COVID AND TRAFFIC CRASHES/IMPACT ON SAFETY TARGETS

Authors

Peter T. Savolainen, Timothy J. Gates, Kakan Dey, Yazmin Dasgar, Sunday Imosemi, Nischal Gupta, Samuel Goodluck, Vahid Bahrami

Sponsoring Organization

Michigan Department of Transportation

Performing Organization

Michigan State University

Department of Civil and Environmental Engineering

428 South Shaw Lane

East Lansing, MI 48824

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16. Abstract
The COVID-19 pandemic resulted in substantial disruptions to travel behavior and transportation systems across the United States. While traffic volumes declined sharply during the early stages of the pandemic, many jurisdictions experienced increases in traffic fatalities and serious injuries. Understanding the factors contributing to these changes is critical for improving roadway safety and informing future policy responses. This study investigates trends in traffic fatalities following the COVID-19 pandemic using a multi-scale analytical framework. The analysis first examines fatality trends at the national level using state-level and county-level data for the period 2019–2023. These analyses provide a broad understanding of how traffic safety outcomes evolved across the United States during and after the pandemic. The study then focuses on Michigan, where more detailed crash data enabled a deeper investigation of contributing factors. Michigan analyses were conducted at multiple spatial and analytical levels, including county-level fatality trend analyses, roadway segment-level crash analyses, and party-involved severity analyses using crash records from the Michigan State Police Traffic Crash Reporting System for the period 2019–2024. The segment-level analyses were conducted separately across five roadway facility types, including freeways, multilane divided highways, multilane undivided highways, rural two-lane roads, and urban two-lane highways. These data were supplemented with roadway inventory information and probe vehicle speed data to examine how roadway characteristics, operating speeds, traffic conditions, and driver-related factors influence crash outcomes and injury severity. The results highlight significant changes in roadway safety trends following the onset of the pandemic. Although reductions in traffic demand initially reduced overall crash frequencies, increases in risky driving behaviors and changes in travel patterns contributed to higher fatality rates in many locations. In particular, the analyses suggest that changes in driver behavior, including increased speeding, higher rates of impaired driving, and reductions in seat belt use, played an important role in the observed increases in fatal and severe injury crashes following the pandemic. Detailed analyses of Michigan crash data provide further insight into the roadway, environmental, and behavioral factors associated with severe crash outcomes across different roadway facility types. Based on these findings, the study identifies several countermeasures that may help mitigate increases in fatalities and serious injuries. These strategies include infrastructure improvements, targeted enforcement efforts, and safety interventions aimed at reducing high-risk driving behaviors and improving protection for vulnerable road users. The findings provide important insights for transportation agencies seeking to improve roadway safety and develop resilient strategies for responding to future disruptions in travel behavior.

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FINAL REPORT

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Principal Investigator
Peter T. Savolainen, PhD., P.E.
MSU Foundation Professor

Co-Principal Investigator
Timothy J. Gates, PhD., P.E., P.T.O.E.
Professor

Kakan Dey, PhD., P.E.
Associate Professor

Authors
Peter T. Savolainen, Timothy J. Gates, Kakan Dey, Yazmin Dasgar, Sunday Imosemi, Nischal Gupta, Samuel Goodluck, Vahid Bahrami

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A report from
Michigan State University
Department of Civil and Environmental Engineering
428 South Shaw Lane
East Lansing, MI 48824

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EXECUTIVE SUMMARY

The COVID-19 pandemic resulted in unprecedented disruptions in travel behavior. In turn, these changes led to unexpected increases in traffic fatalities throughout the United States. Beginning in early 2020, public health restrictions and shifts in work and travel patterns resulted in sharp reductions in traffic demand. Nationally, vehicle miles traveled declined by approximately 11 percent between 2019 and 2020, while Michigan experienced a larger reduction of approximately 15.4 percent. These reductions in travel were accompanied by significant declines in total crashes. However, despite these decreases in travel demand and crash frequency, roadway fatalities increased across much of the United States. National fatalities increased by approximately 7 percent in 2020 and continued rising through 2021. Michigan was among several states that exhibited increases that were higher than the national average, as fatalities rose by 10 percent during this same period. These changes slowed progress toward established safety performance targets and raised concerns regarding the factors contributing to increased crash severity during the pandemic period.

As travel levels gradually rebounded toward long-term averages, fatality rates remained elevated relative to pre-pandemic conditions. To better understand these trends, this study involved a multi-scale evaluation of crash data from 2019 through 2023. Monthly fatality data were analyzed at the state level, allowing comparisons across all 50 states. Additional county-level analyses were conducted within Michigan to examine spatial variation in fatal and serious injury outcomes. Across the United States, fatalities declined briefly during the earliest months of the pandemic in 2020 but, increased sharply thereafter, remaining elevated through 2023 despite the gradual recovery of travel demand. Geographic differences were also evident. Southern states generally exhibited the highest fatalities during the study period, whereas northeastern states experienced comparatively lower fatalities. Within Michigan, substantial regional differences were observed. The Detroit metropolitan region exhibited significantly higher fatal and serious injury outcomes compared with other areas of the state, while the more rural northern regions experienced comparatively lower fatality rates. Increases were particularly concentrated during higher-travel months and were frequently associated with crashes involving alcohol, drugs, and vulnerable road users.

At the national level, fatality trends were analyzed at both the state and county levels across the United States for the period 2019–2023 using data from the National Highway Traffic Safety Administration's Fatality Analysis Reporting System and other publicly available datasets. The more detailed analyses for the state of Michigan incorporated detailed crash, roadway inventory, traffic exposure, and probe vehicle speed data. These datasets were integrated to allow for examination of crash trends at the county-, segment-, and person-level.

Between 2019 and 2021, total fatalities increased by nearly 19 percent nationally, representing the largest increase in roadway fatalities in several decades. Fatality rates per vehicle mile traveled increased even more sharply during the early pandemic period, even as traffic volumes declined. County-level analyses showed that fatality outcomes varied substantially across geographic regions, with some of these differences tied to demographic, socioeconomic, and travel-related factors.

Michigan-specific analyses provide additional insight into these trends. During March and April of 2020, crash counts in Michigan declined by more than 40 percent relative to typical monthly levels observed in 2019. These reductions were closely associated with decreases in traffic demand during the early pandemic period. However, these reductions were temporary. As travel activity recovered during late 2020 and throughout 2021 and 2022, crash frequencies increased. Although total crash counts remained slightly below pre-pandemic levels in some cases, the proportion of crashes resulting in fatal or serious injuries remained elevated.

Probe vehicle speed data show that operating speeds increased during the early stages of the pandemic during periods of reduced congestion. Operating speeds were generally highest during 2021 and 2022, and although speeds moderated somewhat during 2023 and 2024, they remained elevated relative to pre-pandemic levels. These results suggest some general changes in driver behavior that may have arisen during the pandemic.

Segment-level crash analyses were also conducted separately for freeways, multilane divided highways, multilane undivided highways, rural two-lane, and urban two-lane facilities. Traffic exposure (in terms of monthly average daily traffic) was consistently associated with crash frequency across all facility types, though more sensitive for some facility types (e.g., rural two-lane highways) than others (e.g., freeways). Roadway geometry also played an important role. Horizontal curvature was associated with increased crash frequency, while wider shoulders and the presence of medians were generally associated with lower crash frequencies. Seasonal effects were also observed, with crash frequencies typically lower during early spring months and higher during fall months.

Person-level analyses were also conducted, focusing on crash-involved drivers. Separate analyses were again conducted for different roadway facility types to evaluate factors influencing injury severity. Results indicate that pedestrians and bicyclists experience substantially higher injury severity compared with vehicle occupants, reflecting the greater vulnerability of non-motorized roadway users. Age also played an important role, with individuals aged 65 and older experiencing higher injury severity compared with younger age groups. Behavioral factors such as alcohol and drug involvement were strongly associated with increased injury severity. In contrast, seat belt use was consistently associated with lower injury severity across all roadway facility types. Environmental conditions also influenced injury outcomes, with crashes occurring under nighttime conditions generally associated with higher injury severity relative to daytime crashes.

Taken together, the results indicate that the pandemic period produced several important changes in roadway safety conditions. Although reductions in travel demand initially reduced crash totals, changes in operating speeds and driver behavior contributed to increased crash severity. Reduced congestion created conditions that allowed higher operating speeds, and these changes persisted even after travel demand began returning toward pre-pandemic levels. At the same time, risky driving behaviors, including impaired driving, and reduced seat belt use, contributed to higher injury severity outcomes.

Based on these findings, several strategies were identified to help mitigate increases in fatalities and serious injuries. This includes speed management practices to reduce operating speeds and speed variability. Behavioral countermeasures targeting impaired driving and non-use of seat belts are also critical for reducing severe crash outcomes, both of which are proven countermeasures.

Overall, this study shows how roadway safety conditions evolved during and after the COVID-19 pandemic. The findings demonstrate that both changes in travel patterns and shifts in driver behavior contributed to increases in crash severity during the pandemic period. These results provide important insights for transportation agencies seeking to improve roadway safety and to develop strategies capable of reducing fatalities and serious injuries.

1 INTRODUCTION

1.1 Background

The COVID-19 pandemic brought about unprecedented disruptions to daily life, with impacts that reached far beyond public health. The global response to this crisis altered social and economic activities, reshaping travel patterns and transportation safety worldwide. On January 21, 2020, the first case of COVID-19 was reported in the United States, followed by the first related death on March 1, 2020 (WHO, 2020). Since then, the U.S. has recorded over 111 million COVID-19 cases and exceeded 1.2 million deaths (Worldometer, 2024). Due to the disease's rapid spread and severe consequences, the World Health Organization (WHO) declared COVID-19 a pandemic on March 11, 2020 (WHO, 2020).

In response to this emergency, the Centers for Disease Control and Prevention (CDC) and the United States government introduced several measures to disrupt its spread. This included the introduction of mandatory stay-at-home orders, restrictions on non-essential travel, and suspension of public gatherings (CDC, 2023b). Additionally, closures of public offices, non-essential businesses and widespread campaigns promoting social distancing and hygiene became common nationwide (CDC Foundation, 2020; Hale et al., 2023). While vital for controlling the spread of COVID-19, these pandemic response actions profoundly affected everyday life. These actions disrupted routines and restricted movement, leading to drastic shifts in travel behavior (Adanu et al., 2021; Sekadakis et al., 2021; Stavrinos et al., 2020; Wegman & Katrakazas, 2021). Additionally, with reductions in workforce presence, spikes in unemployment, and the sudden shift to remote work, travel demand across urban and rural regions was fundamentally altered (Beland et al., 2023).

With strict limitations on movement, significant decreases in the number of trips and overall vehicle miles traveled (VMT) were recorded. For instance, the American Driving Survey conducted by the AAA Foundation for Traffic Safety reveals significant shifts in daily trip frequency during the COVID-19 pandemic (Tefft et al., 2021). From July to December 2019, U.S. residents averaged 3.7 trips per day across all modes of transportation. This level persisted through early 2020, but average daily trips dropped to 3.0 by March and then further declined to 2.2 in April, marking reductions of approximately 19% and 40%, respectively. Following this sharp decline, trip frequency gradually recovered, reaching an average of 2.5 daily trips by May. For the remainder of 2020, daily trips stabilized at levels consistently 20%–25% lower than those observed in the latter half of 2019. Travel began to increase once these restrictions were relaxed and, ultimately, revoked. Figure 1 presents the percentage increase or decrease in the number of trips for each US county for various time periods. These were chosen based on different events that happened from January 1, 2020, until August 15, 2021 (i.e., before the pandemic, during the pandemic while the stay-at-home order was in place, the discovery of the vaccine, detection of the Delta variant).

In the state of Michigan, the first stay-at-home order, implemented in response to COVID-19, involved a series of phases that evolved as the pandemic progressed. Beginning on March 24, 2020, the directive required all non-essential businesses to suspend operations and mandated residents to stay home except for essential activities, with an initial end date of April 13 (State of Michigan, 2020a). As cases continued to increase, the order was extended on April 9 through April 30, adding restrictions on travel and limiting store capacities (State of Michigan, 2020b). The order continued through further extensions on May 7 and May 22 (ClickOnDetroit, 2020), with the latter pushing the timeline to June 12, while allowing essential sectors like manufacturing to resume under strict guidelines (WXYZ, 2022). Finally, on June 1, the stay-at-home order was lifted, though limits on gatherings, capacity, and mask requirements remained to ensure continued safety (WXYZ, 2022).

Reductions in travel led to notable declines in traffic crashes across the country. The National Highway Traffic Safety Administration (NHTSA) reported an 11% decline in VMT from 2019 to 2020, contributing to a 22% reduction in overall traffic crashes nationally (Stewart, 2023). However, despite this decrease in travel and crashes, traffic fatalities rose by 7.3%, revealing a complex and counter-intuitive trend. In Michigan, VMT dropped by 15.4% during the same period, accompanied by a 21.9% decrease in crashes (Michigan State Police, 2022). However, Michigan saw an even higher increase in traffic fatalities, with a 10% rise (TRIP, 2023). This paradox of reduced travel but rising fatalities underscores the unique and complex risks that emerged on the roads during the pandemic.

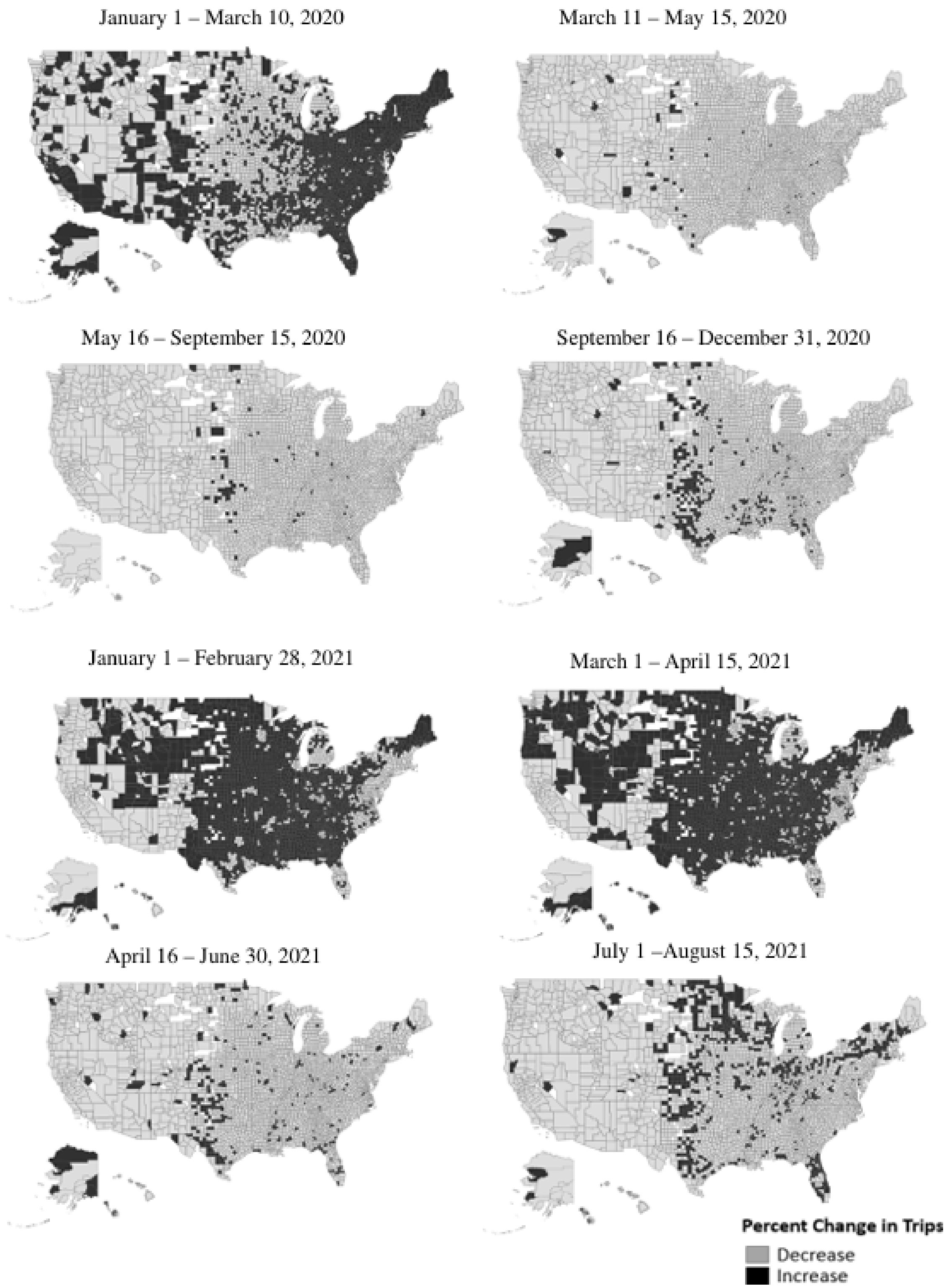

Figure 1: Percentage Change in Number of Trips

1.2 Problem Statement and Objectives

Beyond the societal impacts of these fatality increases, the COVID-19 pandemic also slowed progress toward the goals of the 2019–2022 Michigan State Highway Safety Plan (SHSP). The SHSP included a safety target to reduce traffic fatalities from 974 in 2018 to 945 in 2022 (GTSAC, 2019). Based upon the unexpected increases in fatalities, this target was updated to a more moderate goal of 968.6 fatalities by 2022 (MDOT, 2020; OHSP, 2021). Unfortunately, more recent crash data show that traffic fatalities have continued to increase further since 2020. During calendar years 2020, 2021, and 2022, a total of 1086, 1137, and 1124 traffic fatalities occurred in each of these years, respectively (NHTSA, n.d.-b). As these increases in fatalities have continued even after travel rebounded to normal levels, there appear to be some underlying issues that contributed to the adverse safety impacts during the pandemic, and these effects are still continuing. For example, NHTSA reported that driving patterns and behaviors across the US changed significantly during the COVID-19 pandemic in 2020 including increased incidences of speeding, failure to wear seat belts, and driving under the influence of alcohol or other drugs compared to 2019 (NCSA, 2021b). Research from the state of Michigan also showed similar patterns with some of these effects likely due to differences in terms of driver population that were on roads during the pandemic (Gupta et al., 2023; Rostami et al., 2023). The increases in drivers' risk-taking behavior during 2020 may have continued to following years, which explains some of the increases in fatalities in 2021–2022 compared to 2020. In any case, the data shows the state of Michigan failed to meet the safety targets set in the SHSP.

These continued increases in traffic fatalities have raised several concerns from a safety perspective and require research to understand the underlying issues that may have caused these trends. To that end, this study aims to conduct a comprehensive before-after safety analysis to better understand what factors may have driven the increase in fatalities and serious injuries since the COVID-19 pandemic. This literature review aims to investigate and summarize research on the pandemic's effects on travel patterns, crash frequency, crash severity, and driver behavior across different phases of the COVID-19 period. By examining national and regional studies, this review provides insight into how pandemic-induced travel restrictions and shifts in societal behavior influenced traffic safety outcomes. The findings offer critical implications for understanding not only the immediate impacts of the COVID-19 pandemic but also for preparing responses to future disruptions that may similarly affect transportation systems and road safety.

