use was associated with 2.2 times the odds (Adj OR: 2.24; 95%CI= 2.12 - 2.37) of critical and emergent injury outcomes as compared to low acuity injury severity. During the non-rush hour, substance use was associated with 1.9 times the odds (Adj OR: 1.93; 95%CI= 1.87 – 1.99) of critical and emergent injury outcomes as compared to low acuity injury severity.

The interaction effect of the rush hour period on substance use was associated with significantly elevated odds of critical and emergent injury severity as compared to low acuity injury (Table 2-4). In the unadjusted model, substance use during the rush hour was associated with 25% increased odds of critical and emergent injury severity as compared to low acuity injury (OR: 1.25; 95% CI: 1.19-1.32). After adjusting for age, gender, injured part, and revised trauma score, the odds remained significantly elevated but attenuated to 17% increased odds (Adj. OR: 1.17; 95% CI: 1.10-1.24).

A dose-response relationship existed between substance-use-related crash injury severity and age (Figure 2-2). The probabilities of low acuity crash injury significantly decreased with increasing age while the probabilities of emergent crash injuries increased with increasing age at all times of the day. Among crash victims aged less than 16 years, the probability of low acuity injury was 61.9% (95% CI: 61.0 – 62.9%) while the probability of low acuity injury among those aged 75 years and older was 46.9% (95% CI: 45.8 – 48.2%). The probability of emergent injuries among those less than 16 years was 27.9% (95% CI: 27.0 – 28.9%) while the probability of emergent injuries associated with substance use among crash victims 75 years and older was 38.3% (95% CI: 37.0 – 39.5%). During the rush and non-rush hours, there were approximately equal probabilities of having a substance-use-associated crash injury classified as emergent at 29% (95% CI: 0.28 – 0.30) and critical at 4.0% (95% CI: 0.04 – 0.04) (Table 2-5).

Discussion

Substance use was associated with over two-fold adjusted odds of critical and emergent injury severities, across all times of the day, and during rush and non-rush hours. Although the odds of emergent and critical injuries were slightly higher during the rush hour compared to the non-rush hour, the adjusted probabilities of low acuity, emergent, and critical injuries were close, and may not be of practical importance. Perhaps of more importance is the increasing pattern of substance use-related injury severity with increasing age.

In this study, about 40 percent of crash injury patients sustained their injury during the rush-hour period. This result is comparable with the report from the National Highway Traffic Safety Administration (2019a), which reports a 37 percent proportion using the 2018 Crash Reporting Sampling System. Additionally, this study reports a nonfatal injury severity pattern, divided non-proportionally into low acuity, emergent and critical. Defining injury outcomes based on patient's acuity is a commonly used method of assessing morbidity and potential mortality (Vranas et al., 2018; Yiadom et al., 2018). About three-quarters of the sample population were classified as low acuity, while about a quarter had emergent or critical outcomes. Additionally, this study reports that the proportion of critical and emergency cases during the rush hour were lesser than the proportion in the non-rush hour period.

Earlier studies have reported the increased odds of fatal and nonfatal injury from substance use (G. Li, Brady, & Chen, 2013; Potoglou, Carlucci, Cirà, & Restaino, 2018). Alcohol, marijuana, and opioid are the commonly used substance that impairs driving (National Institute for Drug Abuse, 2019). A decrease in blood alcohol levels is associated with a decreased proportion of fatal and nonfatal crash injuries (Andreuccetti et al., 2011; Elvik, 2016; Gill, Sutherland, McKenney, & Elkbuli, 2020; Oliveira, Yonamine, Andreucceti, Ponce, & Leyton, 2012). Similarly, marijuana is associated with two to four-fold increased odds of fatal and nonfatal crash injury (Blows et al., 2005; Chihuri & Li, 2020). Similarly, opioid use while driving has been associated with two-fold increased odds of crash initiation and fatal crash involvement

(Chihuri & Li, 2019; Guohua Li & Chihuri, 2019). Using the 2019 NEMSIS data, this study reports two-fold increased odds of crash victims with substance use being classified as emergent or critical as compared to low acuity, with the odds slightly higher during the rush hour period.

In this study, the adjusted odds of substance use-related critical and emergent crashes were higher in the rush hour period compared to the non-rush-hour period. Additionally, the interaction of the rush hour and substance use was associated with an elevated odd of emergent and critical injury severity. This finding suggests that substance use, either among drivers or among other car occupants is associated with worse health outcomes while the critical and emergent outcome is marginally heightened during the rush hour period. Earlier studies have reported that driver injury severity that occurs during the rush hour period is associated with worse severity (Estochen, Souleyrette, & Strauss, 1998; Hao, Kamga, & Wan, 2016). A possible explanation for this pattern may be related to crash response time and its difference during the rush and non-rush hours (Estochen et al., 1998). Early crash interventions have been associated with reduced mortality (Byrne et al., 2019) and traffic delay, among other structural delay factors, may be associated with the critical and emergent outcomes among crash victims with substance use.

This study identified demographic characteristics associated with increased probability of low acuity, emergent and critical injuries from substance use. Specifically, there is an increasing probability of emergent injuries with increasing age and the probability of low acuity injuries reduces with increasing age. These injury severity probabilities did not change across rush and non-rush hour periods. The National Institute for Drug Abuse has earlier reported that teens and older adults are the population that commonly engage in drugged driving (National

Institute for Drug Abuse, 2019). In addition, this study reports that injury severity has a higher probability of being more severe among older age groups. Although substance use occurrence occurs more during the non-rush hour period, the probabilities of encountering the injury severity patterns are the same during the rush and rush hour period.

This study has its limitations. It is a retrospective cross-sectional study and causal inferences cannot be made. The large proportion of missing variables in sociodemographic characteristics such as race, a known indicator of health outcome, might either increase or decrease the observed association. Recategorizing the missing variables under race as a separate category did not influence the result of this study. Also, misclassification of substance use is likely as multiple measures were used to identify crash victims with substance abuse. The gold standard of diagnosing substance use remains serological testing (DiMaggio, Wheeler-Martin, & Oliver, 2018). Additionally, the EMS data does not capture four states in the U.S. (Mann et al., 2015), and this study generalized the results to other four non-representative states. Despite these limitations, this study represents one of the few studies that focus attention on rush hour-related crashes. This study identifies substance use as a significant predictor of critical and emergent crash outcomes at all times of the day and during the rush hour period. An additional strength of this study is that car crashes were identified using the International Classification of Disease (ICD) 10 code. Misclassification bias of cases is unlikely using the ICD-10 code although medical coding errors cannot be eliminated. It is unlikely that such errors will disproportionately affect the proportion of substance use and crash injury severity reported in this study. Also, misclassification of the outcome is unlikely as injury severity is based on a complex matrix administered by trained EMS staff.

In conclusion, substance use is associated with critical and emergent crash injury outcomes and the odds are marginally heightened during the rush hour period, though the difference may not be of clinical or practical importance. Future studies may explore specific substances such as alcohol, marijuana, and opioid use while driving during the rush hour period associates with fatal injuries.

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Tables and Figures: Manuscript 2

Table 2- 1: Descriptive statistics of the sociodemographic, injury, and alcohol/drug characteristics at all time and during the rush hour period using the 2019 National Emergency Medical Services Information System database

Variables	All-time Period (N=337,750)	Non-Rush Hour (n=197,616)	Rush Hour (n=140,134)	p-value*
	Frequency (%)	Frequency (%)	Frequency (%)	
Age				
< 16 years	26,171 (7.8)	13,843 (7.0)	12,328 (8.8)	<0.001
16-25 years	79,678 (23.6)	49,087 (24.8)	30,591 (21.8)	
26-35 years	66,322 (19.6)	39,625 (20.1)	26,697 (19.1)	
36-55 years	92,268 (27.3)	52,654 (26.6)	39,614 (28.3)	
56-75 years	59,487 (17.6)	34,204 (17.3)	25,283 (18.0)	
>75 years	13,824 (4.1)	8,203 (4.2)	5,621 (4.0)	
Gender				
Male	149,209 (44.2)	90,466 (45.8)	58,743 (41.9)	<0.001
Female	188,541 (55.8)	107,150 (54.2)	81,391 (58.1)	
Injured Region				
Head and Neck	61,929 (18.3)	35,062 (17.7)	26,867 (19.2)	<0.001
Abdomen and Genitals	8,798 (2.6)	4,785 (2.4)	4,013 (2.8)	
Chest and Back	50,864 (15.1)	28,082 (14.2)	22,782 (16.3)	
Extremities	53,123 (15.7)	30,593 (15.5)	22,530 (16.1)	
General Body	78,394 (23.2)	46,221 (23.4)	32,173 (23.0)	
Unknown	84,642 (25.1)	52,873 (26.8)	31,769 (22.6)	
Revised Trauma Score**				
Mean (SD)	7.79 (0.36)	7.65 (0.62)	7.68 (0.57)	<0.001
Median (IQR)	7.84 (0.00)	7.79 (0.00)	7.80 (0.00)	<0.001
Substance Use				
Yes	35,338 (10.5)	26,638 (13.5)	8,700 (6.2)	<0.001
No	302,412 (89.5)	170,978 (86.5)	131,434 (93.8)	
Injury severity				
Lower acuity	256,693 (76.0)	146,650 (74.2)	110,043 (78.5)	<0.001
Emergent	68,579 (20.3)	43,039 (21.8)	25,540 (18.2)	
Critical	12,478 (3.7)	7,927 (4.0)	4,551 (3.3)	

*Tests of hypothesis conducted between rush hour vs. non-rush hour events. **Mean (standard deviation) and median (interquartile range) reported. T-Test and Mann-Whitney U tests performed for mean and median values respectively, otherwise chi-square test of hypothesis conducted for all other variables.