Building upon the preceding discussion, the primary goal of this research is to identify factors that have contributed to the increase in traffic fatalities and serious injuries that have been experienced since the COVID 19 pandemic. To that end, the specific objectives as per the RFP are to:

- Develop an extensive literature review related to the impacts of COVID-19 on travel behavior.
- Collect traffic safety and other relevant data for the period before and after COVID-19.
- Analyze and identify factors that may have driven the increase in serious injuries and fatalities.
- Identify countermeasures and strategies to mitigate the increasing trends.

1.3 Structure of the Report

This report is structured as follows. Chapter 2 presents an extensive literature review, synthesizing research findings on pandemic-induced shifts in travel patterns, crash frequency, severity, and driver behavior. This review serves as a foundation for understanding the factors that may have contributed to increases in traffic fatalities and serious injuries during and after the COVID-19 pandemic. This is followed by Chapter 3, which presents the results of a national comparison of fatality trends across states from the onset of the pandemic onward. Chapter 4 involves a more detailed national analysis, which is conducted at the county-monthly level. Chapter 5 includes a more detailed analysis of crash data in Michigan at the segment-level, including separate analyses for various road classes. Chapter 6 involves the analysis of police-reported crash data with emphasis on the factors impacting crash severity, particularly post-pandemic. Finally, Chapter 7 summarizes the study, provides conclusions, and presents general recommendations.

2 LITERATURE REVIEW

The impact of the COVID-19 pandemic on travel patterns, traffic safety, and driver behavior has been a topic of considerable research in the last three years. During the pandemic, it was speculated that travel demand would reduce significantly, leading to reductions in traffic volume. Within the context of the US, the travel restrictions resulted in significant reductions in mobility, particularly in urban cities (M. Lee et al., 2020; Warren & Skillman, 2020). However, these effects quickly dissipated due to the mobility resistance phenomenon, and by early May, human mobility recovered to nearly 86% of its status in January 2020 (Xiong et al., 2020). Several studies have investigated changes in traffic volumes, speeds, and crash frequency/severity during the pandemic at various levels of aggregation. For example, a review of national-level data showed significant reductions in traffic volume and roadway fatalities in 33 out of 42 countries from 2019 to 2020 (Yasin et al., 2021). Significant reductions in crashes were reported in Greece (Katrakazas et al., 2020), New Zealand (Christey et al., 2020), Qatar (Muley et al., 2021), Spain (Saladié et al., 2020), and Canada (Rapoport et al., 2021). The following sections provide a summarized review of pertinent literature within the context of the United States.

Table 1 shows the summary of the COVID's effects on traffic safety. The pandemic led to a global trend of reduced road fatalities due to decreased traffic volume, with most countries experiencing notable declines in road fatalities. According to the International Transport Forum (ITF), on average, road fatalities fell by 8.6% across 34 countries, with countries like Iceland, Argentina, Italy, and Spain reporting reductions of over 20% in fatalities compared to pre-pandemic levels (ITF, 2021). These reductions were primarily linked to reduced travel demand and stringent lockdown measures. However, three countries diverged from this trend, experiencing increases in road fatalities during 2020. Ireland reported a 2.1% increase in road deaths, followed by Switzerland with a 4.6% increase. The United States saw the highest rise, with a 5.1% increase in fatalities, attributed to factors such as higher speeds, impaired driving, and reduced seat belt use despite a decrease in vehicle miles traveled. This increase in U.S. fatalities has prompted further investigation into the specific conditions that led to elevated crash severity despite reduced travel, highlighting a unique case among global road safety trends.

Table 1: Summary of COVID-19 Impacts on Traffic Safety

Topic	Before COVID-19	During COVID-19	After COVID-19
Traffic Crashes	Stable trends in crashes and fatalities	Total crashes decreased globally (Katrakazas et al., 2020; Saladié et al., 2020), but crash rates increased in the U.S. (Doucette et al., 2021)	Traffic crashes began to increase as traffic volumes returned toward pre-pandemic levels (NHTSA, 2024, 2025c)
Fatalities	Steady decline in road fatalities globally	Road fatalities decreased globally by 8.6%, but increased in the U.S. by 5.1% (ITF, 2021)	Fatalities remained elevated through 2022, followed by a decline in 2023 compared to 2022 (NHTSA, 2024, 2025c)
Speed	Generally consistent; regional variations in speed limits	Average speeds rose by 2-5 mph (Das et al., 2022; Gupta et al., 2023), and citations for speeds exceeding increased (Caltrans, 2020)	Elevated in many regions, gradual normalization (Gupta et al., 2023)
Seat Belt Usage	High compliance with 90.7% in U.S. (NCSA, 2024b)	Decreased during early pandemic (e.g., unrestrained deaths 50.9% in 2020) (NSC, 2024)	Slight recovery; some regions reported sustained lower use (Gong et al., 2023; Raymo, 2023)
Impaired Driving	Stable rates of alcohol- and drug-related crashes	Increased significantly (e.g., DUI-related fatalities up 14.3% in 2020) (NCSA, 2021a; Thomas et al., 2020)	Declined slightly but remained above pre-pandemic levels (NCSA, 2024a)
Distracted Driving	Ongoing concern; smartphone use was a major issue	Increased, especially smartphone use due to driver boredom (Alrumaidhi & Rakha, 2024; Tucker & Marsh, 2021)	States enacted stricter laws (GHSA, 2024; Michigan State Police, n.d.)

Unlike the broad reductions in road fatalities observed in many countries, the United States experienced a more complex trends during the pandemic. Traffic volumes reduced by as much as 50% in March 2020 compared to 2019 across various states (Goenaga et al., 2021; Z. Liu et al., 2021; Parr et al., 2020). These reductions in volumes were generally accompanied by a reduction in total crashes. However, several states reported an increase in fatal and serious injury crashes despite the reduction in travel and overall crash counts. A study from Missouri found significant reductions in minor and no-injury crashes but no reduction in fatal or serious injury crashes after travel restrictions were introduced (Qureshi et al., 2020). A similar study from Connecticut found that average daily crash frequency reduced after the stay-at-home orders were implemented in the state; however, when accounting for reduced VMT during the same period, crash rates were found to increase significantly (Doucette et al., 2021). In Florida, although overall crashes reduced during March-September 2020, severe run-off-road crashes increased by 12%. Also, compared to the non-pandemic period, the severity of run-off-road crashes during the pandemic was higher for drivers 65 years or older, at sites where no traffic control devices were present, and for drivers exhibiting careless driving behavior (Mokhtarimousavi et al., 2022). In California, a substantial reduction in overall crash counts was recorded during the pandemic. However, the number of severe crashes increased due to higher travel speeds, which were up by 2 mph to 3 mph across the state (Hughes et al., 2022). Subsequent research confirmed that lower traffic volumes were associated with higher crash severity due to higher travel speeds (Stiles et al., 2023) and that the reduction in crashes was mainly attributable to a reduction in low-severity crashes (Brodeur et al., 2021). A similar trend of increased fatalities during the pandemic was observed in Oregon. While VMT dropped by 10.8% and total crashes decreased by 23.91%, fatalities increased by 2.63% in 2020 compared to the previous year (Ghosh et al., 2025). Furthermore, speeding was frequently linked to single-vehicle crashes and incidents on curved road segments, where maintaining vehicle control is more difficult at high speeds.

Research in Michigan investigated both the impacts of speed limit increase as well as changes that coincide with the COVID-19 pandemic (Gupta et al., 2023). The results show that total crashes decreased by 28% to 45% during the first few months of the pandemic. As travel began to rebound, crashes began to increase. However, the 75-mph sites showed significantly larger increases in monthly crashes compared to the 70-mph sites. Moreover, the severity of crashes were also found to increase significantly on all rural freeways. This has been attributed, in part, to higher mean daily speeds, which increased by 2.2 mph and 2.4 mph on 70 mph and 75 mph sites, respectively. Interestingly, as compared to pre-pandemic levels, the increases in crash severity tended to be more pronounced at the 70-mph sites. Figure 2 shows monthly trends in traffic volume and non-animal related crashes separately for 70 mph and 75 mph freeways throughout Michigan. Another study in Michigan reveals that while the total number of congestion-related crashes dropped significantly during the 2020 stay-at-home order, the risk of severe or fatal (KA) injury within those crashes increased (Peterson et al., 2025). Specifically, there was an increased risk of severe outcomes for crashes during typical commute times (27% increase), crashes where congestion was a factor (26% increase) and rear-end crashes (16% increase) compared to 2019.

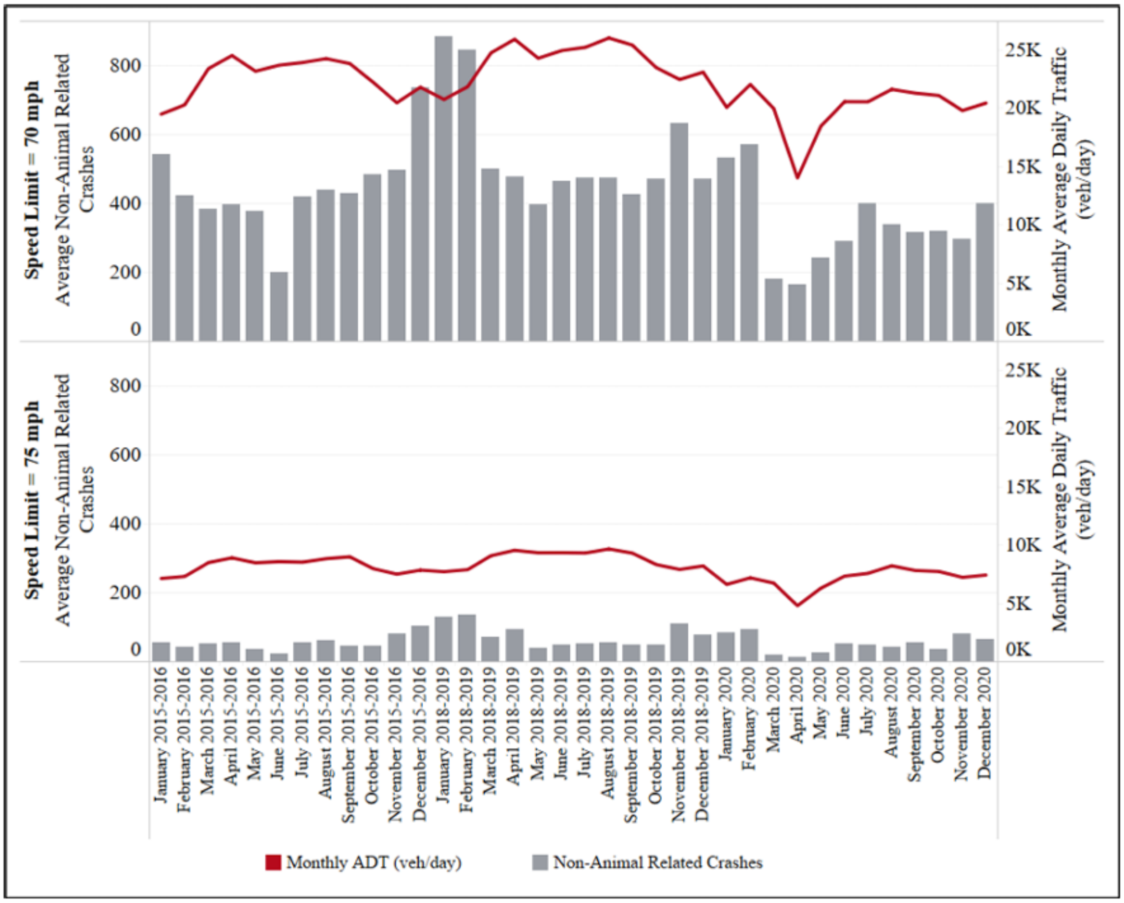

Figure 2: Monthly Trends in Traffic Volume and Non-Animal Related Crashes for 70 mph and 75 mph Freeways Throughout Michigan

Despite the reduction in traffic volumes, the pandemic paradoxically led to an increase in severe traffic incidents, primarily attributed to changes in driver behavior, such as speeding and other risky behaviors due to reduced traffic congestion (Qureshi et al., 2020; Shilling & Waetjen, 2020a). As the world grappled with the immediate effects of the pandemic, deeper insights into these behavioral shifts began to emerge. Changes in travel behavior, such as reduced weekly driving hours and increased speeds on rural freeways, played a crucial role during the early stages of the pandemic (Gupta et al., 2023; Rostami et al., 2023). Research revealed that riskier drivers likely comprised a higher percentage of vehicle miles traveled during the pandemic, explaining the observed increase in injury severities (Islam et al., 2023). Additionally, the pandemic brought about changes in commuting modes, with many shifting from public transportation to private cars due to heightened fears of infection (Yang et al., 2024).

The influence of social isolation on risk-taking behaviors was also significant, as increased social isolation led to greater perceived stress, resulting in higher risk-taking behaviors (Lavan et al., 2024). Increased alcohol consumption during the early phases of the pandemic also significantly impacted traffic safety (Watson-Brown et al., 2024). Understanding these changes and their long-term implications is crucial for developing effective road safety interventions. This research aims to provide a comprehensive analysis of high-risk driving behaviors and their persistence over time, contributing to the existing body of knowledge and offering valuable insights for policymakers and safety advocates.

2.1 Speeding and Risk-Taking

The COVID-19 pandemic led to substantial changes in travel patterns worldwide as lockdowns and social distancing measures reduced overall road traffic. This drop in congestion provided conditions that encouraged riskier driving behavior, particularly speeding. Evidence from studies across the United States and other countries consistently shows that the decrease in traffic volume during the pandemic contributed to an increase in speeding, with these behaviors often linked to a rise in severe crashes, revealing a complex relationship between traffic levels, driver behavior, and crash severity.

A study investigated the factors that influenced drivers' speed choices in low traffic volume conditions (Tucker & Marsh, 2021). Drivers rely heavily on visual information to perceive and control their speed. In low traffic conditions, the reduced visual cues from other vehicles can lead to an underestimation of speed and an increase in speeding. Drivers tend to adjust their behavior to maintain a consistent level of perceived risk. With fewer cars on the road, speeding may feel less risky due to the expanded "field of safe travel". This can encourage drivers to speed up to maintain their desired risk level. In addition, low traffic volume can lead to boredom, prompting drivers to speed or engage in aggressive driving. In typical traffic conditions, drivers gauge appropriate speeds based on other vehicles, establishing a social norm. However, in low traffic situations, this collective guidance diminishes, amplifying the influence of individual motivations and attitudes on driving behavior. The combination of these perceptual, psychological, and personal factors determines how drivers adjust their speed when roads are less crowded (Tucker & Marsh, 2021).

A global trend of increased speeding was observed, with different regions experiencing varying degrees of impact. According to a report by the European Transport Safety Council (ETSC), the COVID-19 lockdowns led to increased speeding across several European countries, despite reduced traffic volumes (ETSC, 2020a). In Spain, speed violations on non-urban roads rose by 39%, as captured by fixed speed cameras, even as overall road deaths declined. Estonia experienced a similar trend, with a 22% increase in the proportion of drivers exceeding speed limits on high-speed rural roads. In contrast, Sweden observed no significant change in speed compliance, highlighting regional variations in driver behavior. In the United Kingdom, telematics data revealed a 15% increase in speeding alerts among young drivers (ETSC, 2020b). France saw a 16% surge in severe speeding offenses, with drivers frequently exceeding the speed limit by more than 50% (Securite Routiere, 2020), while Denmark reported a 10% rise in the proportion of drivers speeding (Transportministeriet, 2020). These findings across Europe, based on ETSC data, underscore a pattern where reduced road congestion during the pandemic encouraged faster driving, posing potential safety risks. A study conducted in Greece shows that reduced traffic volumes led to average speed increases of 6–11% and increased behaviors such as harsh braking, harsh acceleration, and mobile phone use by up to 42% (Katrakazas et al., 2020). Despite these shifts, total trip distances and durations declined, and fewer trips occurred during high-risk hours, resulting in fewer accidents, particularly a 41% reduction in Greece.

Studies examining data from Asia also show similar results. In Japan, a time-series analysis found that while the total number of speed-related fatal motor vehicle collisions (MVCs) during lockdown did not exceed forecasts, the ratio of speed-related to non-speed-related fatal MVCs increased significantly, indicating a greater likelihood of speed-related violations among drivers on the road (Inada et al., 2021). Similarly, in Shanghai, China, average road speeds increased significantly in the early stages of the lockdown due to reduced congestion (J. Li et al., 2021). However, as restrictions eased and work resumed, speeds began approaching pre-pandemic levels, especially during peak hours.

Similar patterns were observed in the United States. A study conducted by Das et al. (2022) examined the influence of the COVID-19 pandemic on operating speeds and crash severity on urban freeways in Dallas, Texas. By analyzing data from 2018 to 2020, the researchers observed that the pandemic-induced reduction in traffic volumes led to increased average speeds and speed variability along urban freeways. For example, on roadways with a 60-mph posted speed limit, the average speed rose by 4.92 mph from 2019 to 2020. Even on higher-speed roads with a 75-mph limit, there was still a measurable increase, with average speeds climbing by 0.46 mph from 2019 to 2020. The analysis showed that in 2020, average speeds rose due to less congested roads, with these increases strongly associated with higher rates of fatal and severe injury crashes (Das et al., 2022). This research highlights the need for adaptive traffic management strategies and speed enforcement to address such risks during periods of disrupted travel patterns.

A study in Connecticut analyzed the impact of the COVID-19 stay-at-home order on traffic patterns, finding that while daily vehicle miles traveled decreased by 43%, single-vehicle crashes, particularly fatal ones, increased post-order (Doucette et al., 2021). The researchers suggest that reduced traffic volumes may have contributed to higher speeds on less congested roads, leading to more severe single-vehicle incidents. This aligns with media reports indicating increased speeding and risky driving behaviors during the pandemic, potentially exacerbated by lower police presence. These findings reinforce the hypothesis that less congestion enables more aggressive driving, which can lead to a rise in crash severity due to increased impact forces at higher speeds. A study of within-day travel speed patterns in Alabama during the COVID-19 pandemic applied dynamic time warping and hierarchical clustering to identify shifts in travel speeds (Shirani-bidabadi et al., 2021). The analysis revealed that travel behavior began changing over two weeks before the state's stay-at-home order, suggesting that drivers adjusted independently of government orders to pandemic conditions. Following the stay-at-home order, a distinct 'new normal' speed pattern emerged, with different within-day speed dynamics observed compared to pre-pandemic levels. These findings indicate that peak and non-peak travel speeds were not uniformly affected, highlighting complex changes in speed behavior during the pandemic period. A study examining crash risks in New York City during the COVID-19 pandemic found that reduced traffic volumes due to more people staying at home likely led to increased driving speeds (Dong et al., 2022). This speed rise contributed to a higher injury risk for motorists, even as pedestrian and cyclist safety improved. The authors suggest that monitoring and setting appropriate speed limits during such periods could help mitigate these risks.

Some of the studies pointed out that even if the average speeds were increased, there were some reductions in minor injury crashes during the pandemic. A study conducted in Florida, analyzing data from run-off-road crashes between April and September in 2019 (pre-pandemic) and 2020 (pandemic), found that reduced traffic volumes during the pandemic permitted higher speeds but had a lower-than-expected impact on injury severity in these crashes (Mokhtarimousavi et al., 2022). Similarly, a report conducted by the UC Davis Road Ecology Center in California found that while traffic volumes on highways decreased significantly by 20-50%, there was a slight increase in peak (1-6 mph) and average (1-9 mph) speeds, primarily on urban highways (Shilling & Waetjen, 2020b). Despite this modest speed increase, the report noted a substantial reduction in collisions and injury/fatal crashes during the pandemic period. A study in Missouri analyzed the effects of the state's mandated lockdown on road traffic accidents (Qureshi et al., 2020). While minor injury crashes decreased significantly, serious and fatal crashes did not show a similar reduction. The researchers propose that higher speeds on less congested roads during the lockdown may have contributed to this outcome, suggesting that reduced traffic volumes may inadvertently lead to riskier driving behaviors, thereby offsetting the anticipated safety benefits of decreased congestion.

A study examining the effects of the COVID-19 pandemic on transportation in New York City and Seattle found that reduced traffic volumes led to notable increases in average speeds (Gao et al., 2020). In Seattle, traffic volumes initially decreased but began to recover gradually by April 2020, while public transit demand remained low, suggesting a shift toward private vehicle use and non-public travel modes. Despite reduced traffic volumes, the severity of crashes rose, potentially linked to higher speeds during the pandemic. In NYC, vehicle speeds rose by up to 108% on some streets, accompanied by a 72% increase in school zone speeding violations (Gao et al., 2020). In Virginia, a study comparing traffic patterns between March-June 2019 and the same period in 2020 revealed that while overall traffic volume decreased by 25%, there was a significant increase in speeding, with 30% to 40% more vehicles exceeding the speed limit by 10 mph or more on most road types, excluding rural arterials (Wang & Cicchino, 2023). They found that speeding increased notably during morning and afternoon commute hours throughout the COVID-19 pandemic. This rise in speeding was also observed in Ohio's three major cities (e.g. Columbus, Cincinnati, and Cleveland), where road monitoring systems indicated an increase in speeding behaviors on less crowded roads, especially among drivers who may have felt emboldened by the lack of traffic and enforcement (J. Lee et al., 2020). Results show a significant increase in speeding across three cities. In Columbus, for example, the proportion of road mileage where speeding was observed tripled from 20.6% to 70.6%. In California, the California Highway Patrol reported an 87% increase in citations for speeds exceeding 100 mph, which was largely attributed to reduced congestion during stay-at-home orders that allowed drivers more freedom to exceed speed limits without fear of being slowed by other vehicles (Caltrans, 2020)

In Michigan, a research paper investigates the effects of the COVID-19 pandemic on driver speed selection and crash risk on rural freeways (Gupta et al., 2023). The researchers analyze speed and crash data from 2015 to 2020 to identify changes that coincided with the onset of the pandemic. They found that travel restrictions led to increased mean speeds by 2.2–2.4 mph across all sites but decreased traffic volume by 28%–45% compared to pre-pandemic years. It is noted that speed limits were increased from 70 mph to 75 mph on some rural Michigan freeways in 2017, and speeds on 70 mph freeways remained elevated for the rest of 2020, while speeds on 75 mph freeways gradually declined towards pre-pandemic levels. Further analysis revealed a significant decrease in crash frequency during the early months of the pandemic, while the severity of crashes increased during this period. This increase in severity is linked to the higher speeds observed during this time (Gupta et al., 2023). More recent studies in Michigan further support the idea that the absence of congestion during the pandemic allowed drivers to maintain higher speeds and likely encouraged or enabled riskier behavior. Consequently, when crashes did occur, even those typically considered low risk, such as rear-end collisions, they resulted in more serious injuries because of the higher speed at impact (Peterson et al., 2025). In Michigan, the prevalence of speeding (driving over the limit or too fast for conditions) in all crashes was 56% higher in 2020 compared to 2019.

Reduced law enforcement presence during the pandemic further contributed to the rise in speeding and other risky behaviors. Many law enforcement agencies redirected resources toward health and safety responses, deprioritizing traffic enforcement (Jennings & Perez, 2020). This decrease in visible police presence may have created a perception among drivers that they were less likely to be penalized for speeding, thereby increasing the prevalence of these behaviors. The sources emphasize the importance of interventions aimed at mitigating the negative safety impacts of increased speeding. These interventions could include strengthening traffic law enforcement, implementing targeted speed reduction strategies, and public awareness campaigns to highlight the risks associated with speeding during and after the pandemic (Patwary & Khattak, 2023). Among the most widely adopted strategies were intensified speed enforcement campaigns and increased deployment of automated speed detection systems. Automated enforcement tools, such as speed cameras, proved to be effective in maintaining control over speeding violations in areas where in-person enforcement was limited due to health risks (FHWA, 2023). Reports on the effectiveness of these systems demonstrated that the presence of speed cameras significantly reduced roadway fatalities and injuries by an estimated 20-37% in monitored zones (R. Li et al., 2015; Montella et al., 2015).

Overall, reviewed studies suggest that the decrease in traffic volume did not necessarily translate to safer roads, as the increased prevalence of speeding led to more severe crashes. The findings underscore the need for continued focus on traffic safety interventions, even during periods of reduced traffic volume, and the importance of addressing the psychological and enforcement aspects of speeding behavior.

2.2 Seat Belt Use

Seatbelt usage has been crucial in reducing traffic fatalities and injuries for decades. A meta-analysis of 24 studies from 2000 onwards revealed that unbelted drivers face 8.3 times higher risk of fatal crashes and 5.2 times higher risk of serious injury crashes compared to belted drivers (Høye, 2016). In 2017 alone, according to the National Center for Statistics and Analysis, seatbelts saved an estimated 14,955 lives and could have saved an additional 2,549 people had they been wearing them (NCSA, 2019).

Prior to the COVID-19 pandemic, seatbelt usage rates were steadily increasing in many countries. A study on self-reported seatbelt usage found that 85% of adults consistently reported using seatbelts (Strine et al., 2010). Regionally, the West exhibited the highest prevalence, with 89.6% of individuals stating they always wore seatbelts, while the Midwest had the lowest at 80.4%. States with primary seatbelt laws demonstrated a higher prevalence of reported seatbelt use compared to states with secondary or no laws. According to the National Highway Traffic Safety Administration (NHTSA), the national seatbelt use rate in the United States reached 90.7% in 2019, marking a significant improvement from previous years (NCSA, 2024b). This increase was attributed to various factors, including stricter seatbelt laws and enforcement, public awareness campaigns, and improved vehicle safety technology. However, the COVID-19 pandemic appears to have negatively impacted seatbelt use. Results from the National Occupant Protection Use Survey (NOPUS) show that the percentage of unrestrained passenger vehicle occupant deaths increased from 46.6% in 2019 to 50.9% in 2020, dropping slightly to 49.8% in 2021 (NSC, 2024).

Figure 3 shows the national seat belt use rate and daytime percentage of unrestrained passenger vehicle occupant fatalities.

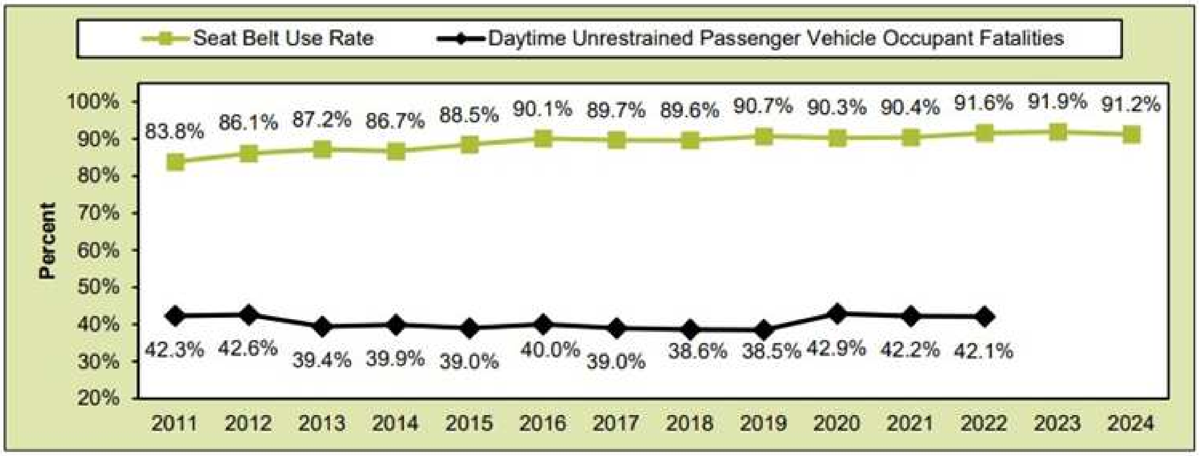

Figure 3: National seat belt use rate and daytime percentage of unrestrained passenger vehicle occupant fatalities (NHTSA, 2025b)

The impact of COVID-19 on seatbelt usage has varied across different regions. One study found that seatbelt use decreased during the early stages of the pandemic (Gong et al., 2023). This aligns with findings from national studies conducted by the National Highway Traffic Safety Administration (NHTSA). However, as the pandemic progressed, seatbelt use increased to levels comparable to those observed before the pandemic (Gong et al., 2023). This pattern suggests that the initial decline in seatbelt use may have been related to heightened risk acceptance among drivers who continued to travel during the early stages of the pandemic when fear of infection was high (Vanlaar et al., 2021). As the pandemic progressed, risk perception likely shifted, and seatbelt use returned to pre-pandemic levels. In Michigan, the seatbelt usage rate fell from 94.4% to 92.4% between 2019 and 2023 (NCSA, 2024c) marking the lowest seatbelt use rate since 2004 (Raymo, 2023).

Several studies have examined the factors affecting seatbelt use. One study utilized a bivariate probit model to account for the potential correlation between seatbelts and cell phone use (Russo et al., 2014). The researchers found a highly significant negative correlation between a driver's decision to use a cell phone and to wear a seatbelt. They identified various factors influencing seatbelt use, including driver demographics (age, gender, race), passenger’s age, vehicle type, time of day, day of the week, and vehicle use. Another study employed a bivariate model to investigate trends and correlations in seatbelt usage among drivers and front-seat passengers (Chakraborty et al., 2021). Seatbelt usage rates varied depending on the gender, age, and race of vehicle occupants. This study also revealed a positive correlation between the seatbelt use of drivers and front-seat passengers. Another study confirmed a positive interdependence between driver and passenger seatbelt usage, suggesting that education and enforcement strategies should focus on influencing driver behavior to impact their passengers (Nambisan & Vasudevan, 2007)

Various interventions and strategies have been proposed in response to the decline in seatbelt usage. Studies emphasize the need for increased legal enforcement (Abu-Zidan et al., 2012). Some regions have implemented "Click It or Ticket" style campaigns to reinforce seatbelt use during the pandemic (NHTSA, n.d.-a). These campaigns aim to raise awareness about the importance of seatbelt compliance through public education and increased law enforcement patrols. Michigan, for instance, has participated in this campaign, with the Michigan State Police (MSP) and other police departments across the state conducting seatbelt enforcement during the campaign period (Raymo, 2023). Additionally, studies have recommended the increased use of in-vehicle reminders and smartphone apps to promote seatbelt use (Høye, 2016; IIHS, 2019b).

The long-term implications of COVID-19 on seatbelt usage remain uncertain. Continued research and monitoring will be crucial to understanding and addressing any persistent changes.

2.3 Impaired Driving

The evidence on whether alcohol consumption increased during the pandemic is inconclusive, with some studies noting a decline in substance use in specific populations. For instance, a study across nine European countries observed reductions in alcohol and tobacco use, possibly due to strict pandemic restrictions that limited social interactions and, in turn, curbed habits like drinking and smoking (Pišot et al., 2020). Similarly, among high-risk drinkers in Belgium, over 90% reported altered drinking patterns, with decreases more common than increases (Pabst et al., 2021). Additionally, a survey by the Canadian Centre on Substance Use and Addiction found that while 70% of Canadians reported no change in their alcohol consumption, 12% noted a decrease in drinking due to fewer social gatherings and 18% indicated an increase, citing reasons such as lack of routine, stress, and boredom. (Nanos Research, 2020).

However, contrasting trends emerged, with reports from some countries indicating a surge in substance use. In China, for example, researchers show that many drinkers and smokers reported increased use largely driven by elevated stress, social isolation, and economic hardship (Ren et al., 2020; Sun et al., 2020). Similarly, in France, 24.8% of adults increased their alcohol consumption, and significant rises were noted for tobacco (35.6%) and cannabis (31.2%) use, especially among younger adults (Rolland et al., 2020). Similarly, in Canada, 14% of adults increased alcohol intake, with younger and financially impacted groups most affected (Zajacova et al., 2020). A study assessed the impact of Canada's Cannabis Act which was passed in 2018 and legalizes the non-medical use of cannabis nationwide (Nazif-Munoz & Ouimet, 2025). Researchers analyzed a five year of affects and found a 12% increase in both drug- and alcohol-related crashes across all major cities, with peaks of 76% drug-related and 43% alcohol-related crashes in specific cities.

The rise in alcohol and drug use during the pandemic was mirrored in an uptick in impaired driving behaviors. Studies identified a rise in impaired driving, particularly among younger drivers and vulnerable populations. For teen drivers, impaired driving, especially drug-related, was identified as a statistically significant factor associated with severe injuries among this vulnerable group (Jang et al., 2024). In a comparative study conducted in September 2020, researchers examined self-reported risky driving behaviors in Canada and the U.S., observing an increase in impaired driving, particularly in the U.S. Results showed that U.S. drivers reported a significantly greater likelihood of alcohol-impaired driving than Canadian drivers. The analysis also highlighted that younger drivers and those with a history of traffic violations were more inclined toward risky behaviors during the pandemic (Vanlaar et al., 2021). A study found that while total passenger-vehicle driver deaths rose by 9% from 2018 to 2022, deaths involving drivers with a high blood alcohol concentration (BAC 0.08%) surged by 22%, increasing from 4,791 in 2019 to 6,042 in 2022 (Eichelberger, 2026). Three major indicators were identified as plausible causes of this trend, state-level alcohol policies, mental health indicators, and law enforcement employment levels.

Further highlighting the pandemic's toll on traffic safety, research from the AAA Foundation shows that fatal crashes involving drivers with a BAC of 0.08 g/dL or higher increased by 20% in 2020, 32% in 2021, and 33% in 2022 compared to expected rates, highlighting a significant rise in DUI-related incidents. The pandemic's impact on traffic safety also underscored existing disparities, as disadvantaged populations, especially Black and Hispanic Americans and individuals with lower educational attainment, experienced disproportionately higher rates of fatalities. Late-night and early-morning crashes saw notable increases, correlating with times when alcohol-impaired driving is most prevalent (Tefft, 2024).

NHTSA observed an increase in alcohol- and drug-impaired driving from March to July 2020. Comparing data from September 2019 to March 16, 2020, with data from March 17 to July 2020, there was a 26.3% rise in seriously or fatally injured drivers testing positive for alcohol and a 27.4% rise in those testing positive for at least one active drug. Notably, active tetrahydrocannabinol (THC) was found more frequently than alcohol among fatally injured drivers (32.7% versus 28.3%), and opioid use among drivers doubled (Thomas et al., 2020).

Report from National Center for Statistics and Analysis (NCSA) demonstrates that from 2019 to 2020, alcohol-impaired-driving fatalities rose sharply by 14.3%, increasing from 10,196 to 11,727, a rate far exceeding the 6.8% increase in overall traffic fatalities during this period. Alcohol-related crashes accounted for 30% of all traffic deaths in 2020, with the national fatality rate jumping to 0.40 per hundred million vehicle miles traveled (HMVMT) , up from 0.31 in 2019 (NCSA, 2021a). This trend continued into 2021, as alcohol-impaired-driving fatalities rose by another 14.2% (from 11,727 to 13,599), surpassing the 10.1% rise in overall traffic fatalities that year. Alcohol-impaired-driving deaths comprised 31% of all motor vehicle fatalities, with the fatality rate reaching 0.43 per HMVMT in 2021 (NCSA, 2023). However, in 2022, a slight decline emerged, fatalities in alcohol-impaired-driving crashes decreased by 0.7%, from 13,599 in 2021 to 13,458, alongside a 1.7% drop in overall traffic fatalities. This decline in the number of alcohol-impaired-driving traffic crashes was further observed in 2023 (NHTSA, 2025a). Traffic fatalities in alcohol-impaired-driving crashes decreased by 7.6 percent (13,458 to 12,429 fatalities) from 2022 to 2023 compared to a 4.3-percent decrease in overall traffic fatalities between 2022 and 2023 (42,721 to 40,901). Despite this reduction, alcohol-impaired-driving fatalities still represented 32% of all traffic deaths, with the fatality rate slightly lowering to 0.42 per HMVMT. Overall, these trends indicate a significant rise in alcohol-impaired-driving fatalities during the pandemic (NCSA, 2024a). Figure 4 shows traffic fatalities and fatality rate per HMVMT in alcohol impaired driving crashes.

Figure 5 displays Michigan's alcohol-impaired driving fatalities and the alcohol-impaired driving fatality rate per HMVMT from 2018 to 2023 (NCSA, 2024a), revealing a pattern similar to national trends. In both 2018 and 2019, Michigan’s alcohol-impaired fatality rate remained steady at 0.26. However, in 2020, this rate experienced a sharp increase to 0.35, reflecting the early pandemic surge seen across the country. Although Michigan’s rate decreased in subsequent years, dropping to 0.34 then to 0.29 from 2021 to 2023, it has consistently remained above pre-pandemic levels.

This sustained elevation highlights the lasting impact of the pandemic period on alcohol-impaired driving in Michigan.

Figure 4: Traffic Fatalities and Fatality Rate per HMVMT in Alcohol Impaired Driving Crashes in USA, 2014–2023 (NHTSA, 2025a)

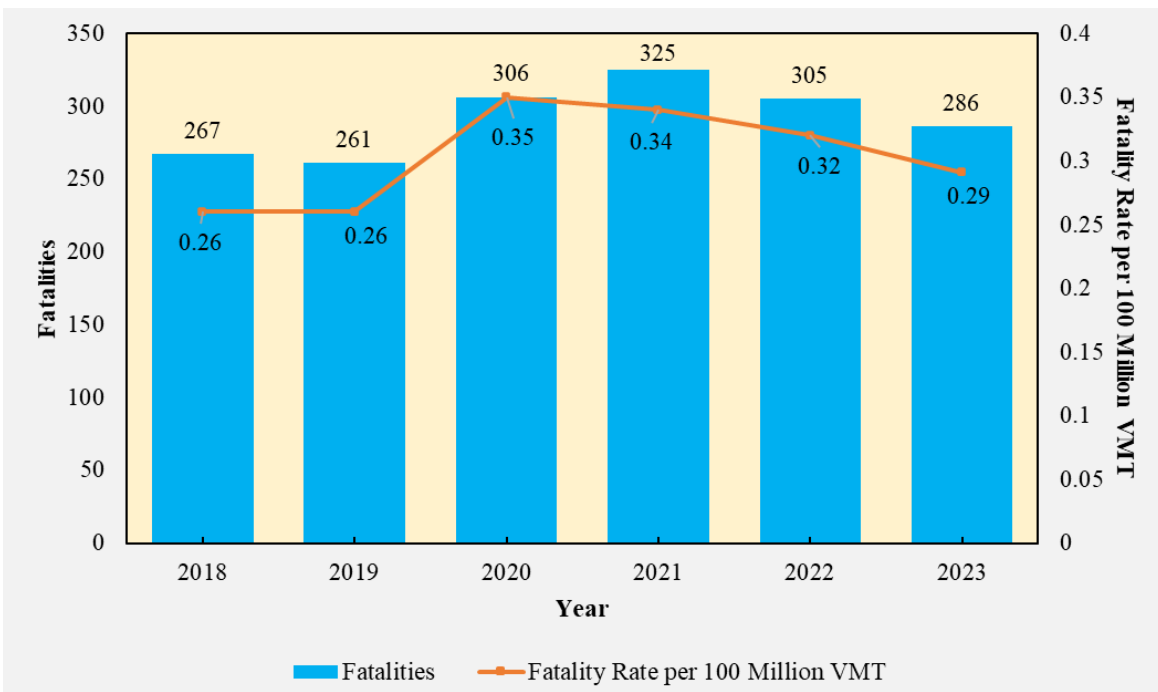

Figure 5: Traffic Fatalities and Fatality Rate per HMVMT in Alcohol Impaired Driving Crashes in Michigan, 2018–2023

2.4 Distracted Driving

Distracted driving, especially cell phone use while driving, poses a significant risk to road safety. Distracted driving is defined as the diversion of attention from driving to engage in secondary tasks including cell phone use, making or receiving calls, eating or drinking, adjusting the radio, grooming, and talking to passengers (Prat et al., 2015; Sajid Hasan et al., 2022; Sullman, 2012). Cell phone use is a particularly dangerous distraction, as it involves both visual and cognitive impairment. A study suggests that the evolution of mobile phones into multifunctional devices has increased their usage while driving (IIHS, 2019a). Distracted driving is a major traffic safety concern in the United States, causing a substantial number of deaths and injuries annually (Hasan et al., 2022). The National Highway Traffic Safety Administration reported that distracted driving claimed 3,142 lives in 2020, accounting for 8.1% of all traffic fatalities (Stewart, 2022). Additionally, it resulted in 2.28 million injuries from motor vehicle crashes in the same year (NHTSA, 2022).