Table 2- 2: Unadjusted odds ratio of emergent and critical health conditions post EMS care during all times and at the rush hour period

Variables	Critical & Emergent vs. Low Acuity Odds Ratio (95% CI)
Age	
16-25 years	**1.40 (1.35 – 1.45)**
26-35 years	**1.45 (1.39 – 1.50)**
36-55 years	**1.39 (1.35 – 1.44)**
56-75 years	**1.49 (1.43 – 1.54)**
>75 years	**1.87 (1.79 – 1.97)**
< 16 years	Ref
Gender	
Male	**1.40 (1.37 – 1.42)**
Female	Ref
Injured Region	
Head and Neck	**0.78 (0.76 – 0.80)**
Abdomen and Genitals	**1.14 (1.09 – 1.19)**
Chest and Back	**0.75 (0.73 – 0.76)**
Extremities	**0.65 (0.63 – 0.66)**
General Body	Ref
Revised Trauma Score	**0.04 (0.04 – 0.04)**
Substance Use	
Yes	**2.73 (2.66 – 2.79)**
No	Ref
Rush Hour	
Yes	**0.79 (0.77 – 0.80)**
No	Ref

Table 2- 3: Adjusted odds of emergent and critical health conditions post-EMS care modeled by Substance Use intake in the rural/wilderness, suburban and urban areas at all times and during the rush hour period

Variables	All-time duration Adjusted Odds (95% CI)	Rush Hour Adjusted Odds (95% CI)	Non-Rush Hour Adjusted Odds (95% CI)
	Critical & Emergent vs. Low Acuity	Critical & Emergent vs. Low Acuity	Critical & Emergent vs. Low Acuity
Substance Use			
Yes	**2.08 (2.02 – 2.14)**	**2.24 (2.12 – 2.37)**	**1.93 (1.87 – 1.99)**
No	Ref	Ref	Ref

Models adjusted for age, gender, injured part, and revised trauma score (RTS).

Table 2- 4: Unadjusted and adjusted odds of emergent and critical health conditions post-EMS care modeled by the interaction effect of Substance Use and Rush Hour period

Variables	Unadjusted Odds (95% CI) Critical & Emergent vs. Low Acuity	Adjusted Odds (95% CI) Critical & Emergent vs. Low Acuity
Substance Use		
Yes	**2.50 (2.43 – 2.56)**	**1.93 (1.87 – 1.99)**
No	Ref	Ref
Rush Hour		
Yes	**0.83 (0.82 – 0.85)**	**0.81 (0.80 – 0.83)**
No	Ref	Ref
Rush Hour x Substance Use		
Yes	**1.25 (1.19 – 1.32)**	**1.17 (1.10 – 1.24)**
No	Ref	Ref

Model adjusted for age, gender, injured part, and revised trauma score (RTS).

Table 2- 5: Predicted probabilities of low acuity, emergent and critical cases secondary to substance use during rush and non-rush hours

Variable	Rush Hour			Non-Rush Hour		
	Low Acuity	Emergent	Critical	Low Acuity	Emergent	Critical
Substance Use						
Yes	0.67 (0.66-0.68)	0.29 (0.28-0.30)	0.04 (0.04-0.04)	0.66 (0.66-0.67)	0.30 (0.29-0.30)	0.04 (0.04-0.04)
No	0.78 (0.78-0.79)	0.18 (0.18-0.18)	0.04 (0.04-0.04)	0.76 (0.76-0.76)	0.20 (0.20-0.21)	0.04 (0.04-0.04)

Models adjusted for age, gender, injured part, and revised trauma score (RTS).

Figure 2- 1: Data selection steps

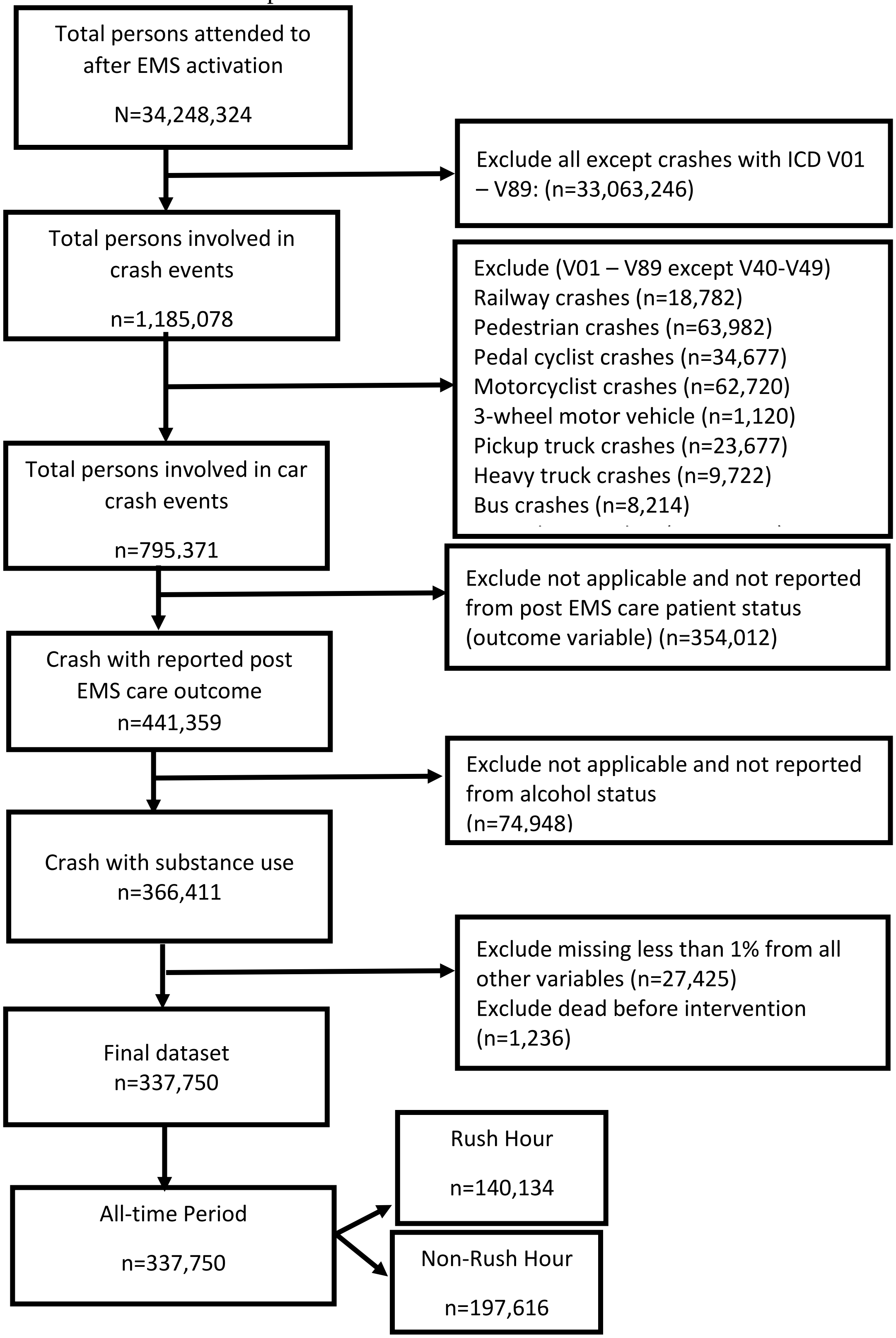
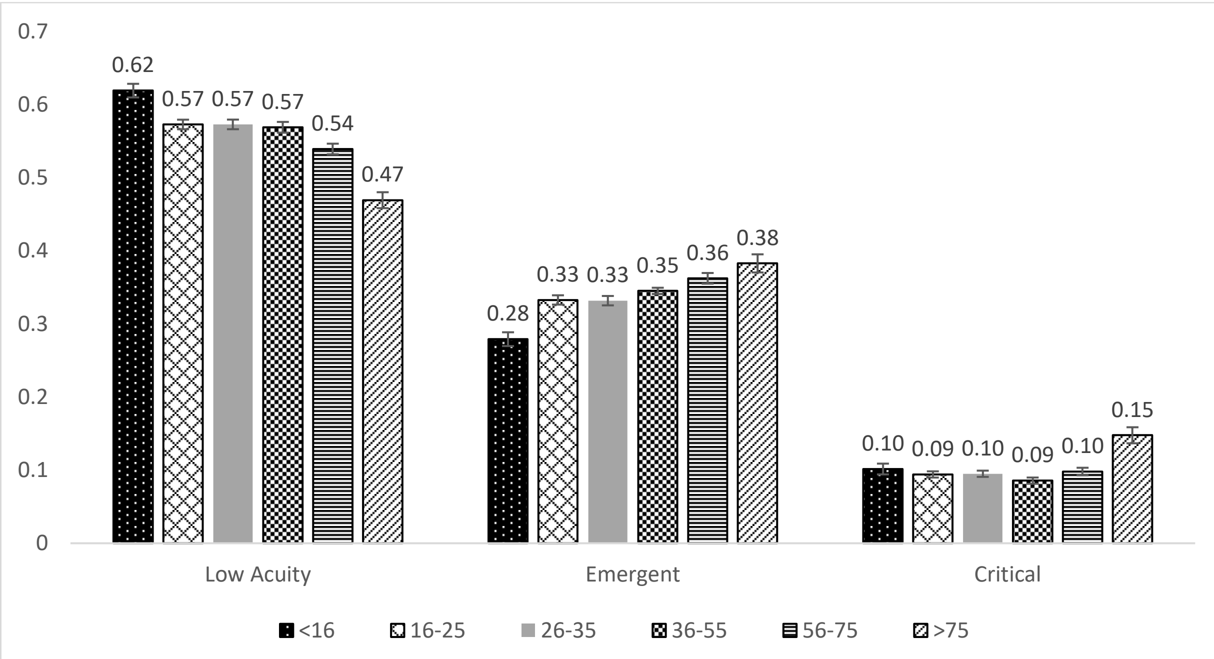


Figure 2- 2: Predicted probabilities of substance used-associated injury outcomes across all age groups at all times of the day



Model adjusted for age, gender, injured part, and revised trauma score (RTS)

Appendix 2: Revised Trauma Score Computation

RTS value	Respiratory Rate	Systolic Blood Pressure	Glasgow Coma Scale Score
4	10 – 29 (normal)	>89	13 – 15
3	> 29 (tachypnea)	76 – 89	9 – 12
2	6 – 9 (bradypnea)	50 – 75	6 – 8
1	1 – 5 (gasping respiration)	1 – 49	4 – 5
0	0 (no respiration)	0	3
RTS = (0.9368*GCS category) + (0.7326 * SBP category) + (0.2908 * RR category)			

Appendix 3: STATA codes

```
version 16.1

*cd "K:\Dropbox (UNC Charlotte)\PhD
Students\Adeyemi_Oluwaseun\Dissertation\Paper_2\data"

clear

capture log close

set more off

log using subst.log, replace

use substanceusev3

numlabel,add

*rename *, lower

*analysis


*descriptive

tab outcome,m

tab alcdrug2,m

tab agecat,m

tab gender,m

tab race,m

tab injpart,m

tabstat rts, statistics (mean, sd, p50, range, iqr)

foreach var of varlist outcome alcdrug2 agecat gender race injpart {

	tab `var' rushhr, col chi

}

tabstat rts, statistics (mean, sd, p50, range, iqr) by(rushhr)


ttest rts2, by(rushhr)

ranksum rts2, by(rushhr)


foreach var of varlist outcome alcdrug2 agecat gender race injpart {
```

```
	tab `var' rur1sub2urb0, col chi
}
tab outcome rur1sub2urb0 if rushhr==1, chi2
tab alcdrug2 rur1sub2urb0 if rushhr==1, chi2
tab agecat rur1sub2urb0 if rushhr==1, chi2
tab gender rur1sub2urb0 if rushhr==1, chi2
tab race rur1sub2urb0 if rushhr==1, chi2
tab injpart rur1sub2urb0 if rushhr==1, chi2
oneway outcome alcdrug2 if rushhr==1

*test for proportionality
omodel logit outcome alcdrug2
brant, detail
*result is significant
*proportionality assumption not met. Use partial proportionality
*non-proportionality is technically not an ordinal variable

*unadjusted
*all
local a alcdrug2 agecat gender  injpart rts2
foreach var of varlist alcdrug2 agecat gender race rur1sub2urb0 injpart rts2 {
	gologit2 outcome i.`var', or
	gologit2 outcome i.`var' i.`a', or				//adjusted
	gologit2 outcome i.`var' if rushhr==1, or
	gologit2 outcome i.`var' i.`a'  if rushhr==1, or		//adjusted
	gologit2 outcome i.`var' if rushhr==0, or
	gologit2 outcome i.`var' i.`a' if rushhr==0, or
gologit2 outcome 1.alcdrug2,or
gologit2 outcome i.agecat,or
gologit2 outcome 1.gender,or
```

```
gologit2 outcome i.race,or
gologit2 outcome i.rur1sub2urb0,or
gologit2 outcome i.injpart,or
gologit2 outcome rts2,or

gologit2 outcome i.alcdrug2 if rushhr==1,or
gologit2 outcome i.agecat if rushhr==1,or
gologit2 outcome 1.gender if rushhr==1,or
gologit2 outcome i.race if rushhr==1,or
gologit2 outcome i.rur1sub2urb0 if rushhr==1,or
gologit2 outcome i.injpart if rushhr==1,or
gologit2 outcome rts2 if rushhr==1,or

*Adjusted
gologit2 outcome 1.alcdrug2 agecat gender  injpart rts2 ,or
gologit2 outcome i.alcdrug2 agecat gender  injpart rts2 if rushhr==1,or

*if rur1sub2urb0==0
gologit2 outcome i.alcdrug2 agecat gender race injpart rts2 if rur1sub2urb0==0,or

gologit2 outcome i.alcdrug2 agecat gender race injpart rts2 if rur1sub2urb0==0 & rushhr==1,or
gologit2 outcome i.alcdrug2 agecat gender race injpart rts2 i.rur1sub2urb0##i.rushhr,or
margins i.rur1sub2urb0##i.rushhr

*if rur1sub2urb0==2
gologit2 outcome i.alcdrug2 agecat gender race injpart rts2 if rur1sub2urb0==2,or
gologit2 outcome i.alcdrug2 agecat gender race injpart rts2 if rur1sub2urb0==2 & rushhr==1,or
```

```
*if rur1sub2urb0==1

gologit2 outcome i.alcdrug2 agecat gender race injpart rts2 if rur1sub2urb0==1,or

gologit2 outcome i.alcdrug2 agecat gender race injpart rts2 if rur1sub2urb0==1 &
rushhr==1,or


gen pyear = 1

ir adverse alcdrug2 pyear

ir adverse alcdrug2 pyear if rushhr==1


*age adjusted

ir adverse alcdrug2 pyear, by(agecat)

ir adverse alcdrug2 pyear if rushhr==1, by(agecat)


poisson adverse i.alcdrug2##i.rushhr, irr exp(pyear)

margins i.alcdrug2##i.rushhr, predict(ir)


poisson adverse i.alcdrug2 i.agecat, irr exp(pyear)

margins i.alcdrug2, predict(ir)

gologit2 outcome i.alcdrug2##i.rushhr i.agecat, or

margins rushhr, at(agecat=(1 2 3 4 5))

marginsplot, noci


gologit2 outcome i.alcdrug2##i.rushhr i.agecat, or

margins alcdrug2, at(rushhr=(0 1))

marginsplot, noci


gologit2 outcome i.alcdrug2##i.rushhr i.agecat, irr exp(pyear)

margins alcdrug2##rushhr, at(agecat=(1 2 3 4 5))

marginsplot, noci
```

```
poisson adverse i.alcdrug2, irr exp(pyear)
margins alcdrug2, predict(ir)

poisson adverse i.alcdrug2 i.agecat, irr exp(pyear)

poisson adverse i.alcdrug2##ib3.agecat, irr exp(pyear)
margins  i.alcdrug2, at(agecat=(1(1)5))

marginsplot, noci

margins i.alcdrug2, predict(ir) by(agecat)

margins i.alcdrug2, predict(ir)

poisson adverse i.alcdrug2 i.agecat, irr exp(pyear)

margins i.alcdrug2, predict(ir) by(GEOID)

bysort agecat: poisson adverse i.alcdrug2 i.agecat, irr exp(pyear)

bysort agecat: poisson adverse i.alcdrug2 i.agecat if rushhr==1, irr exp(pyear)
```

CHAPTER 4: MANUSCRIPT 3

The association of crash response times and death-at-the-scene during the rush and non-rush hour periods.

Abstract

Background: Death-at-the-scenes are crash deaths that occur within minutes after a crash. Rapid crash responses serve as a potential intervention to reduce the occurrence of death-at-the-scene.

Objectives: This study aims to assess the association of crash response time with the occurrence of death-at-the-scene during all times of the day and the rush and non-rush hour periods (6–9 am; 3– 7 pm).

Method: This cross-sectional study used the 2019 National Emergency Medical Services (EMS) Information System. The outcome variable was death-at-the-scene. The predictor variables were crash response times measured as crash notification (EMS notification to departure from the base station) and EMS travel time (base station to crash scene). Age, gender, substance use, region of the body injured, the revised trauma score, and rurality/urbanicity of each injury location were used as potential confounders. Logistic regression was used to assess the unadjusted and adjusted odds of death-at-the-scene.

Results: A total of 1,203,527 were involved in EMS-activated road crash events, with 50.2% of the population exposed to crash events during the rush-hour period. A total of 8,292 persons died at the crash scene. After adjusting for confounders, a minute increase in the EMS travel time was associated with 0.4% (Adjusted OR: 1.004; 95% CI: 1.003-1.006) and 0.7% (Adjusted OR: 1.007; 95% CI: 1.005-1.009) increased odds of death-at-the-scene during all times of the day and the rush-hour period, respectively.

Conclusion: Reducing crash response times may reduce the occurrence of deaths at the crash scene.

Keyword: Rush hour, Death-at-the-scene, Emergency Medical Response, Multivariate logistic regression, Notification time, Travel time

Introduction

Road crashes remain a preventable cause of death in the United States (U.S.). As of 2019, 36,096 crash fatalities were recorded in the U.S., representing 1.1 fatalities per 100,000 vehicle miles traveled (National Center for Statistics and Analysis, 2020). Approximately one person dies in a crash every 14 minutes in the United States (U.S.) (National Center for Statistics and Analysis, 2019). The rush-hour period represents the period of peak road activities. The period varies widely across rural and urban regions, with the peak densities occurring between 6 and 9 am and 3 and 7 pm (Call, Medina, & Black, 2019; Paleti, Eluru, & Bhat, 2010). About a quarter of fatal crash injuries occur during the rush hour period (Jaffe, 2014; National Highway Traffic Safety Administration, 2019).

The U.S. experienced a decline in fatal deaths between 2016 and 2019 (National Center for Statistics and Analysis, 2020; National Highway Traffic Safety Administration, 2020). However, estimates in 2020 – a year uniquely characterized by stay-at-home orders and driving restrictions due to the COVID-19 pandemic (Moreland et al., 2020), indicated higher deaths despite reduced travel (National Safety Council, 2021). Death-at-the-scene represents a unique subset of salvageable and unsalvageable crash deaths that would have occurred within minutes after the crash, probably due to damage to vital structures (Byrne et al., 2015). Although death-at-the-scene is an infrequently reported crash characteristic, cases of death on arrival at the emergency department have been used in previous studies as a proxy in determining cases that either died at the crash scene or in transit (Calland et al., 2012; Khursheed et al., 2015; Roudsari et al., 2007).