The rise in distracted driving during the COVID-19 outbreak suggests that the pandemic influenced drivers' distraction behaviors (Hasan et al., 2023). A study found that the lack of traffic during the pandemic led to overall boredom among drivers, resulting in observed increases in distracted driving (Tucker & Marsh, 2021). A study pointed out that there was a notable increase in the probability of both minor and severe injuries linked to distracted driving in 2020, emphasizing the risks associated with this behavior (Alrumaidhi & Rakha, 2024). This finding is consistent with other research that also highlights the growing concern surrounding distracted driving during stay-at-home orders (Adanu et al., 2021, 2022; Gong et al., 2023). A study analyzing 86,000 crashes during the summer of 2020 found that secondary tasks, particularly cell phone use, contributed to increased crash rates (Zendrive, 2020). Another study used smartphone application data to analyze risky driving activities such as cell phone use during the COVID-19 pandemic in Greece and Saudi Arabia (Katrakazas et al., 2020). This study revealed an increase in cell phone use during the initial two months of the pandemic. A self-reported survey revealed a significant increase in distracted driving behaviors in 2020 compared to previous years, with 41% of respondents admitting to texting, 32% reading emails, 29% using social media, and 36% browsing the internet while driving (State Farm, 2021).

In Washington State, where motorcycle fatalities per billion vehicle miles traveled rose during the pandemic, particularly during warm months, behavioral risks like distracted driving and lane-changing maneuvers were the primary contributors to severe injuries (Timilsina et al., 2026). This is attributed to motorcyclists driving longer distances and weaving through traffic more frequently during better weather. A similar study was conducted in Kentucky to compare distraction-related crash patterns between the pre-pandemic period and the post-pandemic period (Banerjee et al., 2025). It was found that post-pandemic distraction-related angle crashes increased by 8.8%, and single-vehicle crashes rose by 22.4%. These increases were more prevalent on high-speed (55 mph) rural undivided two-lane roads with low traffic volumes. The study further highlights that young drivers (16–29) were involved in the highest percentage of distracted crashes (38%) during both periods.

It suggested that public education and law enforcement initiatives are crucial for addressing the issue of distracted driving (Hasan et al., 2023). These efforts should focus on raising awareness about the dangers of distracted driving and enforcing laws against cell phone use while driving. States exercise their own discretion in limiting phone usage while driving. As of June 2024, 30 states ban handheld phone usage, 49 states ban texting and driving, and 36 states ban all cell phone usage by novice drivers (GHSA, 2024). The "U Text, U Pay Campaign", which happens every April is another way to prevent phone usage, as the police put more efforts toward preventing cell phone use while driving (Shulman, 2023). Michigan enacted the Michigan Distracted Driving Law, which prohibits drivers from holding or supporting a phone or other device with any part of their hands, arms, or shoulders (Michigan State Police, n.d.). This prevents drivers from using their cell phone or other electronic device while driving.

These results underscore the potential dangers of distracted driving, particularly cell phone use, and highlight the need for continued research and interventions to address this growing traffic safety concern.

2.5 Pedestrian and Bicyclist Fatality Trends

In the United States, pedestrian and bicycle fatalities remain a major public health and transportation safety concern. Despite ongoing efforts to improve roadway safety, Pedestrian fatalities have remained persistently high. Between 2010 and 2021, bicycle fatalities have steadily increased (Kirley et al., 2023). Similarly, pedestrian fatalities increased over 2009 and 2022. In total, pedestrian and bicycle fatalities represented 8,480 fatalities, accounting for 20.7% of traffic-related deaths in 2023 (NHTSA, n.d.-b). While these fatalities have been a longstanding concern, the social and travel disruptions caused by the COVID-19 pandemic have exacerbated this issue.

Previous research highlights demographic characteristics, environmental conditions, and risky behaviors all influence pedestrian and bicyclist safety. Males, older adults (70+), Black, and Native American populations experienced disproportionately higher fatality rates (Hu & Cicchino, 2018; Sanders & Schneider, 2022; Zhu et al., 2013). While higher socioeconomic status (SES) generally correlates with lower risk, this protective effect is not significant for Black and Hispanic pedestrians (Gibbons et al., 2025). Temporally, fatalities peak in winter and autumn, with a heightened risk at night a factor that disproportionately impacts Black and Native American pedestrians (Mohamed et al., 2013; Mokhtarimousavi et al., 2020; Sanders & Schneider, 2022). The built environment also plays a critical role, with most fatalities occurring mid-block on arterial roads, particularly in areas with industrial or commercial land use and in Southern and Western states (Hu & Cicchino, 2018; Mahdinia et al., 2026; Schneider, 2020; Ukkusuri et al., 2012). Risky behaviors from both drivers and pedestrians, including alcohol use, distraction, and speeding, further compound these risks (J. Liu et al., 2019; Stimpson et al., 2013).

Similar patterns emerge for bicyclist fatalities. Men and older adults face higher risks, and while higher SES is linked to lower fatality rates, this association is again absent for Black and Hispanic cyclists (Gibbons et al., 2025; G. Li & Baker, 1996). Although research on temporal factors in the U.S. is limited, studies from Europe suggest nighttime increases risk, while U.S. data shows a concentration of fatalities in summer months (Johansson et al., 2009; Weast, 2018). The built environment is equally influential; increased land use diversity is protective, while higher speed limits and crossing roadways (as opposed to riding along them) elevate fatality risk (Chen & Shen, 2016, 2019). Cyclist behavior, including alcohol impairment and failure to yield, increases injury severity, whereas the use of reflective clothing is a significant protective factor (Chen & Shen, 2016; Z. Liu & Stern, 2021).

The COVID-19 pandemic had a large effect on pedestrian and bicycle fatality trends in the USA. Many demographic trends in pedestrian fatalities stayed the same, but the risk of pedestrian fatality increased for middle-aged pedestrians (25 to 45-year-olds) during the pandemic (Bamney et al., 2025). Conversely, trends in the race and gender of pedestrian fatalities experienced no significant differences before versus during COVID-19 (Ferenchak, 2025). While fewer pedestrian fatalities occurred during nighttime during the pandemic, there was also a decrease in pedestrian activity at night during the same period. The relative risk of pedestrian fatality at nighttime increased during the pandemic (Bamney et al., 2025). There were large changes in the effect of population density on pedestrian fatality risks during the pandemic. Census tracts with lower population density there was a significant increase in the likelihood of pedestrian fatalities (Bamney et al., 2025).

Shifts in travel modes also shaped crash outcomes during the pandemic. With decreased driving and increases in biking and walking (Elsayed et al., 2025), risky pedestrian behaviors, such as jaywalking, failing to yield, and walking on the wrong side of the road, became more strongly linked to fatalities (Bamney et al., 2025). A study conducted in Alabama found that pedestrian fatalities involving intoxicated pedestrians declined, but crashes related to DUIs and aggressive driving increased (Adanu et al., 2021). With the rise of active modes of transportation during the pandemic, the temporal and spatial patterns of bicycle traffic underwent significant shifts. In Arlington, Virginia, midday traffic nearly doubled, and there was an increase of bicycle traffic on off-road trails (Monfort et al., 2021). At the same time, driver behavior and crash patterns also changed. There was a significant decrease in the number of drunk drivers per bicycle crash during COVID-19 lockdowns (Ferenchak, 2025). Additionally, bicycle fatalities occurred more frequently on smaller roadways, which contrasts with pedestrian fatalities (Ferenchak, 2025).

After lockdown restrictions eased, pedestrian and bicycle fatalities continued to rise (Mahdinia et al., 2026). In New York City, bicycle fatalities nearly doubled during the reopening period (J. Li & Zhao, 2022). Disadvantaged communities saw disproportionate increases in fatalities, meaning the gap between fatalities in advantaged vs disadvantaged communities widened (Mahdinia et al., 2026). From a demographic perspective, fatality risk among older pedestrians (60+) remained elevated from pre-pandemic levels in 2022 but, decreased slightly from the early pandemic period. Geographically, the location of pedestrian and bicycle fatalities shifted towards the South (Mahdinia et al., 2026). Increases in fatalities were more pronounced in urban areas compared to rural ones (Mahdinia et al., 2026). However, despite increases in fatalities in urban areas, pedestrian fatality risk continued to increase for census tracts with lower population density (Bamney et al., 2025). In addition, risky pedestrian behaviors continued to be more strongly associated with fatalities than they were during the pre-pandemic period (Bamney et al., 2025).

Many potential countermeasures have been proposed by researchers. To reduce the disparities in pedestrian safety, it is proposed to prioritize equitable pedestrian infrastructure in low-income and non-white neighborhoods (Gibbons et al., 2025). Speeding and risky driving behaviors may be targeted by increased traffic enforcement during weekends and at night, as well as technology-based traffic enforcement, which may be effective (Adanu et al., 2021). Graduated license programs that restrict nighttime driving for teens may also help reduce speeding-related pedestrian fatalities (Griswold et al., 2011). Speed reduction programs may also reduce bicycle fatalities. Another countermeasure that may reduce bicycle fatalities is the addition of bike lanes in residential areas and green spaces, while avoiding steep slopes (Chen & Shen, 2019). Several of these strategies have been studied to determine their effectiveness. Implementing traffic signal delays, reducing the distance between crosswalks, and adding bicycle paths were found to reduce fatalities (da Silva & Bezerra, 2024; Xie et al., 2024). Other proposed countermeasures have been less successful, such as implementing pedestrian traffic lights (Xie et al., 2024).

Pedestrian and bicycle fatalities have been affected by demographic, temporal, environmental, and behavioral patterns since before the COVID-19 pandemic. The pandemic and subsequent lockdowns amplified many of these risks. Despite decreases in traffic volume, fatality levels remained stable, partly due to an increase in risky driving behaviors. There were also shifts in traffic mode choice towards walking and bicycling. Following reopening, pedestrian and bicycle fatalities have remained high. These trends underscore the importance of examining fatality trends across pre-pandemic, pandemic, and post-pandemic periods to gain a deeper understanding of risk factors. Continuing to evaluate these patterns is crucial for developing effective countermeasures that mitigate risk for vulnerable road users.

3 STATE-LEVEL ANALYSIS

This section examines changes in roadway fatalities at the state-monthly level across the United States, from 2019 through 2023. The analysis first focuses on total roadway fatalities, with emphasis on comparing trends across states and identifying how Michigan's fatality patterns evolved relative to other states during the pre-pandemic, pandemic, and post-pandemic periods. Monthly temporal patterns are also evaluated to understand broader nationwide changes in fatality levels over time.

Following the total fatality analysis, a separate evaluation of pedestrian and bicyclist involved fatalities was conducted to examine whether recent changes in vulnerable road user fatalities varied across states and whether these variations were associated with demographic and socioeconomic characteristics. This component of the analysis provides additional insight into populations that may have experienced disproportionate impacts during the study period.

Finally, information related to the development and achievement of Highway Safety Improvement Program (HSIP) targets was compiled and compared across states. This comparison was used to examine whether certain states consistently perform better in establishing and meeting safety performance targets and whether these patterns align with observed fatality trends. Together, these components provide a comprehensive understanding of how fatality outcomes evolved across states and the factors that may contribute to differences in safety performance over time.

3.1 Data Collection

This section describes the data sources and variables used to examine monthly roadway fatalities at the state level across the United States from 2019 through 2023. Multiple open data sources were integrated to capture travel exposure and the effects of COVID-19-related policies. The resulting dataset provides a state monthly observations used for statistical modeling and trend analysis.

3.1.1 Fatality

Fatality data were obtained from the Fatality Analysis Reporting System (FARS), maintained by the National Highway Traffic Safety Administration (NHTSA) (NHTSA, n.d.-c). FARS provides a comprehensive census of all motor vehicle crashes in the United States that result in at least one fatality within 30 days of the incident. The dataset includes detailed information about the crash date, location, roadway characteristics, vehicle types, environmental conditions, and the number of fatalities involved.

Each crash record in FARS was matched to its corresponding state using the Federal Information Processing Standards (FIPS) code (CENSUS, 2023). The number of fatalities per crash was then aggregated by state and by month to create a continuous time series of fatality counts covering the period January 2019 through December 2023. This aggregation process produced a set of monthly fatality totals for 50 states and the District of Columbia. The monthly structure allows for tracking broad temporal trends while smoothing out short-term fluctuations that occur in the daily data.

3.1.2 Monthly VMT Data

State-level monthly vehicle miles traveled data were obtained from the Federal Highway Administration (FHWA) Traffic Volume Trends dataset (FHWA, 2026b). The FHWA provides official monthly VMT estimates for each state, which were used directly in this study. Monthly VMT values from January 2019 through December 2023 were compiled for all states and used to examine changes in travel patterns over time. These VMT data were used to provide context for fatality trends and to examine mobility changes during the pre-pandemic, pandemic, and post-pandemic periods across states.

3.1.3 Population and Land Area

Population data was obtained from the U.S. Census Bureau and was used to calculate state population density measures. Annual population estimates for the study period were incorporated to maintain consistency with the analysis's temporal coverage. These demographic indicators provide contextual information for comparing safety outcomes across states with differing population characteristics.

3.1.4 Highway Statistics and Transportation Funding Variables

Additional transportation system and funding variables were obtained from the Federal Highway Administration (FHWA) Highway Statistics Series (FHWA, 2026a). These data include information on state-level roadway characteristics, vehicle registrations, and financial indicators related to highway programs. Specifically, variables were compiled describing total public roadway mileage by state, motor vehicle registrations, and multiple categories of transportation funding, including Federal-aid highway apportionments, obligations, and expenditures administered through FHWA programs. Financial variables were drawn from tables related to the obligation and expenditure of Federal-aid highway funds.

Highway Statistics data are reported on an annual basis; therefore, the values were expanded to the monthly level by assigning each year's value to all corresponding months within that year. This approach allowed these indicators to be merged with the state-monthly fatality and travel datasets while maintaining temporal alignment with other variables included in the analysis.

These transportation system and funding variables were explored to examine whether differences in infrastructure scale, investment levels, or funding utilization across states were associated with variations in roadway fatality outcomes during the study period. However, preliminary modeling efforts did not identify consistent or statistically meaningful relationships between these indicators and fatality trends after accounting for other explanatory factors. Consequently, these variables were not retained in the final model specifications but are documented here to acknowledge their consideration during the data development and evaluation process.

3.2 Aggregate Data Summary

Figure 6 to Figure 10 illustrates the spatial and temporal variations in traffic fatalities and pedestrian/bicyclist fatalities across U.S. states between 2019 and 2023, with Michigan highlighted for comparison. Overall, the maps reveal notable geographic differences in fatality outcomes and clear shifts in trends following 2019.

Figure 6 presents the percent change in total fatalities relative to 2019. Many states experienced increases in fatalities during the early years of the study period. In 2020, several states already showed moderate increases, while others experienced slight declines. Michigan experienced an increase of approximately 10.1% in total fatalities in 2020 compared to 2019. The increase became more pronounced in 2021, when Michigan's fatalities rose by about 15.3% relative to 2019, consistent with the broader national pattern in which many states experienced substantial increases in crash fatalities during the pandemic period. By 2022, Michigan's increase remained elevated at approximately 14.0% above 2019 levels, though some states began to show stabilization or modest declines. By 2023, the increase in Michigan declined slightly to about 11.0% above 2019, suggesting a partial moderation of the earlier surge in fatalities. Nationally, the maps indicate that although some states began to stabilize after 2021, many still remained above pre-pandemic fatality levels.

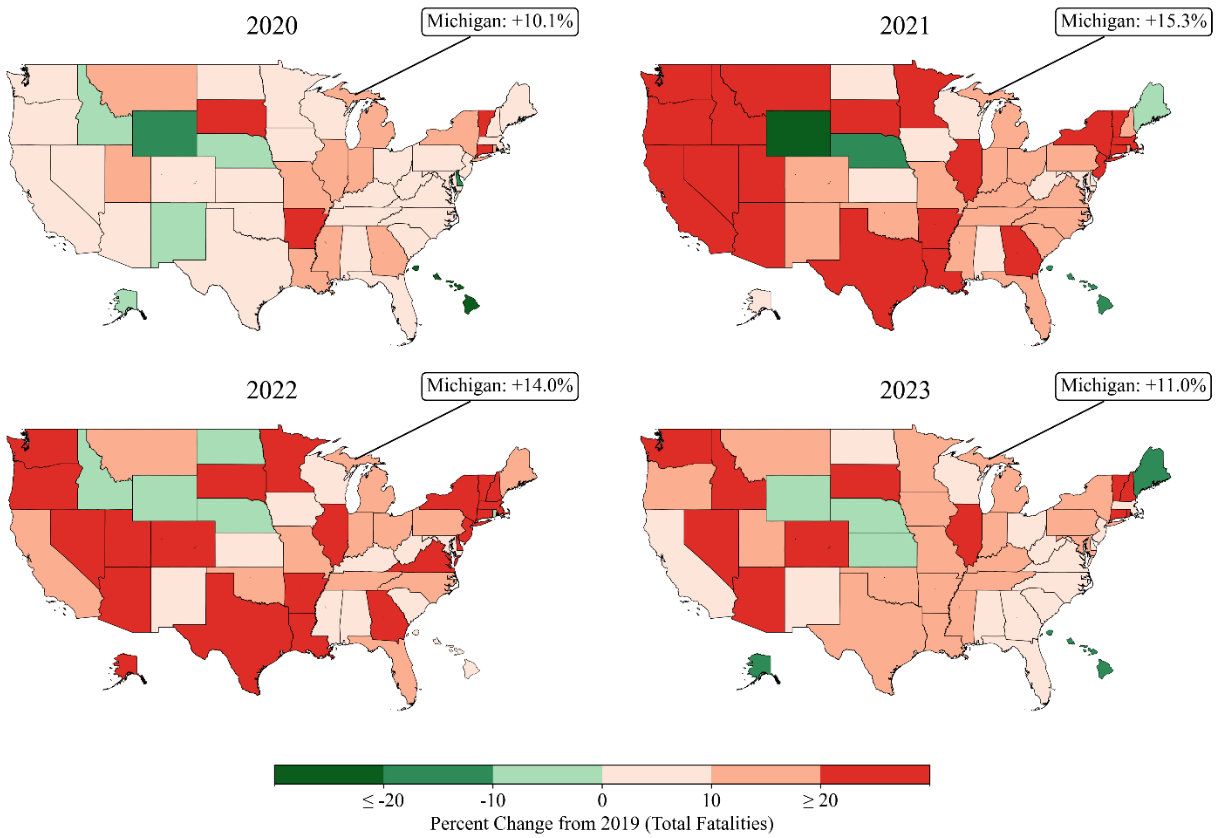

Figure 6: Comparing Yearly Percentage Change in Total Fatalities with 2019

Figure 7 shows the total fatality rates per hundred million vehicle miles traveled. This provides additional insight into crash risk after accounting for exposure. Nationally, fatality rates appear to have increased from 2019 to 2021 in many states before gradually moderating in subsequent years. Michigan follows a similar trajectory. The fatality rate in Michigan increased from approximately 0.97 in 2019 to about 1.27 in 2020, and further to roughly 1.30 in 2021. This pattern suggests that the rise in fatalities during the pandemic period was not solely driven by exposure changes but also reflected increased risk per mile traveled. In 2022, the rate increased further to approximately 1.50, before declining slightly to about 1.10 in 2023, indicating some improvement in fatality risk relative to the peak years.