Central to preventing fatal crash events is a rapid crash response (Byrne et al., 2019). Acute blood loss, one of the major clinical presentations of crash injury victims, is a time-dependent diagnosis that requires interventional care within minutes of its occurrence (Stainsby, MacLennan, & Hamilton, 2000). The Emergency Medical Services (EMS) crash response can be conceptualized to occur in three non-overlapping temporal phases: the period from crash occurrence to EMS notification, from EMS notification to EMS arrival, and from EMS arrival to hospital arrival (Emergency Medical Services, 2020; Lee, Abdel-Aty, Cai, & Wang, 2018). Delay at any of the three phases may potentially increase the odds of unfavorable health outcomes.

There is compelling evidence that reducing crash response time is associated with improved survival (Babiarz, Mahadevan, Divi, & Miller, 2016; Byrne et al., 2019; Gauss et al., 2019), although some crash cases may be unsalvageable (Calland et al., 2012). Although 40% of all crashes involving at least one death occur during rush hour (National Highway Traffic Safety Administration, 2019), this crash characteristic is not commonly studied. To date, no study in the public domain has assessed the association between crash response times and death-at-the-scene. This study aims to estimate the occurrence of cases classified as death-at-the-scene and how this occurrence varies during the rush and non-rush hour periods. Additionally, this study will assess the association of crash response time with the occurrence of death-at-the-scene. It is hypothesized that prolonged response times during the rush hour and all-time period will be associated with increased odds of death-at-the-scene.

Methods

Study Design

This population-based study used the 2019 National Emergency Medical Services Information System (NEMSIS), a census of all the EMS activations across the continental U.S. excluding

Idaho, Missouri, Massachusetts, and Ohio (National Emergency Medical Services Information System, 2019). Cases in the NEMSIS represent trauma and non-trauma emergency cases, pooled from all regional EMS agencies (Mann, Kane, Dai, & Jacobson, 2015; National Emergency Medical Services Information System, 2019).

Inclusion and Exclusion Criteria

A total of 35,214,824 persons were involved in all EMS activations. All road crashes were selected. Crashes were identified using the International Classification of Disease (ICD) code, version 10. Specifically, cases identified as ICD V01 to V89 were selected. These cases represented crashes involving pedestrians (V01-V09), pedal cyclists (V10-V19), motorcycle (V20-V29), three-wheeled motor (V30-V39), cars (V40-V49), trucks (V50-V59), heavy transport vehicle (V60-V69), bus (V70-V79), and other land transport (V80-V89) (n=1,222,005). Cases whose crash outcome was classified as "canceled" were excluded (n=1,532). Cases with missing crash response times were excluded (n=6,486). The final sample included 1,203,527 persons, with 603,860 persons sustaining injuries during the rush hour period (Figure 3-1).

Rush and Non-Rush Hour Period

Rush hour period was defined as crash injuries occurring between 6 - 9 am and 3 - 7 pm (O. J. Adeyemi, Arif, & Paul, 2021). The non-rush hour period represents the intervening period of the day and night that is not the rush hour period. Time of the crash was determined using the time the emergency call (911) was received. Crash times with missing information during the hour the 911 call was initiated were replaced with the hour the EMS team was notified. The difference in the period from the 911 call to EMS notification was measured in seconds in the NEMSIS. Hence, it was appropriate to use the hour of the day the EMS was notified as a proxy for handling missing data for rush hour determination.

Outcome Variable: Death at the Crash Scene

The main outcome variable was death-at-the-scene, defined as cases classified as dead at the incident by EMS personnel. The original variable used to measure death-at-the-scene was "e-disposition.12". Unlike other variables that measure crash outcomes, eDisposition.12 was a mandatory entry for all patients irrespective of the outcome. eDisposition.12 describes the incident patient disposition, and it includes cases that were not treated and discharged, treated and discharged at the scene, refused care, treated and transported either by the EMS or other forms of transport, were assisted by the EMS and non-EMS personnel, and those that died at the scene with or without resuscitation. eDisposition.12 was recoded into two categories: death-at-the-scene and otherwise.

Predictor Variables: Crash Response Times

Two crash response times were defined. The first predictor is the duration from EMS notification to the EMS team departure from its base ("EMS Chute Time Mins"). The second predictor is the duration from the EMS team's departure from its base ("EMS Scene Response Time Min") to the time the team arrived at the crash scene (eTimes.06). These crash durations were pre-computed in the dataset.

Confounding

Age, gender, substance use, region of the body injured, revised trauma score, geographical location of the crash injury was used as potential confounders. The region of the body injured was recoded into five categories: head and neck, abdomen and genitals, chest and back, extremities, and multiple body injuries. The geographical location where the crash injury occurred was measured in three categories: rural/wilderness, suburban, and urban.

The revised trauma score was computed using the Glasgow Coma Scale score (GCS), Respiratory Rate (RR), and Systolic Blood Pressure (SBP). These three variables were re-categorized into five categories ranging from 0 to 4 as defined in the original documentation (Champion et al., 1989), and the final RTS was calculated as the sum of (0.9368*GCS category) + (0.7326*SBP category) + (0.2908*RR category). Missingness in the RTS was addressed by using the EMS final patient disposition as a proxy. The EMS final patient disposition, a variable that captures the clinical outcome after EMS intervention, was measured as multiple categorical variables: critical, emergent, low priority, and dead. To address the missing values in RTS, missing values in the GCS, RR, and SBP categories identified as a low priority were given a score of 4 since these patients would have stable vital signs, otherwise would not be categorized as low priority. Also, missing values in GCS, RR, and SBP categories that were categorized as critical, emergent, or dead were assigned values of 3, 2, and 1, respectively.

Analysis

Frequency distribution of the sociodemographic, crash, and injury characteristics were computed during the all-time, rush hour, and non-rush hour periods. Similarly, the mean (standard deviation) and the median (interquartile range) of the crash response times and the revised trauma scores were summarized. The prevalence of dead-at-the-scene was computed during the all-time and rush hour period. Logistic regression analysis was performed to assess the relationship between the crash response time and death-at-the-scene. Data were analyzed using STATA version 16 (StataCorp, 2020).

Results

A total of 1,203,527 persons were involved in all forms of road crashes, with 50.2% of these crashes occurring during the rush hour period (Table 3-1). The majority of the population were aged 36 – 55 years (27.5%) with an approximately equal male-female distribution. Multiple injuries over the general body (23.5%) followed by injury to the extremities (16.3%) and the head and neck (15.9%), were the commonly injured body parts. The median (IQR) RTS was 7.80 (0.29). Substance use-associated crash injury represented about 7.7% of the cases, and most of the cases occurred in the urban areas (83.4%). The median (IQR) crash notification time was 0.9 (1.5) minutes, while the median EMS travel time was 5.50 (5.80) minutes. Approximately 8,292 individuals (0.7%) died before the arrival of the EMS personnel.

There were statistically significant differences in the sociodemographic and crash characteristics during the rush and non-rush hour periods (Table 3-1). A larger proportion of crashes during the rush hour period involved individuals aged 35 to 55 years (Rush Hour (RH):28.1% vs. Non-Rush Hour (NRH): 26.9). More females were involved in rush hour-related (52.3%) crashes than in non-rush hour-related crashes (48.2%; $p<0.001$). Injuries to the head and neck (RH:16.2% vs. NRH:15.7%) were significantly higher during the rush hour period as compared to the non-rush hour period ($p<0.001$). The proportion of cases associated with substance use in the rush hour period (4.9%) were less than half the proportion of cases occurring in the non-rush hour period (10.5%; $p<0.001$). Further, the proportion of urban-related cases was slightly higher during the rush hour period than the non-rush hour period (RH: 83.7% vs. NRH:83.0%; $p<0.001$). The median crash notification time was shorter in the rush hour period (RH:0.88 minutes vs. NRH:0.97 minutes; $p<0.001$) while the median travel time was significantly longer during the rush hour period (RH:5.53 minutes vs. NRH:5.48 minutes; $p<0.001$). Dead on EMS arrival was higher during the non-rush hour period (0.8%) compared to the rush hour period (0.5%; $p<0.001$).

Age, gender, injured body region, substance use, geographical location of the injury, and RTS were significantly associated with death-at-the scene at all times of the day and the rush and non-rush hour periods (Table 3-2). Across all times of the day and during the rush hour period, the odds of deaths-at-the-scene increased with increasing age. The odds ratios were accentuated during the rush hour period, with crash victims older than 75 years having about 5-fold increased odds of being classified as death-at-the-scene. Males had approximately three-fold increased odds of being classified as death-at-the-scene compared to females during the all-time (OR: 2.74; 95% CI: 2.61-2.87) and rush hour periods (OR: 2.70; 95% CI: 2.50-2.91). Compared to multiple body injuries, cases of death-at-the-scene were less likely to be an injury to a specific part of the body during the all-time and rush hour periods. Further, substance use was associated with 21% and 56% increased odds of death-at-the-scene at all times of the day and during the rush hour, respectively. At all times of the day, crash injuries in rural/wilderness and suburban areas were 2.5 times (OR: 2.47; 95% CI: 2.33-2.62) and 1.9 times (OR: 1.93; 95% CI: 1.79-2.09) more likely to be classified as death-at-the-scene. During the rush hour period, the odds were further heightened with crash injuries in rural/wilderness and suburban areas 3.3 (95% CI: 2.98-3.55) and 2.2 (95% CI: 1.90-2.44) times more likely to be classified as death-at-the-scene. A unit increase in RTS was associated with 73% reduced odds of death-at-the-scene (OR: 0.27; 95% CI: 0.27-0.28) during the all-time period and the rush hour period.

In the unadjusted model, a minute increase in EMS notification time was associated with 2.5% (OR: 1.025; 95% CI: 1.018-1.031) and 3.4% (OR: 1.034; 95% CI: 1.024-1.044) increased odds of death at the scene at all times of the day and during the rush hour period, respectively (Table 3-2). Also, a minute increase in the EMS travel time was associated 0.4% (OR: 1.004; 95% CI: 1.003-1.005) and 0.6% (OR: 1.006; 95% CI: 1.004-1.007) increased odds of death-at-the-scene during all ties of the day and the rush hour period, respectively. After adjusting for age, gender, injured parts, substance use, RTS, and location of each crash, there was no substantial difference in the point estimates (Table 3-2). An interaction effect between the crash response time and location of crash (rural/suburban/urban) did not produce significantly elevated estimates (results not shown).

Discussion

About half of the crash injuries occurred during the rush-hour period. Cases classified as death-at-the-scene comprised less than 1% of all crashes that occurred at all times of the day and during the rush and non-rush-hour period. The median crash notification time was less than a minute during the rush and non-rush hours. EMS travel time was slightly longer during the rush hour period compared to the non-rush hour period. After adjusting for sociodemographic and crash characteristics, a minute prolongation of the EMS travel time was significantly associated with increased odds of death-at-the-scene, with the odds higher during the rush hour period.

Earlier studies that used the FARS dataset have reported that crashes involving at least one fatal event occurring during the rush hour period comprise approximately 40 percent of crash events (National Highway Traffic Safety Administration, 2019). Our study found that more than 50% of all persons involved in crash events in 2019 were exposed to crash events during the rush hour period. This difference in the estimates may be due to the differences in the population captured in the FARS and the NEMSIS datasets. While the FARS datasets report crashes in which at least one fatal event occurred during the crash event, the NEMSIS is all-encompassing of all crash events during which the EMS was activated. Thus, the NEMSIS may be a more representative pool of crash events across the U.S. with 50% of all crash victims sustaining crash injuries during the rush hour period.

The 2019 estimates of fatal crash counts ranged between 36,096 and 38,800 (National Center for Statistics and Analysis, 2020; National Safety Council, 2020). This study reports that cases classified as death-at-the-scene were a total of 8,292 – approximately 21 to 23 percent of all fatal crashes in 2019. Achieving zero fatality by 2050 (Ecola, Popper, Silberglitt, & Fraade-Blanar, 2018; Federal Highway Administration, 2020) would require interventions focused on reducing death-at-the-scene where about a quarter of crashes occur. The Trauma Quality Improvement Program coined the terms Dead on Arrival (DOA) and Died in Emergency (DIE) (Calland et al., 2012). This categorization was useful in eliminating bias when assessing performance of trauma centers (Calland et al., 2012). From an epidemiologic perspective, identifying death-at-the-scene cases may create an area of intervention, especially with regards to identifying the risk factors and which death types are salvageable and unsalvageable on the field.

This study provides an estimate of crash notification and travel times. From the time a 911 call was received to the time the EMS team leaves its base, the average duration was less than a minute. Additionally, the average travel time is less than seven minutes. These statistics may represent the underlying characteristics aiding the gradual decline in fatal crash counts (National Center for Statistics and Analysis, 2020; National Highway Traffic Safety Administration, 2020). However, the lack of a sharp decline may equally suggest that there is yet to be a successful intervention designed to target outlier regions. Bryne and colleagues (2019) reported a dose-response relationship with increasing crash response times and crash fatality. Additionally, earlier studies have estimated the disparity in the crash reported longer response and transport times in rural communities with hospital closures (Miller, James, Holmes, & Van Houtven, 2020). Optimal citing of EMS centers, especially in regions with prolonged crash response times, may strengthen the EMS nationally and may reduce deaths-at-the-scene.

This study reports that a minute increase in travel time was associated with increased odds of deaths-at-the-scene. From a prevention perspective, a minute reduction in the travel time is associated with 0.4% reduction in death-at-the-scene. In practice, if every EMS station can achieve a three-minute reduction in their travel times, about 100 lives may be saved, barring unsalvageable injuries. This study reports that the median response time is approximately six minutes and there are areas with much higher response times (right skewness). It is important, therefore, to identify areas with long EMS travel times to reduce death-at-the-scene.

The odds of death-at-the-scene are heightened during the rush hour period. The possibility exists that drivers and other road users may engage in risky driving behavior during the rush hour period, increasing the risk of death-at-the-scene. A meta-analysis reported that the rush hour period is associated with increased odds of fatal crash injuries (O. J. Adeyemi et al., 2021) Assessing factors associated with delay in crash response, therefore, becomes appropriate to design local, regional, and national interventions that will reduce delays. An earlier study, using the Fatality Analysis and Reporting System dataset, reported that a minute increase in crash fatality rate was associated with a three percent increased fatality risk (O. Adeyemi, Paul, & Arif, 2020). The rush hour period, therefore, may be a proxy for interventions for crash response times.

This study has its limitation. This is a cross-sectional study, with data pooled over a single study year. Therefore, causal inferences cannot be established. Since the EMS data were pooled across different agencies, the possibility of data entry errors cannot be eliminated. Misclassification of the outcome is highly unlikely since a diagnosis of death is a terminal outcome provided by trained personnel. While the results provide national estimates, NEMSIS data does not include four states. However, it is unlikely that these states' results will alter the estimates or disproportionately affect the crash response times or deaths-at-the-scene. The absence of county-level identifiers limits the generalization of this result for policy recommendations and practice. It is unlikely that the dependence of death on response time will exhibit a global pattern across the U.S. since different states have different crash response times. Additionally, small sample analytical bias is a concern as less than 1% of the sample population experienced death-at-the-scene. However, with over 8,000 cases of death-at-the-scene rarity of the event, which would have required logistic regression for rare events (King & Zeng, 2001) or the penalized likelihood method (Firth method) (Wang, 2014) is not indicated. It is unlikely that the maximum likelihood estimation will suffer from a small sample bias based on the cell counts (Allison, 2012). Despite these limitations, this study represents one of the few studies that report the proportion of death-at-the-scene and its association of crash response with these deaths during the rush hour period.

Conclusion

A substantial proportion of deaths occur at the crash scene. Approximately half of the persons involved in crash events were exposed to crashes during the rush hour period. EMS travel time was associated with increased odds of death-at-the-scene, and the odds of a case classified as death-at-the-scene is heightened during the rush hour period. Interventions aimed at reducing crash fatality rates may consider focusing on deaths-at-the-scene, while interventions aimed at shortening EMS travel time may consider using the rush hour period as a proxy.

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Tables and Figures: Manuscript 3

Table 3 - 1: Frequency distribution and summary statistics of the EMS crash response times, sociodemographic, clinical, and location-based characteristics

Variables	All Period (N=1,203,527)	Rush Hour (n=603,860)	Non-Rush Hour (n=599,667)	p-value*
	Frequency (%)	Frequency (%)	Frequency (%)	
Age				
< 16 years	101,446 (8.4)	59,462 (9.9)	41,984 (7.0)	<0.001
16-25 years	274,703 (22.8)	129,277 (21.4)	145,426 (24.3)	
26-35 years	233,371 (19.4)	113,986 (18.9)	119,385 (19.9)	
36-55 years	331,013 (27.5)	169,942 (28.1)	161,071 (26.9)	
56-75 years	216,022 (18.0)	109,053 (18.1)	106,969 (17.8)	
>75 years	46,972 (3.9)	22,140 (3.7)	24,832 (4.1)	
Gender				
Male	598,292 (49.7)	287,960 (47.7)	310,332 (51.8)	<0.001
Female	605,235 (50.3)	315,900 (52.3)	289,335 (48.2)	
Injured Region				
Head and Neck	191,514 (15.9)	97,621 (16.2)	93,893 (15.7)	<0.001
Abdomen and Genitals	26,129 (2.2)	13,342 (2.2)	12,787 (2.1)	
Chest and Back	146,467 (12.2)	75,239 (12.5)	71,228 (11.9)	
Extremities	196,699 (16.3)	97,987 (16.2)	98,712 (16.5)	
General Body	282,806 (23.5)	137,991 (22.8)	144,815 (24.1)	
Unknown	359,912 (29.9)	181,680 (30.1)	178,232 (29.7)	
Substance Use				
Yes	92,858 (7.7)	29,827 (4.9)	63,031 (10.5)	<0.001
No	753,065 (62.6)	392,952 (65.1)	360,113 (60.1)	
Unknown	357,604 (29.7)	181,081 (30.0)	176,523 (29.4)	
Geographical location				
Rural/Wilderness	99,869 (8.3)	48,245 (8.0)	51,624 (8.6)	<0.001
Suburban	61,896 (5.1)	30,354 (5.0)	31,542 (5.3)	
Urban	1,003,256 (83.4)	505,513(83.7)	497,743 (83.0)	
Unknown	38,506 (3.2)	19,748 (3.3)	18,758 (3.1)	
Revised Trauma Score				
Mean (SD)*	7.56 (0.69)	7.58 (0.65)	7.55 (0.73)	<0.001
Median (IQR)**	7.80 (0.29)	7.84 (0.29)	7.84 (0.29)	<0.001
EMS notification time				
Mean (SD)*	1.35 (2.58)	1.28 (2.44)	1.42 (2.71)	<0.001
Median (IQR)**	0.92 (1.52)	0.88 (1.40)	0.97 (1.65)	<0.001

Table 3-1 (Continued)

Variables	All Period (N=1,203,527)	Rush Hour (n=603,860)	Non-Rush Hour	
EMS travel time				
Mean (SD)*	7.04 (8.67)	7.00 (7.60)	7.09 (9.63)	<0.001
Median (IQR)**	5.50 (5.72)	5.53 (5.70)	5.48 (5.71)	<0.001
Mortality Status				
Dead	8,292 (0.7)	3,238 (0.5)	5,054 (0.8)	<0.001
Not Dead	1,195,235 (99.3)	600,622 (99.5)	594,613 (99.2)	

*Independent sample T-test performed; **Mann Whitney U test performed

Table 3 - 2: Summary of the odds of fatal cases associated with EMS response times, sociodemographic, clinical, and location-based characteristics, measured across all periods and the rush hour period.