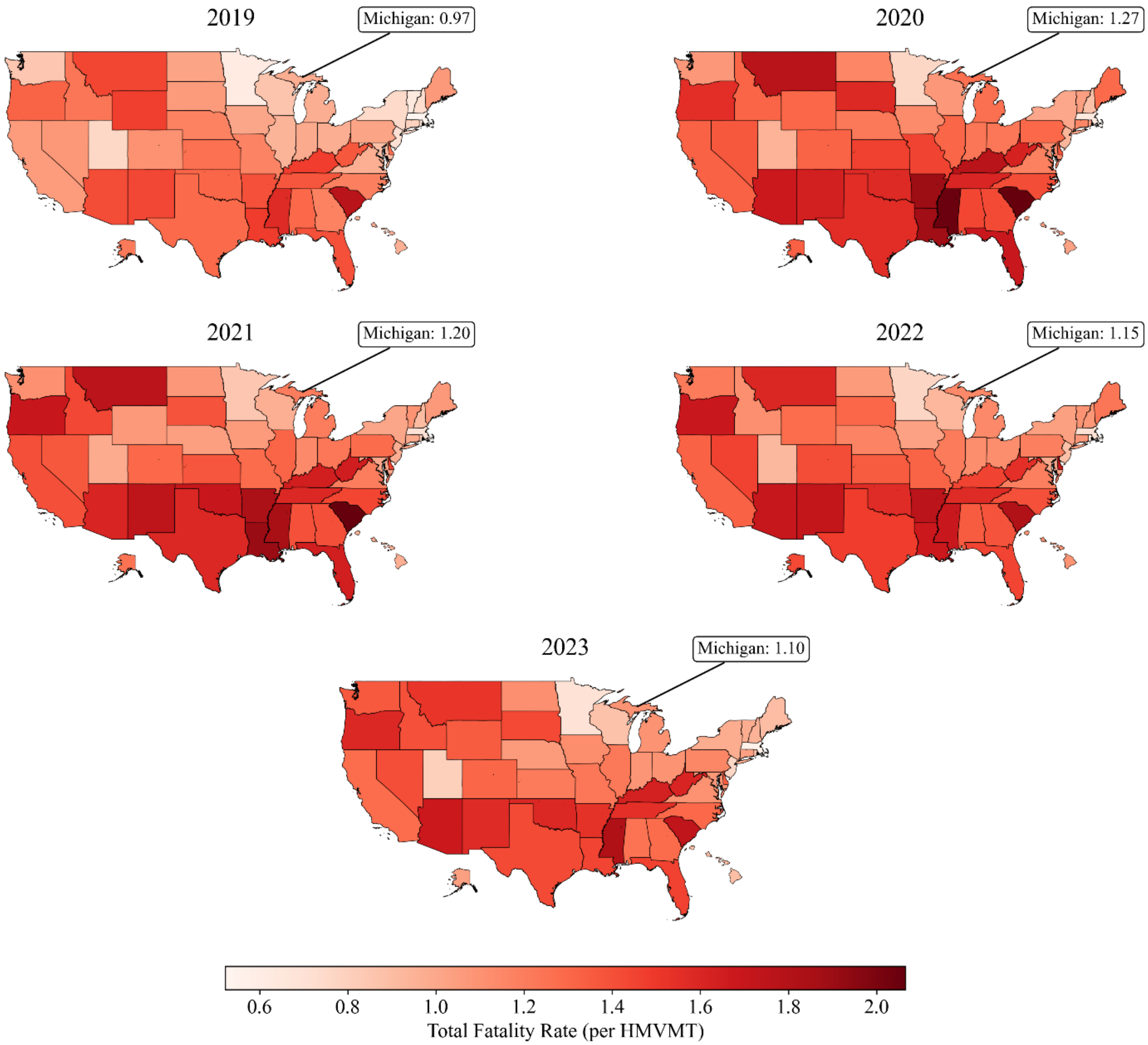

Figure 7: Total Fatality Rate per HVMT per State (2019–2023)

A similar but more variable pattern was observed for pedestrian and bicyclist fatalities. Figure 8 presents the percent change in pedestrian and bicyclist fatalities compared to 2019. Michigan experienced a substantial increase of approximately 29.2% in 2020, followed by a 26.1% decrease in 2021, indicating fluctuations in vulnerable road user fatalities during the early pandemic period. In 2022, pedestrian and bicyclist fatalities in Michigan increased again by about 25.5% relative to 2019, before declining by roughly 22.4% in 2023. Across the nation, many states experienced increases in vulnerable road user fatalities, particularly in the western and southern regions, highlighting growing safety concerns for pedestrians and bicyclists.

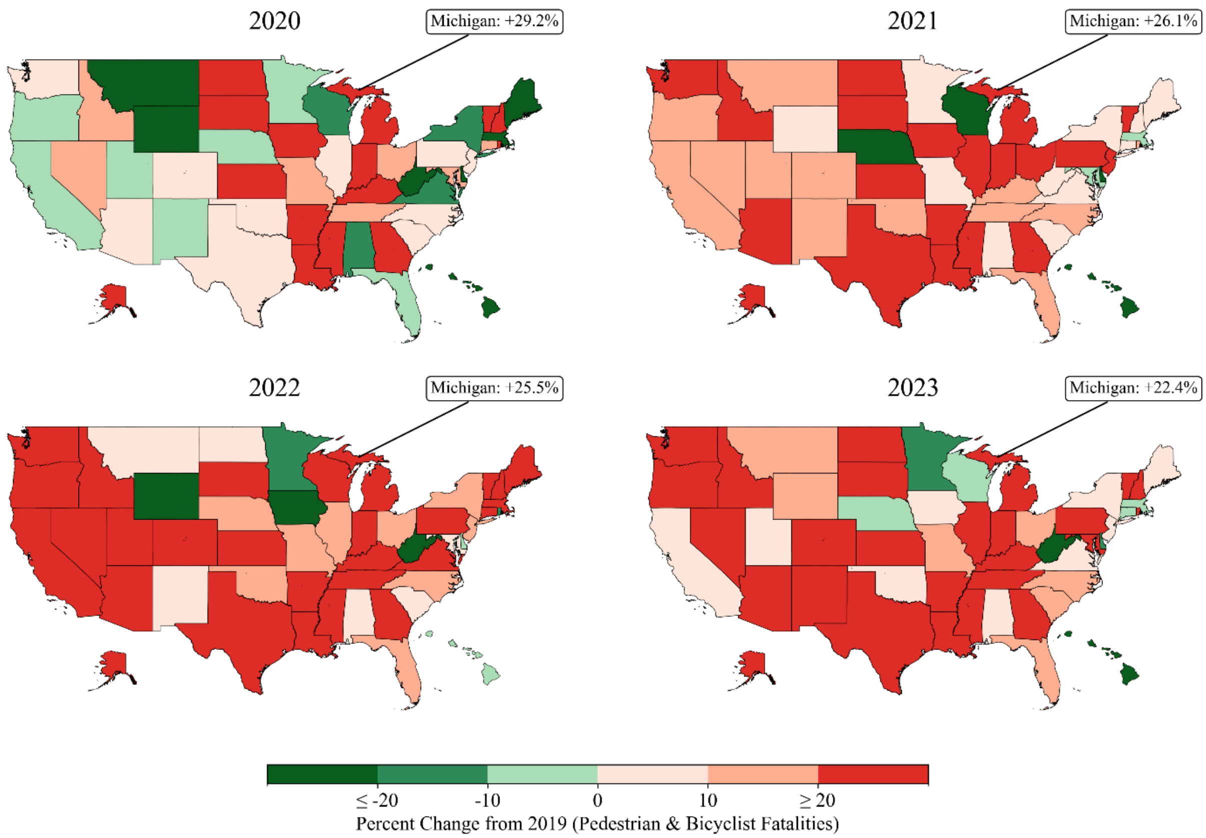

Figure 8: Comparing Yearly Percentage Change in Pedestrian and Bicyclist Fatalities with 2019

The pedestrian and bicyclist fatality rates per HMVMT further illustrate these trends, as seen in Figure 9. Michigan's rate increased from approximately 0.16 in 2019 to about 0.24 in 2020, before declining to around 0.21 in 2021 and remaining near 0.21 in 2022. By 2023, the rate slightly decreased to about 0.20, indicating modest improvement but still elevated levels compared with pre-pandemic conditions.

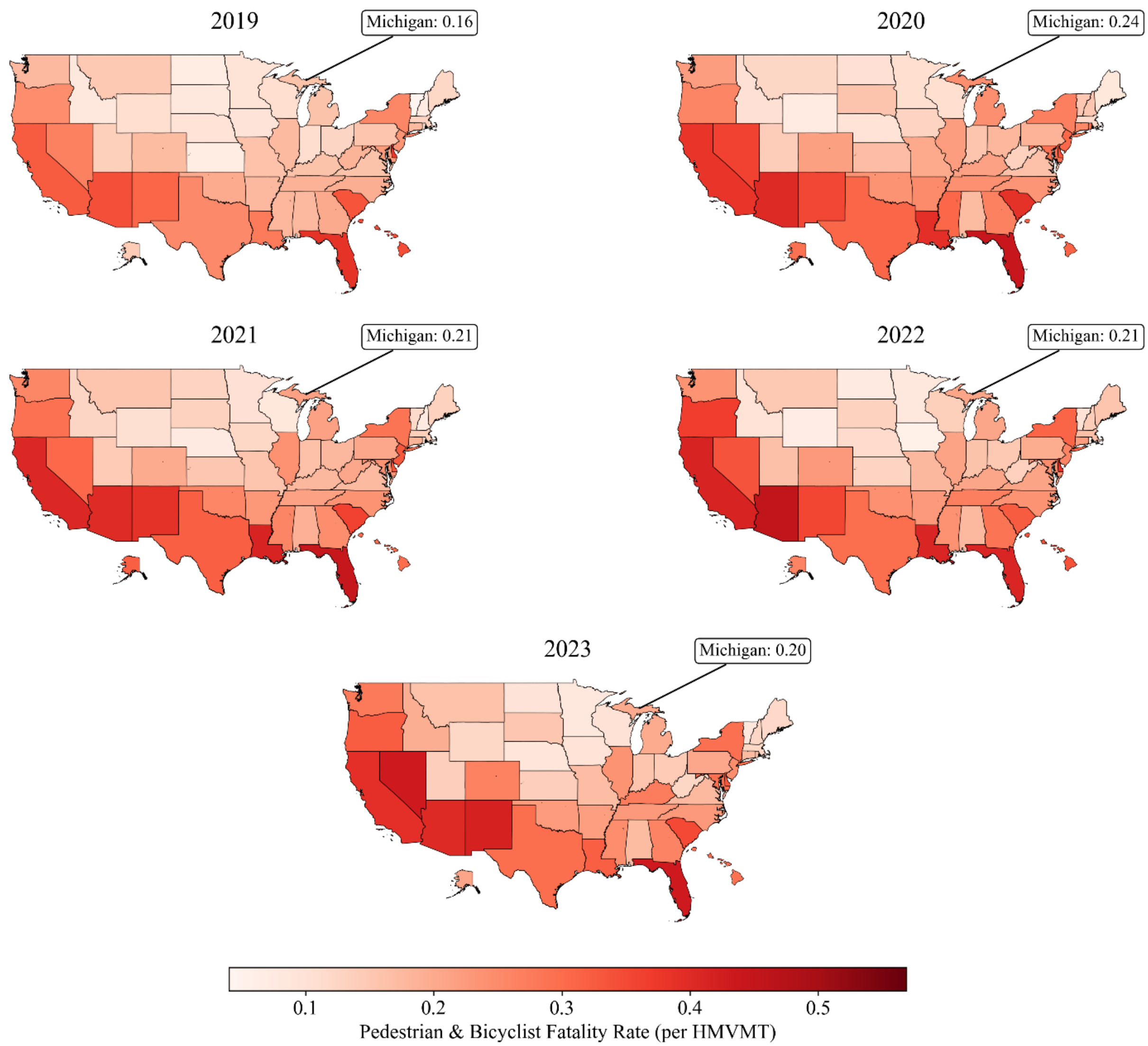

Figure 9: Pedestrian and Bicyclist Fatality Rate per HMVMT by State (2019–2023)

When examining pedestrian and bicyclist fatality rates per 100,000 population, the national maps again show geographic disparities, as seen in Figure 10. Michigan's rate increased from approximately 0.13 in 2019 to about 0.17 in 2020, remained around 0.17 in 2021 and 2022, and then declined slightly to approximately 0.16 in 2023. This pattern suggests that although Michigan experienced increases in vulnerable road user fatalities during the early pandemic period, conditions began to stabilize in the later years of the study period, but it has not reached the pre-pandemic level.

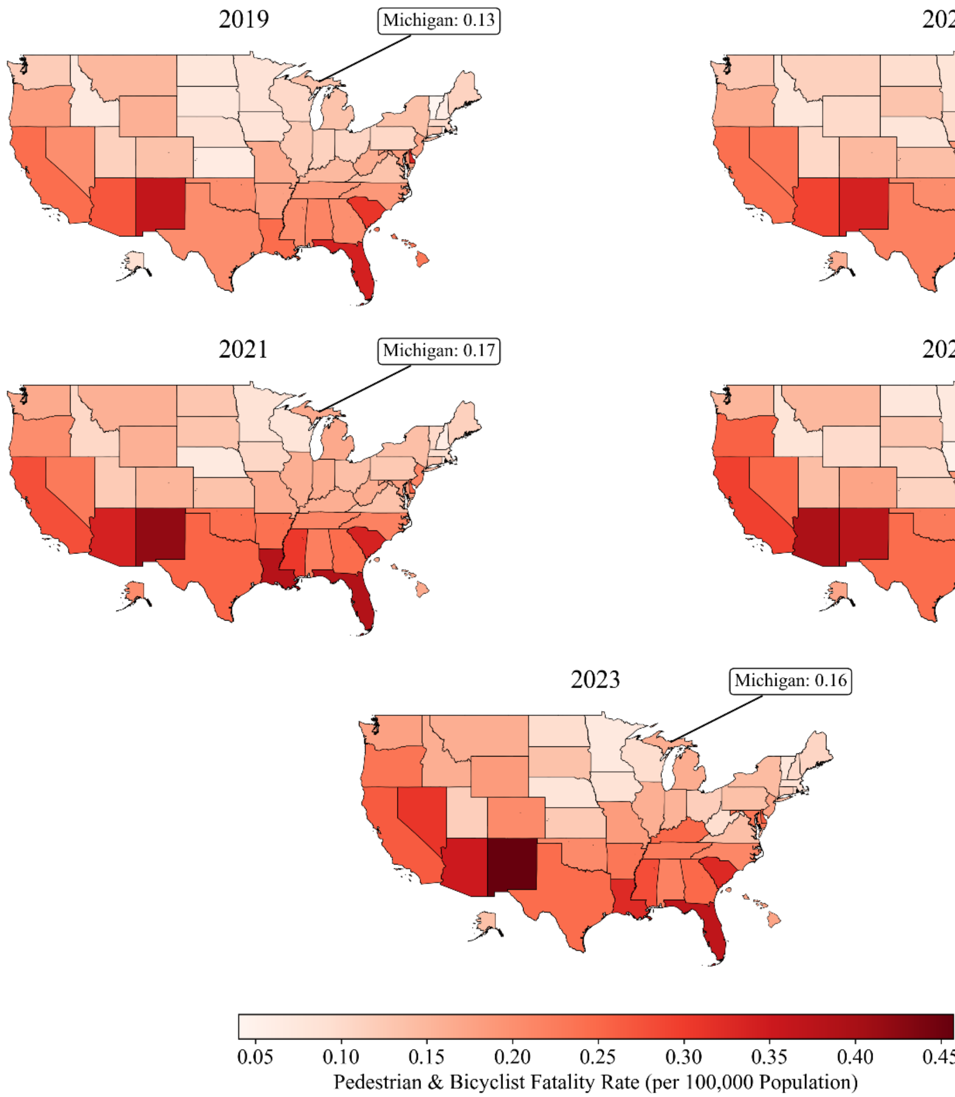

Figure 10: Pedestrian and Bicyclist Fatality Rate per 100,000 Population by State (2019–2023)

Overall, the data demonstrates that while fatality trends varied across states, many jurisdictions experienced increases in traffic fatalities and fatality rates following 2019, particularly during 2020–2022. Michigan's trends generally align with these national patterns, showing an initial increase in fatalities and fatality risk followed by a slight improvement by 2023. These findings highlight the continued need for targeted safety interventions to reduce both overall traffic fatalities and fatalities among vulnerable road users.

3.3 Statistical Analysis

This section presents the statistical analyses conducted to evaluate temporal and geographic variation in traffic fatalities during the 2019–2023 study period. The analyses evaluated changes in fatalities across states and over time relative to pre-pandemic conditions.

3.3.1 Statistical Methodology

This section describes the statistical modeling framework used to evaluate monthly fatality outcomes at the state level from January 2019 through December 2023. Two dependent variables were examined: (1) total roadway fatalities and (2) pedestrian and bicyclist fatalities. Both outcomes are non-negative integer counts observed repeatedly for each state over time, forming a longitudinal state-month panel dataset. Since the dependent variables represent count data, count regression methods were employed.

3.3.2 Modeling Framework

Let y_{st} denote the number of fatalities observed in state $s$during month t. Under a Poisson specification, the probability of observing y_{st} fatalities is given by Equation (1):

$$P(y_{st}) = \frac{e^{-\lambda_{st}} \lambda_{st}^{y_{st}}}{y_{st}!} \tag{1}$$

where λ_{st} represents the expected number of fatalities in state s during month t. The Poisson model assumes that the conditional mean equals the conditional variance. However, fatality data frequently exhibit overdispersion, meaning the variance exceeds the mean. To account for this feature, a Negative Binomial (NB) regression model was estimated. In the NB framework, the conditional mean function is specified as shown in Equation (2):

$$\lambda_{st} = \exp(\beta X_{st}) \times E_{st} \tag{2}$$

Where X_{st} is a vector of explanatory variables, β is a vector of estimable parameters, and E_{st} represents the exposure term.