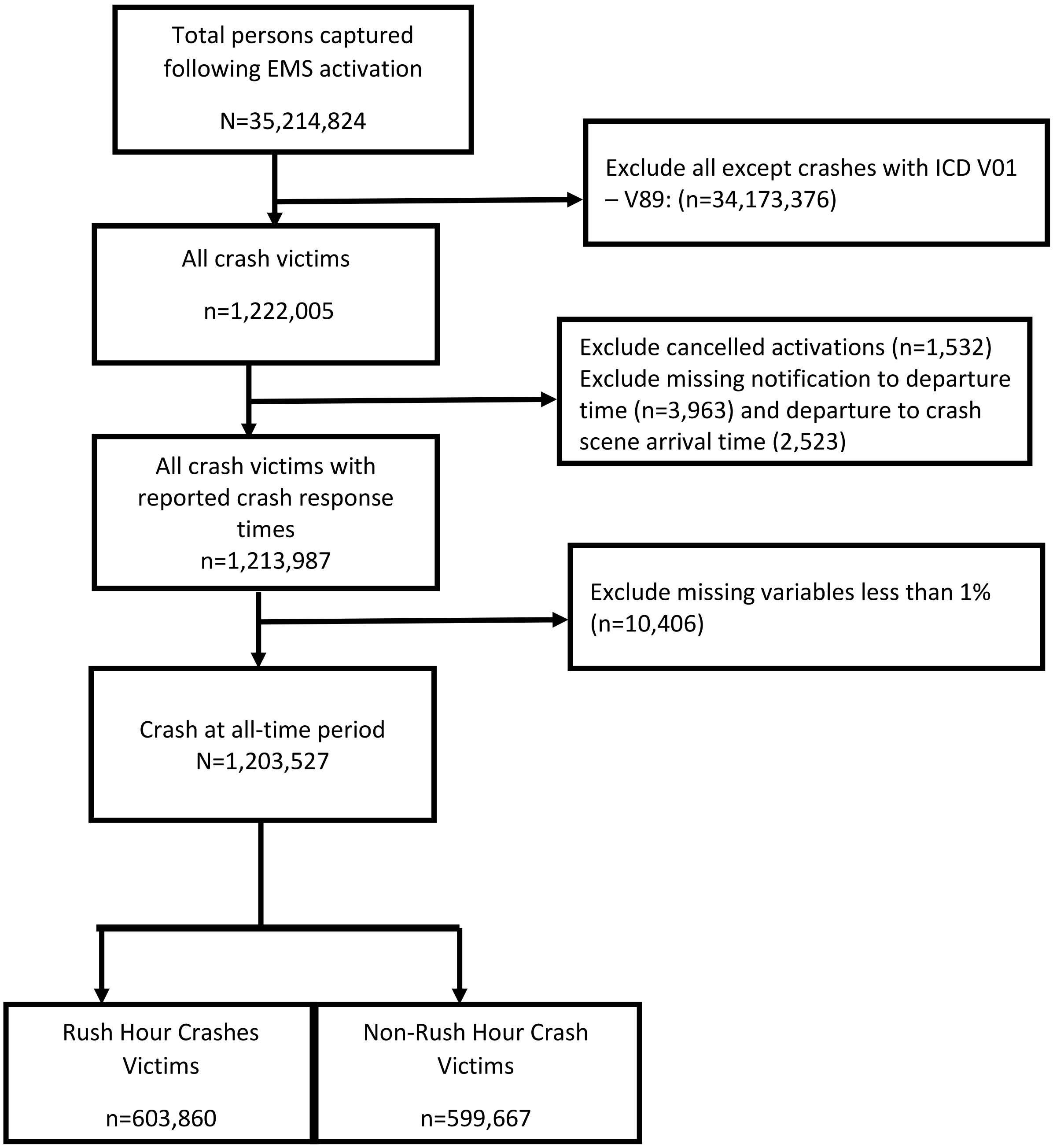
Variables	All Period (N=1,203,527)	Rush Hour (n=603,860)	Non-Rush Hour (n=599,667)
	Odds Ratio (95% CI)	Odds Ratio (95% CI)	Odds Ratio (95% CI)
Age			
16-25 years	2.45 (2.14 – 2.81)	2.28 (1.85 – 2.80)	2.33 (1.94 – 2.79)
26-35 years	3.38 (2.95 – 3.87)	3.06 (2.50 – 3.75)	3.30 (2.75 – 3.96)
36-55 years	3.14 (2.75 – 3.58)	3.04 (2.50 – 3.71)	3.01 (2.51 – 3.60)
56-75 years	3.52 (3.08 – 4.03)	3.96 (3.24 – 4.84)	3.02 (2.52 – 3.64)
>75 years	4.04 (3.45 – 4.73)	5.52 (4.38 – 6.94)	2.90 (2.33 – 3.61)
< 16 years	Ref	Ref	Ref
Gender			
Male	2.74 (2.61 – 2.87)	2.70 (2.50 – 2.91)	2.69 (2.52 – 2.86)
Female	Ref	Ref	Ref
Injured Region			
Head and Neck	0.20 (0.18 – 0.22)	0.18 (0.15 – 0.21)	0.22 (0.19 – 0.24)
Abdomen and Genitals	0.04 (0.03 – 0.06)	0.03 (0.01 – 0.07)	0.04 (0.02 – 0.08)
Chest and back	0.14 (0.13 – 0.16)	0.14 (0.11 – 0.17)	0.14 (0.12 – 0.17)
Extremities	0.01 (0.01 – 0.02)	0.02 (0.01 – 0.03)	0.01 (0.01 – 0.02)
Multiple Body Injury	Ref	Ref	Ref
Substance Use			
Yes	1.21 (1.10 – 1.32)	1.56 (1.33 – 1.83)	0.97 (0.87 – 1.09)
No	Ref	Ref	Ref
Geographical location			
Rural/Wilderness	2.47 (2.33 – 2.62)	3.25 (2.98 – 3.55)	2.01 (1.86 – 2.17)
Suburban	1.93 (1.79 – 2.09)	2.16 (1.90 – 2.44)	1.79 (1.61 – 1.98)
Urban	Ref	Ref	Ref
Revised Trauma Score**	0.27 (0.27 – 0.28)	0.27 (0.26 – 0.27)	0.28 (0.27 – 0.28)
EMS notification time	1.025 (1.018 – 1.031)	1.034 (1.024 – 1.044)	1.016 (1.007 – 1.024)
EMS travel time	1.004 (1.003 – 1.005)	1.006 (1.004 – 1.007)	1.003 (1.002 – 1.004)

Table 3 - 3: Summary of the adjusted logistic regression models across all time and during the rush hour period, estimating the odds of fatal cases across different EMS response times.

Variables	All Period	Rush Hour	Non-Rush Hour
	Adjusted Odds Ratio (95% CI)	Adjusted Odds Ratio (95% CI)	Adjusted Odds Ratio (95% CI)
EMS notification time	0.974 (0.965 – 0.983)	0.983 (0.969 – 0.999)	0.967 (0.954 – 0.979)
EMS travel time	1.004 (1.003 – 1.006)	1.007 (1.005 – 1.009)	1.003 (1.002 – 1.005)

Models adjusted for age, gender, injured parts, substance use, location of crash (rural/urban/suburban)

Figure 3- 1: Data selection steps



Appendix 4: STATA Codes

```
tab binoutcome,m

tab agecat,m

tab gender,m

*tab race2,m

tab injpart,m

tab alcdrug2,m

tab rur1sub2urb3,m

tabstat rts2, statistics (mean, sd, p50, range, iqr)

tabstat notdep, statistics (mean, sd, p50, range, iqr)

tabstat depscene, statistics (mean, sd, p50, range, iqr)

tab binoutcome if rushhr==1,m

tab agecat if rushhr==1,m

tab gender if rushhr==1,m

tab injpart if rushhr==1,m

tab alcdrug2 if rushhr==1,m

tab rur1sub2urb3 if rushhr==1,m

tabstat rts2 if rushhr==1, statistics (mean, sd, p50, range, iqr)

tabstat notdep if rushhr==1, statistics (mean, sd, p50, range, iqr)
```

```
tabstat depscene if rushhr==1, statistics (mean, sd, p50, range, iqr)

tab binoutcome if rushhr!=1,m

tab agecat if rushhr!=1,m

tab gender if rushhr!=1,m

*tab race2 if rushhr!=1,m

tab injpart if rushhr!=1,m

tab alcdrug2 if rushhr!=1,m

tab rur1sub2urb3 if rushhr!=1,m

tabstat rts2 if rushhr!=1, statistics (mean, sd, p50, range, iqr)

tabstat notdep if rushhr!=1, statistics (mean, sd, p50, range, iqr)

tabstat depscene if rushhr!=1, statistics (mean, sd, p50, range, iqr)

replace rur1sub2urb3 = 9 if rur1sub2urb3==.

tab binoutcome rushhr, chi2 m

tab agecat rushhr, chi2 m

tab gender rushhr,chi2 m

tab race2 rushhr,chi2 m

tab injpart rushhr,chi2 m

tab alcdrug2 rushhr,chi2 m
```