Indicator variables for each state were included to explicitly account for persistent, time-invariant differences across states. A primary objective of this analysis was to compare fatality trends across states and evaluate how Michigan’s experience differed from other states during the study period. Including state indicator variables allows direct estimation of state-specific effects and facilitates interpretation of how baseline fatality levels vary across states relative to Michigan and other reference categories. Since these state-specific intercept shifts were modeled directly using indicator variables, an additional random-effects structure was not required for the total fatality specification.

Models were estimated using maximum likelihood methods. The standard error for each of the estimates is provided in parenthesis and the statistically significant parameter estimates at 95% confidence level are marked by an asterisk.

3.4 Model Results

Negative binomial regression models with a log link were estimated for (1) total fatalities and (2) pedestrian and bicyclist fatalities. Given the log-link specification, exponentiated coefficients were estimated. The exponentiated coefficients represent the multiplicative change in the fatalities associated with a one-unit change in a predictor variable. The results of the model are presented in Table 2.

Table 2: Negative Binomial Model for Total and Pedestrian & Bike Fatalities

Parameter	Estimate (Std. Error)	
	Total Fatalities	**Ped/Bike Fatalities**
Intercept	-1.40 (0.38)*	-2.38(0.62)*
Ln (VMT)	0.63 (0.04)*	0.57(0.07)*
State		
Michigan	Baseline	Baseline
Alabama	0.07 (0.03)*	-0.26(0.06)*
Alaska	-0.96 (0.14)*	-1.04(0.24)*
Arizona	0.26(0.03)*	0.56(0.05)*
Arkansas	0.04(0.05)	-0.33(0.09)*
California	0.58(0.06)*	1.17(0.09)*
Colorado	-0.09(0.04)*	-0.20(0.07)*
Connecticut	-0.54(0.06)*	-0.52(0.11)*
Delaware	-0.62(0.11)*	-0.44(0.18)*
District of Columbia	-1.32(0.16)*	-0.65(0.26)*
Florida	0.63(0.04)*	1.11(0.07)*
Georgia	0.27(0.03)*	0.33(0.05)*
Hawaii	-0.96(0.11)*	-0.52(0.18)*
Idaho	-0.47(0.08)*	-1.22(0.15)*
Illinois	0.07(0.03)*	0.09(0.05)*
Indiana	-0.08(0.03)*	-0.39(0.06)*
Iowa	-0.46(0.06)*	-1.16(0.11)*

Kansas	-0.25(0.06)*	-0.93(0.11)*
Kentucky	0.09(0.04)*	-0.27(0.07)*
Louisiana	0.16(0.04)*	0.31(0.07)*
Maine	-0.73(0.09)*	-1.31(0.17)*
Maryland	-0.31(0.04)*	0.02(0.06)
Massachusetts	-0.77(0.04)*	-0.62(0.07)*
Minnesota	-0.63(0.04)*	-0.99(0.08)*
Mississippi	0.14(0.05)*	-0.18(0.08)*
Missouri	0.05(0.03)	-0.26(0.06)*
Montana	-0.39(0.09)*	-1.17(0.18)*
Nebraska	-0.56(0.08)*	-1.41(0.15)*
Nevada	-0.30(0.06)*	-0.03(0.11)
New Hampshire	-0.95(0.10)*	-1.45(0.19)*
New Jersey	-0.39(0.03)*	0.19(0.05)*
New Mexico	-0.10(0.06)	0.05(0.10)
New York	-0.11(0.03)*	0.42(0.04)*
North Carolina	0.25(0.03)*	0.19(0.05)*
North Dakota	-0.91(0.11)*	-1.77(0.23)*
Ohio	0.05(0.03)	-0.21(0.05)*
Oklahoma	0.03(0.04)	-0.19(0.08)*
Oregon	-0.04(0.05)	-0.04(0.09)
Pennsylvania	0.06(0.03)*	-0.06(0.05)
Rhode Island	-1.27(0.12)*	-1.41(0.22)*
South Carolina	0.33(0.04)*	0.33(0.06)*
South Dakota	-0.67(0.11)*	-1.41(0.20)*
Tennessee	0.25(0.03)*	0.05(0.05)
Texas	0.67(0.05)*	0.84(0.08)*
Utah	-0.64(0.06)*	-0.80(0.10)*
Vermont	-1.14(0.13)*	-1.88(0.26)*
Virginia	-0.07(0.03)*	-0.21(0.05)*
Washington	-0.19(0.04)*	-0.06(0.06)
West Virginia	-0.31(0.08)*	-0.99(0.15)*
Wisconsin	-0.34(0.04)*	-0.80(0.07)*
Wyoming	-0.70(0.11)*	-1.71(0.22)*
Year		
2019	Baseline	Baseline
2020	0.15(0.01)*	0.13(0.02)*
2021	0.18(0.01)*	0.18(0.02)*
2022	0.16(0.01)*	0.20(0.02)*
2023	0.12(0.01)*	0.18(0.02)*
Month		
January	Baseline	Baseline
February	-0.04(0.02)*	-0.10(0.03)*
March	-0.03(0.02)	-0.18(0.03)*

April	0.05(0.02)*	-0.26(0.03)*
May	0.13(0.02)*	-0.26(0.03)*
June	0.17(0.02)*	-0.26(0.03)*
July	0.19(0.02)*	-0.18(0.03)*
August	0.22(0.02)*	-0.08(0.03)*
September	0.22(0.02)*	0.01(0.03)
October	0.21(0.02)*	0.10(0.03)*
November	0.14(0.02)*	0.09(0.03)*
December	0.10(0.02)*	0.10(0.03)*
Negative Binomial	0.01(<0.01)	<0.01(<0.01)

3.4.1.1 State Effects

Substantial cross-state differences are observed in both total and pedestrian/bicyclist fatality rates. For total fatalities, Texas exhibits expected fatalities after accounting for exposure and temporal variation; the fatality rate is nearly twice that observed in Michigan. Florida and California also show elevated fatalities, compared to Michigan (greater than 1.7). Louisiana, North Carolina, and South Carolina demonstrate statistically significant increases of a smaller magnitude.

In the pedestrian and bicyclist fatality model, state-level differences are generally larger in magnitude. California, Florida, and Texas again show substantially higher fatalities relative to Michigan, and Arizona, Georgia, Louisiana, North Carolina, and South Carolina also demonstrate statistically significant positive differences. The stronger effects in the pedestrian and bicyclist model suggest that cross-state variation is more pronounced for vulnerable road users. This may be attributable to differences in pedestrian exposure, transit usage, population density, land-use patterns, and the extent to which roadway infrastructure accommodates non-motorized users. States with larger urban populations and higher pedestrian activity levels may therefore exhibit greater divergence from Michigan.

3.4.1.2 Year Effects

Relative to 2019, fatalities increased in all subsequent years in both models. For total fatalities, the largest increase occurred in 2021. Although moderate reductions are observed in 2022 and 2023, rates remain above pre-pandemic levels. This pattern aligns with national trends indicating elevated risk during the pandemic period, potentially associated with higher operating speeds, reduced enforcement visibility, increased impairment, and changes in the composition of drivers on the roadway.

For pedestrian and bicyclist fatalities, rates increased beginning in 2020 and remained elevated through 2023, with limited evidence of sustained decline. The persistence of elevated vulnerable road user fatalities suggests that pandemic-related behavioral changes and shifts in mobility patterns may have had longer-lasting effects for non-motorized users. Increased walking activity in certain areas, combined with higher vehicle speeds and reduced congestion, may have contributed to sustained elevated risk. The divergence between total fatalities (which show partial stabilization) and pedestrian/bicyclist fatalities (which remain elevated) indicates that recovery patterns differ across crash types.

3.4.1.3 Monthly Effects

Seasonal patterns are evident in both models, though the timing differs. In the total fatality model, fatalities increase during late spring and summer, with peak effects observed in August and September relative to January. This pattern is consistent with seasonal increases in travel activity, recreational driving, and favorable weather conditions that increase overall exposure and mobility.

In contrast, pedestrian and bicyclist fatalities show increases during the fall months, particularly October through December. This seasonal shift may reflect reduced daylight hours, visibility challenges, and continued pedestrian activity during periods when driver expectations and environmental conditions are less favorable. The fall peak also coincides with school return periods and urban activity patterns that may elevate pedestrian exposure.

3.5 HSIP Target-Setting and Performance Measures (2018–2023)

To provide additional context for the modeled fatality trends, the following section examines HSIP-reported performance measures for all states during the 2018–2023 reporting period. This analysis shifts from regression-based evaluation of fatality counts to descriptive assessment of state-level target-setting practices and reported progress under the federal HSIP framework.

3.5.1 Overview of HSIP and Annual State Reporting

The Highway Safety Improvement Program (HSIP) is a federal-aid program focused on reducing roadway fatalities and serious injuries through data-driven safety investments. As part of HSIP implementation and accountability, each state prepares an annual HSIP report that documents statewide safety performance targets, progress toward those targets, and program activities. These reports provide a standardized set of safety performance measures that enable comparisons over time within a state and across states.

3.5.2 HSIP Performance Measures Extracted

For this study, HSIP reports were collected for all states for the 2018–2023 reporting years and used to compile a state-year dataset. Each record represents one state in one reporting year and includes performance measures commonly reported in HSIP documents. The compiled dataset includes the following core HSIP performance measures:

1. Number of Fatalities
2. Number of Serious Injuries
3. Fatality Rate
4. Serious Injury Rate
5. Number of Non-Motorized Fatalities and Serious Injuries

For each performance measure, the dataset includes (1) the reported value, (2) the reported five-year average, and (3) the state's target for the reporting year. These fields were compiled directly from the HSIP reports to support year-to-year comparisons and assessment of performance relative to targets.

3.5.3 Progress Tracking and Target Achievement Indicator

HSIP reports include a summary indicating whether a state is making progress toward its established safety performance targets. In this study, target achievement was based directly on each State's reported assessment of whether its safety performance targets were met, as documented in the HSIP annual reports.

Rather than applying a uniform numerical comparison between observed values and target values, this approach relies on the determination published by each State. This distinction is important, as States may use different methodologies when establishing and evaluating targets, including variations in how baseline performance, target values, and evaluation criteria are defined.

A binary "Met Target?" indicator was therefore assigned for each performance measure using the State-reported outcome (i.e., whether the State identified the target as met or not met). This approach ensures consistency with officially reported HSIP results while preserving the methodological differences across States.

These indicators support descriptive comparisons of performance outcomes, while also reflecting differences in how States define and achieve safety targets within their HSIP frameworks.

3.5.4 Data Organization and Use in the State-Level Chapter

The final HSIP dataset was structured as a state-year file with standardized identifiers (State name, State FIPS, and postal code) and a consistent set of HSIP performance and program fields for 2018–2023. The HSIP dataset was used for descriptive comparisons across states, with emphasis on (1) how Michigan's targets and progress compare to other states, (2) whether specific states consistently met targets across multiple measures, and (3) how performance trends align with broader fatality patterns observed in the state-month analysis.

HSIP variables were compiled and compared descriptively to summarize patterns in target-setting and target achievement across states. No statistical modeling was conducted using HSIP target-setting variables in this chapter.

3.5.5 Target Aggressiveness Across HSIP Performance Measures

Before interpreting whether a state met or did not meet its performance targets, it is important to recognize that differences in target achievement may reflect variations in how targets are established rather than differences in safety performance alone. For example, some states adopt highly aggressive targets that are substantially below recent historical trends. In extreme cases, such as Florida, targets were set at zero for all measures, which results in those states consistently appearing not to meet targets despite the outcome reflecting the target-setting approach rather than deteriorating safety conditions. Consequently, understanding how targets are established provides essential context for interpreting target achievement outcomes.

Figure 11 illustrates the average level of target aggressiveness for each state across the five Highway Safety Improvement Program (HSIP) safety performance measures during the 2018–2023 period. Target aggressiveness was quantified as the percentage difference between the state-established target and the corresponding five-year moving average baseline for each performance measure and year, with negative values indicating more aggressive targets (below historical trends) and positive values indicating less aggressive targets (above historical trends). The values shown in the figure represent the average aggressiveness across the six reporting years for each state.

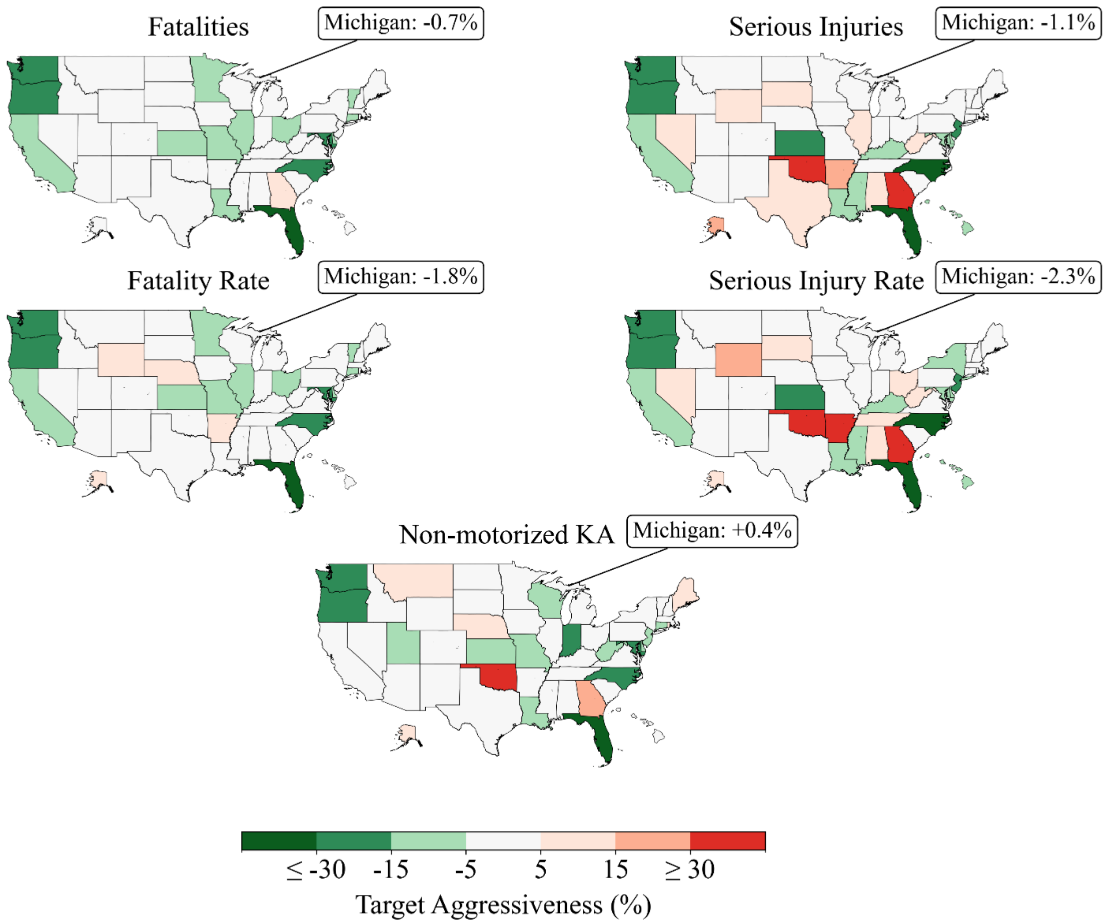

Figure 11: HSIP Target Aggressiveness for different Safety Measures

Across the United States, most states establish targets that are generally close to the five-year moving average baseline, which is consistent with Federal guidance and reflects a common practice of using recent historical performance as the basis for target development. However, some deviations are observed, particularly in the years following 2020. During this period, several states maintained targets similar to prior years rather than increasing targets in response to observed increases in fatalities and serious injuries. This approach reflects differences in policy decisions regarding whether targets should adjust upward in response to worsening trends or remain anchored to prior expectations. Other states more directly followed the updated five-year moving averages when setting targets, resulting in targets that increased in parallel with observed outcomes during the pandemic period.

Michigan's targets across the five performance measures were generally established close to the corresponding five-year moving averages throughout the study period, indicating a moderate and consistent target-setting approach relative to other states. The average aggressiveness values for

Michigan shown in the figure are near zero for most measures, suggesting that targets were neither substantially more aggressive nor substantially less aggressive than recent historical trends. This pattern indicates that Michigan's performance relative to targets is less influenced by unusually strict or lenient target selection and more reflective of underlying safety outcomes.

Overall, the figure demonstrates that variation in target achievement across states should be interpreted in the context of how targets are established. States with highly aggressive targets may appear to underperform relative to targets, whereas states with less aggressive targets may more frequently meet targets, even when underlying safety trends are similar.

3.5.6 National Trends in HSIP Performance Measures (2018–2023)

The HSIP performance measures provide a consistent framework for examining how safety outcomes evolved across states during the study period, including the years immediately preceding and following the onset of the COVID-19 pandemic. Across the five core performance measures, substantial variation was observed both temporally and geographically. As shown in Figure 12, the trends in HSIP performance relative to the reported five-year averages are presented for both the national average across states and for Michigan specifically, allowing comparison of how Michigan's safety outcomes evolved relative to broader national patterns during 2018–2023.

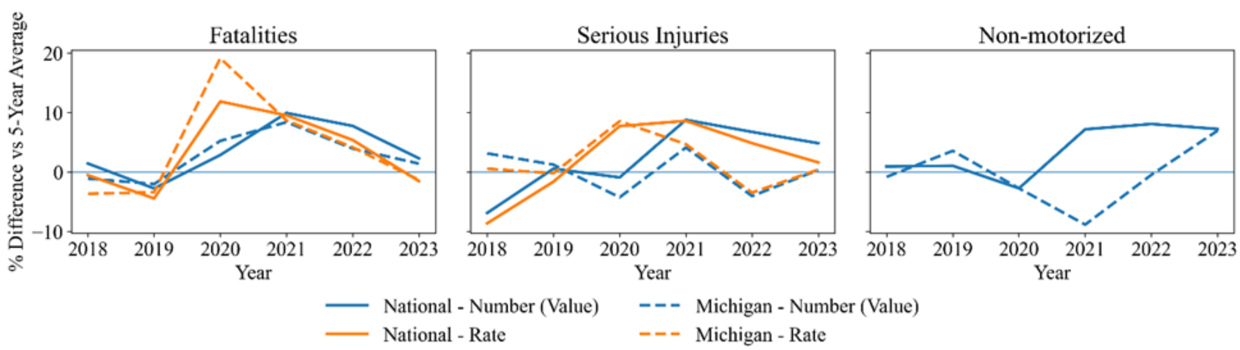

Figure 12: HSIP Safety Performance Trends Relative to 5-Year Moving Average

The fatality measures exhibit the largest deviations from the five-year moving averages, particularly beginning in 2020. Both nationally and in Michigan, fatalities and fatality rates increased substantially relative to historical baselines during 2020 and remained elevated through 2021. Michigan experienced a larger increase in fatality rate relative to its five-year average in 2020 compared to the national average, indicating a greater departure from expected trends during the early pandemic period. In subsequent years, deviations decreased, with both national and Michigan values moving closer to baseline levels by 2023.