tab rur1sub2urb3 rushhr, chi2 m

ttest rts2, by(rushhr)

ttest notdep, by(rushhr)

ttest depscene, by(rushhr)

ranksum rts2, by(rushhr)

ranksum notdep, by(rushhr)

ranksum binoutcome, by(rushhr)

tab crowd,m

tab nolocate,m

tab distance,m

tab diversion,m

tab routeobs,m

tab staff,m

tab traffic,m

tab weather,m

tab crowd binoutcome, chi2 col m

tab nolocate binoutcome, chi2 col m

tab distance binoutcome, chi2 col m

```
tab diversion binoutcome, chi2 col m

tab routeobs binoutcome, chi2 col m

tab staff binoutcome, chi2 col m

tab traffic binoutcome, chi2 col m

tab weather binoutcome, chi2 col m

tab nolocate if rushhr==1,  m

tab distance if rushhr==1,  m

tab routeobs if rushhr==1,  m

tab traffic if rushhr==1,  m

tab weather if rushhr==1,  m

tab nolocate if rushhr!=1,  m

tab distance if rushhr!=1,  m

tab routeobs if rushhr!=1,  m

tab traffic if rushhr!=1,  m

tab weather if rushhr!=1,  m

tab nolocate binoutcome if rushhr==1, chi2 col m

tab distance binoutcome if rushhr==1, chi2 col m

tab routeobs binoutcome if rushhr==1, chi2 col m
```

tab traffic binoutcome if rushhr==1, chi2 col m

tab weather binoutcome if rushhr==1, chi2 col m

tab nolocate binoutcome if rushhr!=1, chi2 col m

tab distance binoutcome if rushhr!=1, chi2 col m

tab routeobs binoutcome if rushhr!=1, chi2 col m

tab traffic binoutcome if rushhr!=1, chi2 col m

tab weather binoutcome if rushhr!=1, chi2 col m

logistic binoutcome i.agecat

logistic binoutcome 1.gender

logistic binoutcome i.race2

logistic binoutcome i.injpart

logistic binoutcome i.alcdrug2

logistic binoutcome i.rur1sub2urb3b

logistic binoutcome rts2

logistic binoutcome notdep

logistic binoutcome depscene

logistic binoutcome i.agecat if rushhr==1

logistic binoutcome 1.gender if rushhr==1 logistic binoutcome i.race2 if rushhr==1

logistic binoutcome i.injpart if rushhr==1

logistic binoutcome i.alcdrug2 if rushhr==1

logistic binoutcome i.rur1sub2urb3b if rushhr==1

logistic binoutcome rts2 if rushhr==1

logistic binoutcome notdep if rushhr==1

logistic binoutcome depscene if rushhr==1

logistic binoutcome i.agecat

logistic binoutcome 1.gender

logistic binoutcome i.race2

logistic binoutcome i.injpart

logistic binoutcome i.alcdrug2

logistic binoutcome i.rur1sub2urb3b

logistic binoutcome rts2

logistic binoutcome notdep

logistic dead depscene

logistic binoutcome notdep i.agecat 1.gender i.race2 i.injpart i.alcdrug2 i.rur1sub2urb3b rts2

```
logistic binoutcome depscene i.agecat 1.gender  i.race2 i.injpart i.alcdrug2
i.rur1sub2urb3b rts2

logistic binoutcome notdep i.agecat 1.gender  i.race2 i.injpart i.alcdrug2 i.rur1sub2urb3b
rts2 if rushhr==1

logistic binoutcome depscene i.agecat 1.gender  i.race2 i.injpart i.alcdrug2
i.rur1sub2urb3b rts2  if rushhr==1

gen rur1sub2urb3b = rur1sub2urb3

replace rur1sub2urb3b = 0 if rur1sub2urb3==3

gen alcdrug2b = alcdrug2

replace alcdrug2b=0 if alcdrug2==2

tab binoutcome,m

tab agecat,m

tab gender,m

tab race2,m

tab injpart,m

tab alcdrug2,m

tab rur1sub2urb3,m

tabstat rts2, statistics (mean, sd, p50, range, iqr)

tabstat notdep, statistics (mean, sd, p50, range, iqr)
```

```
tabstat depscene, statistics (mean, sd, p50, range, iqr)

logistic  binoutcome nolocate

logistic  binoutcome distance

logistic  binoutcome routeobs

logistic  binoutcome traffic

logistic  binoutcome weather

logistic  binoutcome nolocate if rushhr==1

logistic  binoutcome distance if rushhr==1

logistic  binoutcome routeobs if rushhr==1

logistic  binoutcome traffic if rushhr==1

logistic  binoutcome weather if rushhr==1

qreg depscene nolocate, quantile(50)

qreg depscene distance, quantile(50)

qreg depscene routeobs, quantile(50)

qreg depscene traffic, quantile(50)

qreg depscene weather, quantile(50)

qreg depscene nolocate if rushhr==1, quantile(50)

qreg depscene distance if rushhr==1, quantile(50)
```

```
qreg depscene routeobs if rushhr==1, quantile(50)

qreg depscene traffic if rushhr==1, quantile(50)

qreg depscene weather if rushhr==1, quantile(50)

tab dead,m

tab agecat,m

tab gender,m

*tab race2,m

tab injpart,m

tab alcdrug2,m

tab rur1sub2urb3,m

tabstat rts, statistics (mean, sd, p50, range, iqr)

tabstat notdep, statistics (mean, sd, p50, range, iqr)

tabstat depscene, statistics (mean, sd, p50, range, iqr)

tab binoutcome if rushhr==1,m

tab agecat if rushhr==1,m

tab gender if rushhr==1,m

*tab race2 if rushhr==1,m

tab injpart if rushhr==1,m
```

```
tab alcdrug2 if rushhr==1,m

tab rur1sub2urb3 if rushhr==1,m

tabstat rts2 if rushhr==1, statistics (mean, sd, p50, range, iqr)

tabstat notdep if rushhr==1, statistics (mean, sd, p50, range, iqr)

tabstat depscene if rushhr==1, statistics (mean, sd, p50, range, iqr)

tab binoutcome if rushhr!=1,m

tab agecat if rushhr!=1,m

tab gender if rushhr!=1,m

*tab race2 if rushhr!=1,m

tab injpart if rushhr!=1,m

tab alcdrug2 if rushhr!=1,m

tab rur1sub2urb3 if rushhr!=1,m

tabstat rts2 if rushhr!=1, statistics (mean, sd, p50, range, iqr)

tabstat notdep if rushhr!=1, statistics (mean, sd, p50, range, iqr)

tabstat depscene if rushhr!=1, statistics (mean, sd, p50, range, iqr)

destring eVitals_19 eVitals_20 eVitals_21, generate(ev19 ev20 ev21) force

gen gcs= ev19 + ev20 + ev21

replace gcs =. if gcs > 15
```

```
gen sbp = eVitals_06

gen rr = eVitals_14

replace sbp =. if sbp > 1000

replace rr=. if rr > 1000

gen gcscat = .

replace gcscat=4 if gcs >=13 & gcs <=15

replace gcscat=3 if gcs >=9 & gcs <=12

replace gcscat=2 if gcs >=6 & gcs <=8

replace gcscat=1 if gcs >=4 & gcs <=5

replace gcscat=0 if gcs ==3

gen sbpcat =.

replace sbpcat= 4 if sbp > 89

replace sbpcat= 3 if sbp >= 76 & sbp<= 89

replace sbpcat= 2 if sbp >= 50 & sbp<= 75

replace sbpcat= 1 if sbp >= 1 & sbp<=49

replace sbpcat= 0 if sbp ==0

gen rrcat=.

replace rrcat = 4 if rr >=10 & rr <=29
```

replace rrcat = 3 if rr >29

replace rrcat = 2 if rr >=6 & rr <=9

replace rrcat = 1 if rr >=1 & rr <=5

replace rrcat = 0 if rr ==0

replace gcscat=4 if outcome==0 & gcscat==.

replace gcscat=3 if outcome==1 & gcscat==.

replace gcscat=2 if outcome==2 & gcscat==.

replace gcscat=1 if outcome==3 & gcscat==.

replace gcscat=4 if rrcat==4 & gcscat==.

replace gcscat=3 if rrcat==3 & gcscat==.

replace gcscat=2 if rrcat==2 & gcscat==.

replace gcscat=1 if rrcat==1 & gcscat==.

replace gcscat=0 if rrcat==0 & gcscat==.

replace rrcat=4 if outcome==0 & rrcat==.

replace rrcat=3 if outcome==1 & rrcat==.

replace rrcat=2 if outcome==2 & rrcat==.

replace sbpcat=4 if outcome==0 & sbpcat==.