Serious injury measures show more moderate deviations compared with fatalities. Nationally, serious injuries increased relative to the five-year average beginning in 2020 and peaked around 2021 before declining toward baseline levels in later years. Michigan exhibited greater year-to-year variability, including a decrease relative to the five-year average in 2020, followed by increases in 2021, before returning closer to baseline conditions by 2023.

For non-motorized fatalities and serious injuries, national trends indicate sustained increases above the five-year average beginning in 2021 and continuing through 2023. Michigan showed a temporary decrease relative to its five-year average in 2021, followed by increases in later years, highlighting differences in local exposure conditions and variability across states. Overall, the figure demonstrates that the largest departures from HSIP baseline conditions occurred during the pandemic-period years, particularly for fatality-related measures.

3.5.7 Safety Performant Targets

3.5.7.1 Performance Measure: Number of Fatalities

As shown in Figure 13, a larger proportion of states met their fatality targets during the pre-pandemic years, particularly in 2018 and 2019, when many states recorded fatality levels at or below the targets established in their HSIP plans. Beginning in 2020, however, a substantial shift is evident, with most states failing to meet their fatality targets. This change coincides with the increase in roadway fatalities observed nationally during 2020, when fatality counts rose relative to prior years and exceeded expected levels reflected in state targets. Consistent with these patterns, the state of Michigan did not meet its fatality target beginning in 2020, reflecting the increase in fatalities experienced during the pandemic period.

The pattern persists through 2021 and 2022, during which only a limited number of states achieved fatality levels below their established targets. The widespread failure to meet targets during these years reflects the broader national increase in roadway fatalities observed during the pandemic period and the difficulty states faced in anticipating the magnitude of safety changes during this timeframe. By 2023, some improvement is visible, with more states meeting their fatality targets compared to the preceding two years, although performance remained weaker than in the pre-pandemic period.

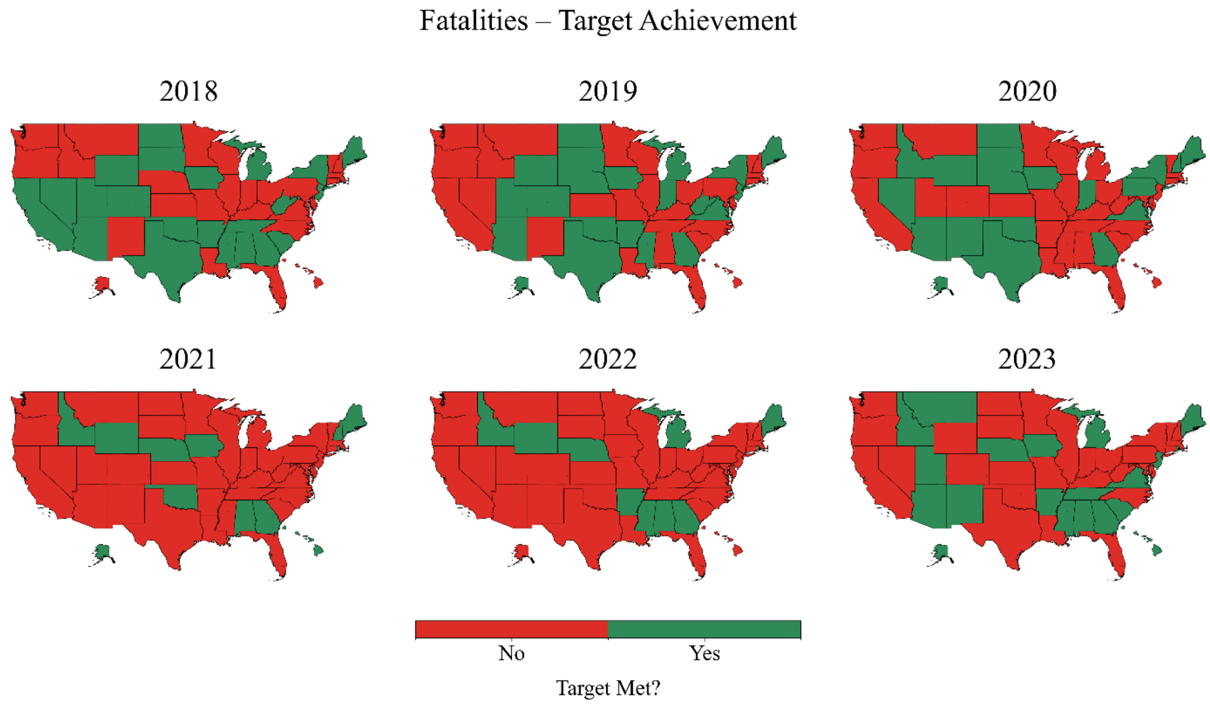

Figure 13: HSIP Fatality Target Achievement

3.5.7.2 Performance Measure: Fatality Rate

When accounting for changes in travel exposure by considering fatality rates (per hundred million vehicle miles traveled), a similar but more pronounced pattern is observed. Figure 14 presents the spatial distribution of whether states met the fatality rate targets for each reporting year from 2018 through 2023. Prior to the pandemic, most states met their fatality rate targets, indicating that observed fatality risk levels were generally consistent with or below the levels anticipated in state target-setting processes. In 2020, a noticeable shift emerged, which intensified and peaked in 2021, with 40 states and the District of Columbia failing to meet their fatality rate targets. This widespread pattern reflects elevated fatality risk during the pandemic period, when vehicle miles traveled declined but fatalities did not decrease proportionally, resulting in higher fatality rates than anticipated. In the following years, gradual improvement is evident, with a larger number of states meeting fatality rate targets by 2023 compared to 2021 and 2022. Michigan followed a pattern generally consistent with national trends, failing to meet its fatality rate target during the pandemic-period years but achieving its fatality rate target in 2023, indicating improvement relative to the target levels established by the state.

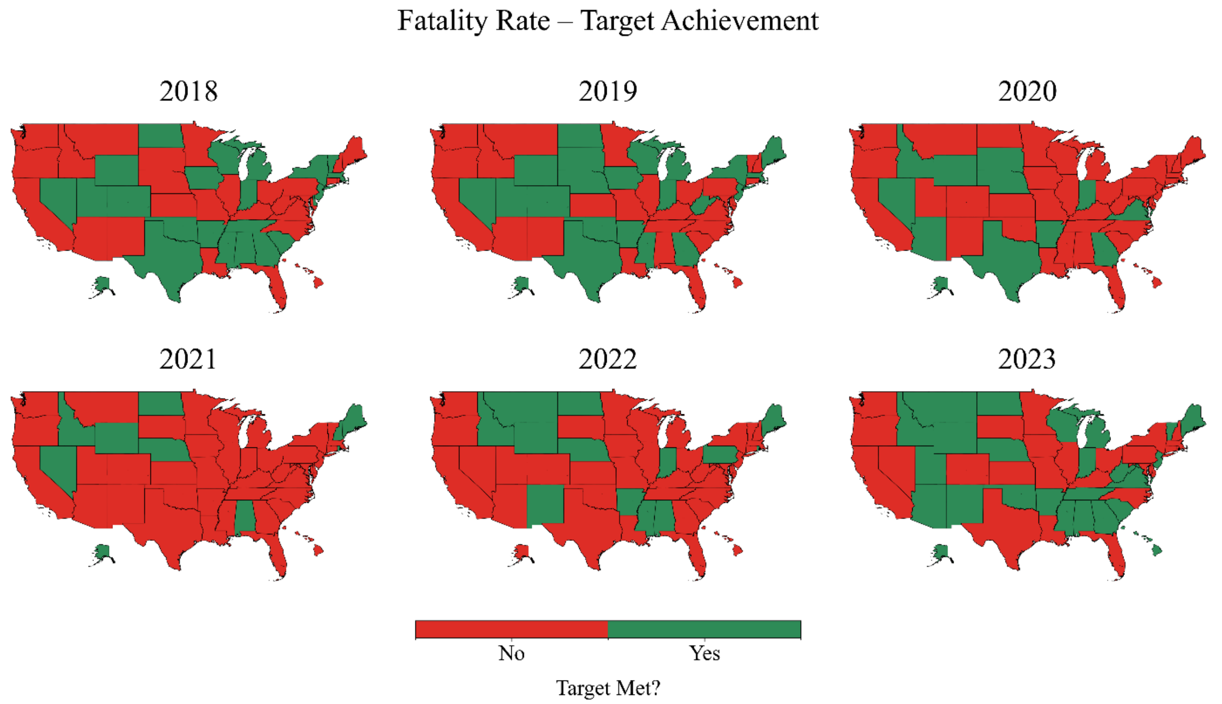

Figure 14: HSIP Fatality Rate Target Achievement

3.5.7.3 Performance Measure: Number of Serious Injuries

Figure 15 presents the spatial distribution of whether states reported meeting their serious injury targets for each year from 2018 through 2023. Prior to the pandemic, most states met their targets, indicating that observed serious injury levels were generally consistent with expectations established in state target-setting processes.

Beginning in 2020, a shift becomes apparent, with a growing number of states failing to meet their targets. This pattern intensifies in 2021 and persists through 2022 and 2023, as serious injury counts increased beyond anticipated levels. The widespread non-attainment during these years suggests that pandemic-related disruptions had a sustained impact on serious injury outcomes, with many states reporting performance that exceeded their target thresholds. In the later years, only limited improvement is observed, with many states continuing to report not meeting their targets. Michigan did not meet its serious injury target from 2018 through 2021, however, this pattern shifted in the later years, with Michigan meeting its serious injury target in both 2022 and 2023.

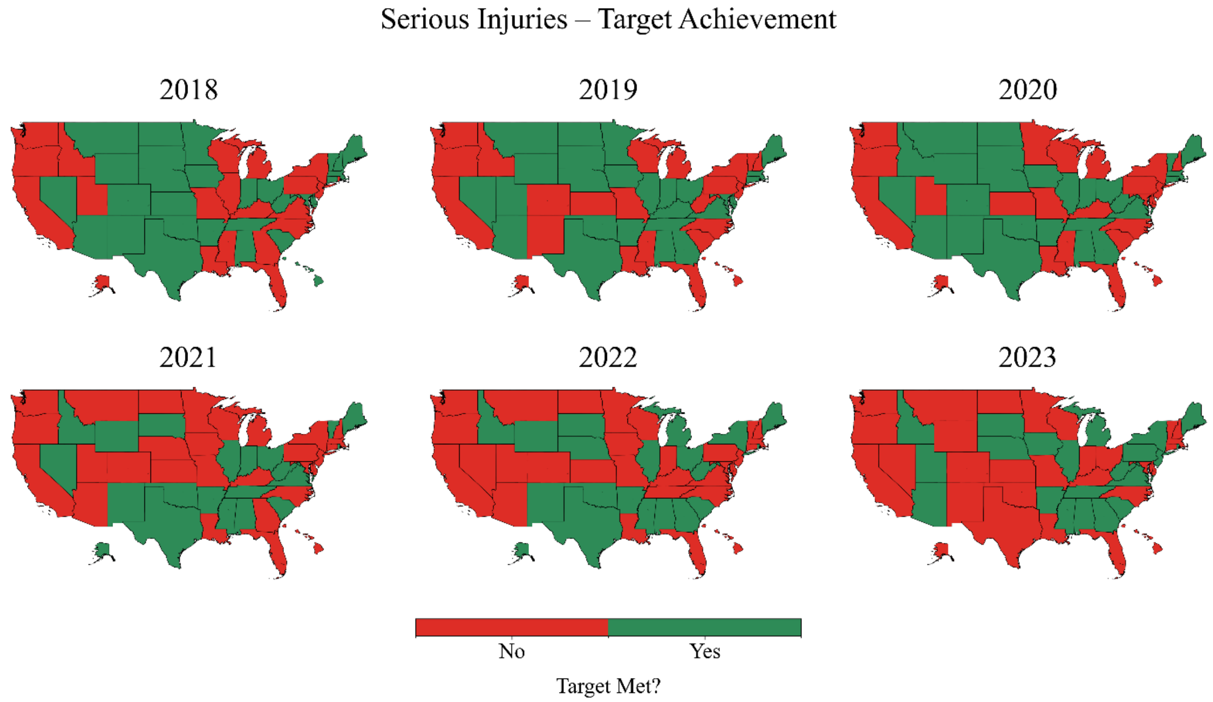

Figure 15: HSIP Serious Injury Target Achievement

3.5.7.4 Performance Measure: Serious Injury Rate

When accounting for changes in travel exposure by considering serious injury rates, a similar but somewhat more gradual pattern is observed compared with the serious injury counts. Figure 16 presents the spatial distribution of whether states met the serious injury rate targets for each reporting year from 2018 through 2023. Prior to the pandemic, most states met their serious injury rate targets. Beginning in 2020 and continuing through 2022, a larger number of states failed to meet their targets, reflecting increases in serious injury risk.

In more recent years, improvement is evident across several states, with a greater number meeting serious injury rate targets in 2023. Michigan demonstrates a similar pattern, with the state not meeting its serious injury rate target during the early pandemic years but meeting the target in the more recent reporting years. This improvement suggests that serious injury risk in Michigan moved closer to the levels anticipated in the state's targets as travel conditions and roadway safety outcomes began to stabilize following the pandemic period.

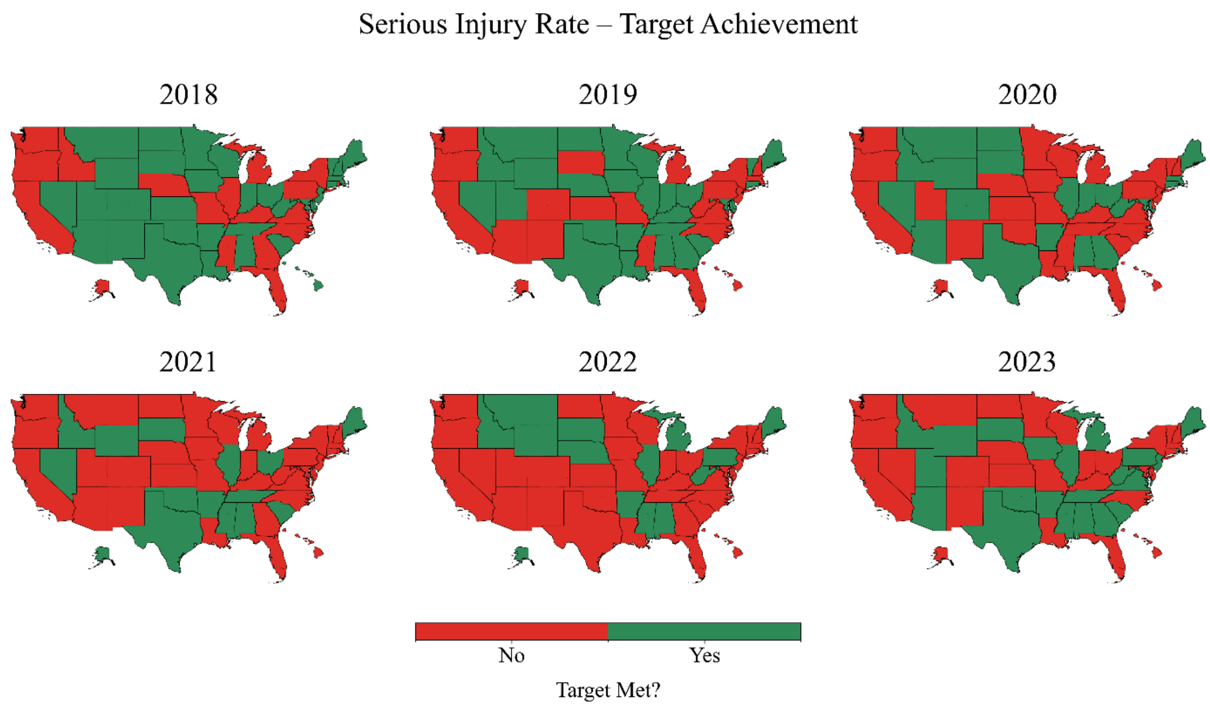

Figure 16: HSIP Serious Injury Rate Target Achievement

3.5.7.5 Performance Measure: Total Number of Non-Motorized Fatalities and Serious Injuries

Figure 17 presents the spatial distribution of whether states met the non-motorized target for each reporting year from 2018 through 2023. Prior to the pandemic period, a mix of states met and did not meet their targets, reflecting variability in non-motorized safety outcomes across the country. Beginning in 2021 and continuing through 2023, however, a larger proportion of states failed to meet their non-motorized targets, indicating increases in non-motorized fatalities and serious injuries that exceeded anticipated levels in many locations.

Michigan exhibits a notable change over time in this measure. While some improvement was observed in 2021 and 2022 following the early pandemic period, non-motorized fatalities and serious injuries increased again in 2023, resulting in the state not meeting its target. This reversal indicates a deterioration in performance relative to established targets, despite the temporary improvement observed in the preceding years.

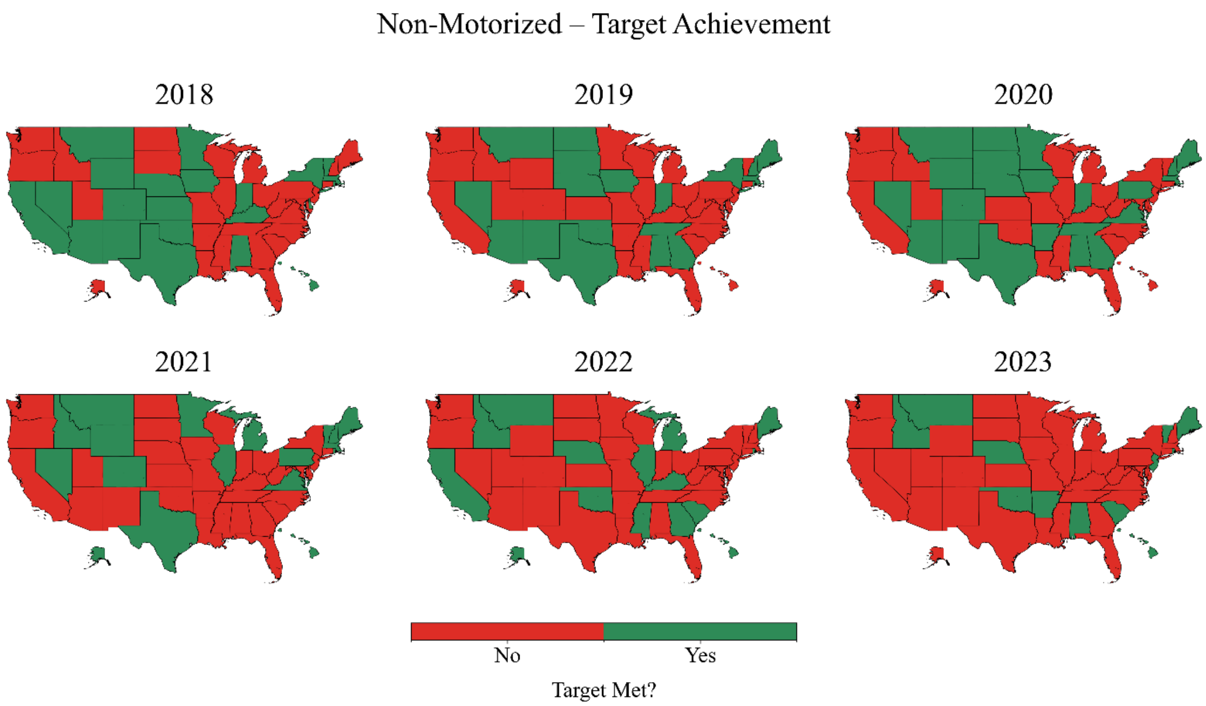

Figure 17: HSIP Non-motorized Fatalities & Serious Injuries Target Achievement

Overall, the figure highlights the increasing difficulty many states experienced in achieving non-motorized safety targets in recent years and underscores the importance of continued emphasis on vulnerable road user safety.