replace sbpcat=3 if outcome==1 & sbpcat==.

```
replace sbpcat=2 if outcome==2 & sbpcat==.

gen rts = (0.9368 * gcscat) + (0.7326 * sbpcat) + (0.2908 * rrcat)

tab dead,m

tab agecat,m

tab gender,m

*tab race2,m

tab injpart,m

tab alcdrug2,m

tab rur1sub2urb3,m

tabstat rts, statistics (mean, sd, p50, range, iqr)

tabstat notdep, statistics (mean, sd, p50, range, iqr)

tabstat depscene, statistics (mean, sd, p50, range, iqr)

bysort rushhr_new: tab dead,m

bysort rushhr_new: tab agecat,m

bysort rushhr_new: tab gender,m

*tab race2,m

bysort rushhr_new: tab injpart,m

bysort rushhr_new: tab alcdrug2,m
```

bysort rushhr_new: tab rur1sub2urb3,m

bysort rushhr_new: tabstat rts, statistics (mean, sd, p50, range, iqr)

bysort rushhr_new: tabstat notdep, statistics (mean, sd, p50, range, iqr)

bysort rushhr_new: tabstat depscene, statistics (mean, sd, p50, range, iqr)

ab dead rushhr_new, chi2 m

tab agecat rushhr_new, chi2 m

tab gender rushhr_new,chi2 m

*tab race2 rushhr_new,chi2 m

tab injpart rushhr_new,chi2 m

tab alcdrug2 rushhr_new,chi2 m

tab rur1sub2urb3 rushhr_new, chi2 m

ttest rts, by(rushhr_new)

ttest notdep, by(rushhr_new)

ttest depscene, by(rushhr_new)

ranksum rts, by(rushhr_new)

ranksum notdep, by(rushhr_new)

ranksum depscene, by(rushhr_new)

logistic dead i.agecat

```
logistic dead 1.gender

logistic dead i.injpart

logistic dead i.alcdrug2

logistic dead i.rur1sub2urb0

logistic dead rts

logistic dead notdep

logistic dead depscene

gen rur1sub2urb0 = rur1sub2urb3

replace rur1sub2urb0=0 if rur1sub2urb3==3

logistic dead i.agecat if rushhr_new==1

logistic dead 1.gender if rushhr_new==1

*logistic dead i.race2 if rushhr_new==1

logistic dead i.injpart if rushhr_new==1

logistic dead i.alcdrug2 if rushhr_new==1

logistic dead i.rur1sub2urb0 if rushhr_new==1

logistic dead rts if rushhr_new==1

logistic dead notdep if rushhr_new==1

logistic dead depscene if rushhr_new==1
```

*adjusted

logistic dead notdep i.agecat 1.gender i.injpart i.alcdrug2 i.rur1sub2urb0 rts

logistic dead depscene i.agecat 1.gender i.injpart i.alcdrug2 i.rur1sub2urb0 rts

logistic dead notdep i.agecat 1.gender i.injpart i.alcdrug2 i.rur1sub2urb0 rts if rushhr_new==1

logistic dead depscene i.agecat 1.gender i.injpart i.alcdrug2 i.rur1sub2urb0 rts if rushhr_new==1

CHAPTER 5
Summary of Findings

Summary of Findings

Epidemiology of Rush-Hour Crash Injuries

This dissertation set out to assess the characteristics of fatal and non-fatal crash injury rush-hour-related crash injuries across three domains: environmental determinants of crash injuries, substance use, and crash response time. Using the FARS dataset, the model-adjusted prevalence of rush-hour-related fatal crashes was 7.3 per 100,000 population. The age-adjusted prevalence of fatal crash injuries between 2010 and 2018, estimated using the Centers for Disease Prevention and Controls' WISQAR tool, was 11.5 per 100,000 (WISQAR, 2020). An earlier study had reported elevated fatal crash rates among males and those aged 20 to 24 years (National Highway Traffic Safety Administration, 2016).

The spatial location of fatal crash injuries is important crash injury information as these information guides decisions on national, state, and local policies on crash injury prevention, funding of projects, and the design of interventions. This dissertation identified clusters of fatal crash injuries during the rush-hour period in counties in Idaho, Montana, Nevada, California, Wyoming, Utah, New Mexico, Texas, Colorado, Arkansas, Kentucky, Tennessee, and Alabama. These clusters identified counties with significantly elevated fatal crash injury risks due to environmental factors. A similar procedure could be computed with other risk factors such as substance use, seat belt use, distracted driving, and speeding. An earlier study, using spatial clustering techniques, identified multiple counties in South Dakota, Texas, and Mississippi, as areas with elevated fatal crash injuries from non-use of seat belt among older drivers (Adeyemi, Paul, & Arif, 2020b).

Environmental Risk Factors of Rush Hour-Related Fatal Crash Injury

This dissertation reports that the case-specific fatality rates from interstates, highways, roads, streets, intersections, rain, fog, and snow were higher than the median fatality rates. Additionally, during the rush hour period, fatal crash injury rates were significantly elevated on interstates, highways, roads and streets, intersections, driveways, and work zones.

An earlier report had estimated that, between 2007 and 2016, rain accounted for up to 46% of all weather-related fatal crashes while snow and fog account for 13% and 9% of all weather-related fatal crashes(Federal Highway Administration, 2020). Also, earlier studies have reported increased weather-related fatal crash risks on raining days, during the evening rush-hour period (Black, Villarini, & Mote, 2017; Call, Medina, & Black, 2019).

Rurality and urbanicity are factors that are infrequently considered when reporting spatial fatal crash injury patterns (Adeyemi, Paul, & Arif, 2020a; Byrne et al., 2019). In this dissertation, the median crash fatality rates were significantly higher in rural counties as compared to urban counties. Elevated fatality rates from in rural areas as compared to urban areas, has been reported in earlier studies (National Center for Statistics and Analysis, 2012, 2019). The additional contribution of this dissertation are the estimates provided during the rush-hour period and the association of the environmental characteristics.

Substance Use as a Risk Factor for Non-Fatal Crash Injury

This dissertation reports increased odds of critical and emergent injuries among crash victims with substance use. Substance use was associated with over two-fold adjusted odds of critical and emergent injury severities, across all times of the day, and during the rush and non-rush hour periods. The relationship of injury severity and alcohol had never been in doubt as evidence from numerous studies have reported a significant association between alcohol and fatal and non-fatal crash injury or events (Albalate, 2008; Allamani et al., 2013; Chen, Tsai, Fortin, & Cooper, 2012; Compton & Berning, 2015). Also, there is compelling evidence that marijuana use is associated with elevated crash injury risks (Blows et al., 2005; Bondallaz et al., 2016; M. C. Li et al., 2012; Santaella-Tenorio et al., 2020). This dissertation did not seek to separate the different components measured as substance use.

Crash Response Time as a Risk Factor for Deaths at the Crash Scene

About half of the crash injuries occurred during the rush hour period. Cases classified as death-at-the-scene comprised less than 1% of all crashes that occurred at all times of the day and during the rush hour period. Also, the median crash notification time was less than a minute during the rush and non-rush hours. EMS travel time was slightly longer during the rush hour period compared to the non-rush hour period. After adjusting for sociodemographic and crash characteristics, a minute prolongation of the EMS travel time was significantly associated with increased odds of death-at-the-scene, with the odds higher during the rush hour period.

Implications for Public Health Policy and Practice

Fatal crash injuries are preventable and non-fatal crash injuries rates can be reduced. This dissertation identifies some of the human, environmental, and institutional factors associated with fatal and non-fatal crash injuries in the rush hour period. There may be a need for policies that will make the road environment safer for road users, especially during the rush-hour period. Strengthening policies on substance use while driving and crash response times may be required as injury severity and fatality are significantly affected by these risk factors, respectively.

This dissertation identifies spatial clusters of fatal crash injury modeled based on the environmental risk factors. In identifying locations with significantly elevated fatal crash injury rates, this dissertation provides information on areas that might need focused intervention. In the presence of competing public health needs, this study can guide decisions on states and counties that need funding for intervention-based projects.

The harm associated with substance use has never been in question. Several studies have quantified the associated risks of substance use of crash events (Blows et al., 2005; Bondallaz et al., 2016; Bramness, Skurtveit, Mørland, & Engeland, 2012; Kumar, Bansal, Singh, & Medhi, 2015; G. Li, Brady, & Chen, 2013; M. C. Li et al., 2012; Thomas et al., 2020). This dissertation, using a clinical assessment, estimated the odds of critical and emergent injuries. This information is useful in prehospital planning of prehospital care, predicting the severity of injury from relevant 911 calls, and provide adequate care for crash injury patients with substance use.

The rush-hour period may be a proxy in assessing risk factors of fatal and non-fatal crash injuries. The rush-hour period, however, is not a well-researched area. However, with human, vehicular, and environmental exhibiting complex interactions during the rush-hour period, the rush-hour may be a useful period to conduct crash prevention interventions.

Future Directions

The rush-hour period may serve as a proxy for crash prevention interventions, as some crash characteristics are elevated during this period. Future studies may assess the trend of rush hour fatal crash counts and events during the rush-hour period. Additionally, the possibility remains that a single fatal crash may be associated with multiple fatalities. It is not known if rush-hour-related fatal crash events are associated with multiple fatalities. These studies may further identify the rush-hour period as an area for crash-related intervention.

Rurality and urbanicity may play a role in substance-use injury severity since crash response times are longer in rural areas compared to urban areas. With death-at-the-crash-scene, an infrequent outcome of crash response, estimating its prevalence, and rural and urban differences may present areas for future research. Additionally, assessing how risky driving behaviors such as substance use, speeding, seat belt use, and distracted driving differ by rurality and urbanicity and their association to crash injury severity may present additional areas of research. Further, the literature is sparse on the spatial clusters of risky driving behaviors and risky driving-related fatal crash injuries.

The delay factors associated with crash response time are an important domain of research. No study has evaluated how delay factors are mediated by the crash response time. Understanding the association of crash response time and the delay factors may provide insight into areas in need of EMS structural and policy-based strengthening. It is unknown how these delay factors vary by rural and urban locations. Further, assessing the optimal location of EMS base stations in rural locations that will achieve adequate crash coverage remains an unexplored area of research. The incorporation of telehealth, helicopter services, and drones into emergency response systems has the potential to shorten crash response time and provide additional areas of research.

Conclusion

Substantial fatal and non-fatal crash injuries occur during the rush-hour period. Natural factors such as rain, fog, and snow are associated with elevated fatal crash injury rates during the rush-hour period and elevated fatal crash injuries occur on interstates, highways, roads, streets, and intersections during the rush hour period. Substance use is associated with elevated odds of critical and emergent injuries and delay in EMS travel time is associated with elevated odds of deaths at the crash scene.

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