3.5.8 Summary

This chapter examines roadway fatality trends across the United States from 2019 through 2023, with particular emphasis on comparing Michigan's safety outcomes with national patterns. The analysis integrates multiple datasets to evaluate how fatalities, travel demand, and safety performance targets evolved during the pre-pandemic, pandemic, and post-pandemic periods. The Highway Safety Improvement Program (HSIP) performance measures were evaluated to provide a comprehensive overview of changes in roadway safety outcomes across states.

State-level fatality data was obtained from the Fatality Analysis Reporting System (FARS), which provides data on nationwide fatal crashes. Monthly fatality counts were aggregated for each state from January 2019 through December 2023. To account for travel exposure, monthly vehicle miles traveled data from the Federal Highway Administration were incorporated. Additional demographic and transportation system indicators, including population estimates, roadway mileage, vehicle registrations, and federal highway funding measures, were also compiled. Although these infrastructure and funding variables were evaluated during preliminary modeling, they were not retained in the final statistical models because they did not show any consistent relationships with fatality trends.

An examination of the dataset reveals substantial geographic variation in roadway fatalities across states and over time. Many states experienced increases in fatalities beginning in 2020, coinciding with the COVID-19 pandemic. Michigan followed a similar pattern, with fatalities increasing relative to 2019 during the early pandemic years before showing partial stabilization in later years. Fatality rates per hundred million vehicle miles traveled also increased nationally between 2019 and 2021, indicating that the rise in fatalities was not solely due to changes in travel demand but also reflected increased risk per mile traveled. Although some improvement occurred by 2023, fatality rates in many states remained above pre-pandemic levels.

Pedestrian and bicyclist fatalities displayed even greater variability across states. Many states, particularly in the western and southern regions, experienced increases in vulnerable road user fatalities during the study period. Michigan experienced fluctuations in pedestrian and bicyclist fatalities, with increases in some years followed by temporary declines. However, vulnerable road user fatality rates generally remained elevated compared with pre-pandemic levels, reflecting broader national concerns about pedestrian and bicyclist safety.

Negative binomial regression models were estimated for total fatalities and pedestrian/bicyclist fatalities. The models incorporated state indicator variables, year effects, and monthly seasonal indicators while accounting for travel exposure through VMT. The results indicate significant cross-state differences in fatality levels after controlling for exposure and temporal variation. States such as Texas, Florida, and California exhibited substantially higher fatality levels compared with Michigan, while several states showed significantly lower fatality levels. State differences were even more pronounced in the pedestrian and bicyclist fatality model, suggesting greater geographic variability in vulnerable road user risk. Temporal effects reveal that fatalities increased in all years after 2019, with the largest increase occurring in 2021. Although fatalities declined slightly in 2022 and 2023, levels remained above those observed before the pandemic. Monthly effects indicate clear seasonal patterns, with total fatalities peaking during summer months and pedestrian and bicyclist fatalities increasing during fall months.

HSIP performance measures were also evaluated from 2018 through 2023 to assess how states set and achieved safety targets. The analysis highlights considerable variation in target aggressiveness across states and demonstrates that target achievement must be interpreted in the context of how targets are established. Nationally, many states failed to meet fatality and fatality rate targets beginning in 2020 due to the unexpected increase in roadway deaths during the pandemic period. Michigan exhibited patterns broadly consistent with national trends, failing to meet several targets during the early pandemic years but showing improvement in more recent years. However, non-motorized safety outcomes have remained challenging, both nationally and in Michigan, emphasizing the need for continued focus on pedestrian and bicyclist safety.

4 NATIONAL COUNTY-LEVEL ANALYSIS

This section examines changes in roadway fatalities at the county-monthly level across the United States from 2019 through 2023. The county-level dataset was originally developed using daily fatality records; however, due to a large number of zero-fatality observations and high short-term variability, the data was aggregated to a monthly scale. The monthly aggregation provides a more reliable measure of underlying trends, minimizes issues related to sparse daily counts, and enhances comparability across counties and years.

The analysis focuses on identifying general trends in monthly fatalities and the factors that influenced those trends over time. Emphasis is placed on variations associated with demographic, socioeconomic, and behavioral characteristics, as well as differences between pre-pandemic, pandemic, and post-pandemic periods. This approach allows for a clearer understanding of how fatality outcomes evolved and which conditions contributed to the observed patterns at the county level nationwide.

4.1 Data Collection

This section describes the data sources and variables used to examine monthly roadway fatalities at the county level across the United States from 2019 through 2023. Multiple open data sources were integrated to capture travel exposure, demographic, socioeconomic conditions, and the effects of COVID-19 related policies. The resulting dataset provides a national-scale panel of county-monthly observations used for statistical modeling and trend analysis.

4.1.1 Fatality

Fatality data was obtained from the Fatality Analysis Reporting System (FARS), maintained by the National Highway Traffic Safety Administration (NHTSA) (NHTSA, n.d.-c).

Each crash record in FARS was matched to its corresponding county using the Federal Information Processing Standards (FIPS) code (CENSUS, 2023). The number of fatalities per crash was then aggregated by county and by month to create a continuous time series of fatality counts covering the period January 2019 through December 2023. This aggregation process produced a set of monthly fatality totals for 3,144 counties across all 50 states and the District of Columbia.

In addition to total fatalities, supplemental variables were derived from the FARS dataset to support further analysis. These included indicators of involvement of vulnerable road users (pedestrians and bicyclists), and the presence of contributing factors such as alcohol or speeding. While these variables were not directly used in the main model, they provided valuable context for understanding the conditions under which fatal crashes occurred before, during, and after the pandemic.

4.1.2 County-Level Monthly VMT Estimation

Accurate estimation of county-level vehicle miles traveled is critical for normalizing fatality counts and quantifying exposure across geographic areas and time periods. Since direct monthly VMT estimates are not available at the county level nationwide, a multi-step approach was developed to estimate county-monthly VMT using publicly available datasets. The procedure integrates county-level trip data from the Bureau of Transportation Statistics (BTS) (BTS, n.d.) and state-level monthly VMT totals from the Federal Highway Administration (FHWA) (FHWA, 2026b), ensuring consistency between local estimates and official state-reported travel volumes.

4.1.2.1 County-Level Monthly Trip Estimation

This process began with the daily number of trips reported by the BTS mobility dataset, which provides counts of trips for each county by distance category (e.g., 0-1 mile, 1-3 miles, 3-5 miles, etc.). To prepare for VMT estimation, the trip data were first aggregated to a monthly level for each county. The aggregation involved summing up the number of daily trips in each distance category for all days within a month, producing a complete count of trips by distance category per county-month.

Missing daily data points were rare however, to ensure coverage continuity, missing points were addressed through simple imputation. Missing days within a month were replaced with the county's average daily trip count for that month. This ensured uniform monthly totals and avoided artificial dips in calculated travel activity caused by incomplete data reporting.

4.1.2.2 Translating Trips into Estimated Monthly VMT

For each county-month, trips were converted into estimated vehicle miles traveled by multiplying the number of trips in each distance category by the average midpoint distance of that category.

As mentioned before the BTS mobility dataset provides trip counts across multiple predefined distance intervals including 0-1 mile, 1-3 miles, 3-5 miles, 5-10 miles, 10-25 miles, 25-50 miles, 50-100 miles, 100-250 miles, 250-500 miles, and 500+ miles. To approximate average trip length within each interval, midpoint distances were assigned. For instance, 7.5 miles for the 5-10 miles range and 17.5 miles for the 10-25 miles range. The smallest distance category (0-1 mile) was conservatively treated as 1 mile, while the largest open-ended category (greater than 500 miles) was assigned a representative distance of 500 miles. For each county, previously calculated monthly trip counts for each distance category were multiplied by its corresponding midpoint value, and the products were summed across all distance categories to obtain the initial estimated monthly VMT for that county.

4.1.2.3 Aggregating County VMT to State Level

The next step involved aggregating the estimated monthly county-level VMT values to the state level. This was achieved by summing all county-level estimates within each state for a given month, producing a statewide estimated monthly VMT derived entirely from the BTS-based county trip data. These values represent a model-based approximation of how much vehicle travel occurred in each state each month based on aggregated mobility data.

4.1.2.4 Calibration with FHWA Observed State VMT

The FHWA Highway Statistics provide official state-level monthly VMT estimates, derived from continuous traffic monitoring and vehicle classification data. To ensure that the county-level estimates aligned with these official values, a calibration factor (ratio) was computed for each state and month. This ratio was calculated using Equation (3):

$$Correction\ Ratio_{s,m} = \frac{FHWA\ State\ VMT_{s,m}}{Estimated\ State\ VMT_{s,m}} \tag{3}$$

Where s represents the state and m represents the month.

This ratio quantifies the adjustment needed to align the aggregated BTS-based estimates with FHWA's official totals. In effect, it scales the preliminary county estimates so that, when summed, they exactly match FHWA's observed monthly state VMT.

4.1.2.5 Adjusting County VMT Using State-Level Ratios

Finally, each county's estimated monthly VMT value was multiplied by its corresponding state–month correction ratio. This ensures that county-level values reflect realistic relative variation in travel activity across counties while maintaining consistency with verified state totals. The corrected VMT values represent the final exposure variable used in modeling and descriptive analyses. Mathematically, the adjustment can be expressed as Equation (4):

$$Corrected\ County\ VMT_{c,s,m} = Estimated\ County\ VMT_{c,s,m} \times Correction\ Ratio_{s,m} \tag{4}$$

Where c denotes county, s denotes state, and m denotes month.

After applying these corrections, validation was performed by comparing aggregated county totals with FHWA state-level reports for each month. Across all states and years, the adjusted estimates achieved near-perfect alignment. Internal consistency checks also confirmed that seasonal fluctuations and recovery patterns in the corrected county VMT data corresponded with trends observed in independent sources, including BTS mobility indices and FHWA regional summaries. These county-level VMT estimates were subsequently used as the exposure variable in the regression analysis to normalize fatality counts and quantify risk per unit of travel.

4.1.3 COVID-19 Cases and Deaths

Information on COVID-19 cases and deaths was obtained from the Johns Hopkins University (JHU) Center for Systems Science and Engineering (CSSE) COVID-19 Data Repository (CSSE, 2023). This dataset integrates official statistics from federal, state, and local public health agencies, providing comprehensive temporal coverage and consistency across jurisdictions.

The JHU dataset includes, for each U.S. County and date, the cumulative number of confirmed cases and cumulative number of deaths attributed to COVID-19. These values represent the total number of cases and deaths recorded since the beginning of the pandemic up to each date. The records span all 50 states and the District of Columbia, covering the period from January 2020 to May 2023.

Prior to aggregation, data quality control procedures were applied to ensure internal consistency and to preserve the cumulative structure of the dataset. These procedures included checks for non-monotonic sequences (instances where cumulative counts decreased between consecutive days), duplicate records, and missing values. When daily decreases were identified, typically due to reporting adjustments or data reconciliation at the source, values were corrected to maintain a strictly non-decreasing cumulative trend within each county.

To align with the county-monthly analytical framework, the daily cumulative counts were converted into monthly totals. Monthly new cases and new deaths were derived by taking the difference between the cumulative totals reported at the end of consecutive months. This approach ensures that each value represents the number of newly reported cases or deaths occurring within a specific month, rather than cumulative totals. For example, if County X reported 1,000 cumulative cases at the end of April 2020 and 1,300 at the end of May 2020, the monthly new cases for May 2020 were calculated as 300. This method captures the temporal evolution of COVID-19 spread and mortality while maintaining the accuracy of cumulative reporting. The final data was also cross-checked with the dataset of weekly United States COVID-19 cases and deaths by county provided by Centers for Disease Control and Prevention (CDC) (CDC, 2025).

The monthly new COVID-19 cases and monthly new COVID-19 deaths were used to capture the intensity of local pandemic conditions. These indicators provide important context for understanding changes in travel behavior and roadway safety outcomes during and after the pandemic period.

4.1.4 COVID-19 Vaccination Data

Information on COVID-19 vaccination coverage was obtained also provided by Centers for Disease Control and Prevention (CDC) COVID-19 Public Datasets (CDC, 2023a). This dataset provides county-level vaccination statistics based on the jurisdiction and county of residence of the vaccine recipient. It then integrates records from multiple vaccination providers across the United States.

The CDC dataset compiles vaccination data reported by a wide range of vaccine administration partners, including jurisdictional public health clinics, retail pharmacies, long-term care facilities, dialysis centers, Federal Emergency Management Agency (FEMA) and Health Resources and Services Administration (HRSA) partner sites, as well as federal entity facilities. Together, these sources provide comprehensive county-level reporting of vaccination activity across all 50 states and the District of Columbia. For each county and date, the dataset includes the percentage of people who have completed a primary vaccination series**,** defined as individuals who received either both doses of a two-dose vaccine or one dose of a single-dose vaccine. This measure represents the share of the county population that has completed the initial vaccination regimen and provides an indicator of the level of population immunity within each county.

County-level vaccination data is publicly available from December 2020, corresponding with the initial rollout of COVID-19 vaccines in the United States, and through May 2023, which represents the last available reporting date used in this study. For the purposes of dataset integration and to maintain a continuous temporal structure consistent with the county-monthly framework, vaccination values were set to zero for months prior to December 2020, reflecting the period before vaccines were available.

To align with the county-monthly analytical structure used throughout this study, the daily vaccination data were aggregated to monthly values. For each county and month, the vaccination variable represents the reported percentage of the population that had completed a primary vaccination series as of the end of that month. This approach preserves the cumulative nature of vaccination coverage while ensuring temporal consistency with other county-level indicators used in the analysis.

The resulting vaccination variable captures the progression of vaccine uptake across counties over time and serves as an indicator of local public health conditions during the later stages of the pandemic. Changes in vaccination coverage may influence travel behavior, risk perception, and economic activity, all of which may indirectly affect roadway safety outcomes.

4.1.5 COVID-19 Policy Variables

Information on COVID-19 mitigation policies, including stay-at-home orders and related restrictions, was obtained from the Centers for Disease Control and Prevention (CDC) COVID-19 Public Datasets (CDC, n.d.). These datasets document when and where jurisdictions implemented public health measures to limit the spread of SARS-CoV-2, the virus that causes COVID-19. Beginning in March 2020, states and territories across the United States issued a range of policies such as mandatory or advisory stay-at-home orders, gathering bans, and restrictions on businesses and public activities. These measures were intended to reduce person-to-person contact and population movement.

4.1.5.1 Stay-at-Home Orders

CDC compiled stay-at-home orders by reviewing official state and territorial government websites, executive orders, and press releases (CDC, 2021d). Each order was classified into categories that describe both who the order applied to and how restrictive it was. The original CDC dataset is structured at the county-daily level, indicating whether each order type was active for a given county on a specific day. Since the analytical dataset operates at the county-monthly level, these daily records were aggregated to summarize the proportion of each month during which the orders were in effect.

For every county and month, the share of days each order type was active was calculated. For instance, if a county had a mandatory stay-at-home order in effect for 15 out of 31 days in March 2020, the value for that variable was 0.48. This method produced continuous variables ranging from 0 to 1, representing the percentage of the month that each policy category was active. For months in which no stay-at-home order of any type was in effect, the variables corresponding to restrictive orders (such as mandatory or advisory categories) were assigned a value of 0, while the "no order" variable was assigned a value of 1. This ensured that the variables accounted for the full distribution of policy conditions in each month, even when no restrictions were in place.

This conversion from daily to monthly structure preserved local variation in policy implementation while maintaining consistency with other data sources such as fatalities, vehicle travel, and weather. These variables provide an important measure of policy intensity and duration, capturing the evolution of community mitigation efforts over time and across counties during the pandemic.

4.1.5.2 Gathering Bans

Information on gathering restrictions was also obtained from the Centers for Disease Control and Prevention (CDC) database (CDC, 2021b). These measures were implemented alongside stay-at-home orders to reduce in-person contact and limit opportunities for virus transmission through social and commercial activities.

The CDC dataset documents restrictions on public gatherings at the county-daily level, categorized by maximum allowed group size. Categories include bans on gatherings of over 1-10, 11-25, 26-50, 51-100, and more than 100 people, as well as an indicator for gathering bans of any size. Each record indicates which restrictions were active for each county and day.

To align with the county-monthly framework used in this analysis, the daily data were aggregated to calculate the percentage of days in each month that a particular restriction was in effect. For example, if a county prohibited gatherings of more than 50 people for 20 out of 30 days in April 2020, the variable "*Gathering Ban Over 50*" would have a value of 0.67.

Importantly, these measures were also calculated excluding the days under a mandatory stay-at-home order. In other words, a separate set of "exclusive" variables was generated to represent the proportion of the month during which gathering bans were active and no mandatory stay-at-home order was in place. This distinction isolates the direct effect of gathering restrictions independent of broader mobility restrictions. Months with no restrictions were coded as 0, and months with continuous restrictions were coded as 1.

However, the analysis revealed no clear or statistically significant relationship between gathering bans and monthly fatality counts after accounting for other factors. Consequently, these variables were excluded from the final model specification.

4.1.5.3 Restaurant and Bar Restrictions

Data on restaurant and bar operational status were obtained from CDC database (CDC, 2021a, 2021c). These variables indicate whether establishments were open or closed and specify the operating conditions imposed by local or state public-health directives. Categories include Closed, Curbside/Carryout/Delivery Only, Open with Social Distancing or Reduced Capacity, Authorized to Fully Reopen, and No Restrictions (Normal Operation).

The daily CDC data were again aggregated to the monthly level, with each variable representing the fraction of days per month during which a given policy was active in each county. For example, if restaurants were permitted to open with limited seating for half of June 2020, the value of variable named "*Restaurant Open with Limitations*" would be 0.50.

As with the gathering bans, restaurant and bar restrictions were also calculated excluding mandatory stay-at-home orders, capturing only those periods when these policies were active while residents were not already subject to stay-at-home mandates. This approach ensures that restaurant and bar restrictions reflect standalone operational limitations rather than overlapping effects of stay-home policies.

Months without any restrictions on restaurant or bar operations were assigned a value of 0 for all restriction categories and 1 for the "No Restrictions" variable. This consistent treatment allows comparisons of policy intensity and timing across all counties and months.

4.1.6 Additional Variables and Supporting Data

Several additional data sources were incorporated to capture environmental, demographic, and geographic conditions that may influence roadway fatalities. These variables provide broader contextual information and were merged with the fatality and VMT data at the county-month level using five-digit FIPS codes as the common key.

4.1.6.1 Weather Variables

Monthly weather data was obtained from the National Oceanic and Atmospheric Administration (NOAA) (NCEI, 2026). For each county, average temperature (°F) and total precipitation (inches) were obtained for every month from 2019 through 2023. These indicators capture seasonal and climatic variations that can affect driving conditions, visibility, and crash risk. For example, precipitation can reduce roadway friction and increase crash likelihood, while extreme temperature shifts can influence travel demand.

4.1.6.2 Population and Land Area

Population and land area data was obtained from the U.S. Census Bureau (CENSUS, n.d.). County population figures were used to standardize exposure metrics and to compute population density (persons per square mile). Land area was used as the denominator in this calculation to ensure comparability among counties of different sizes.

Population data corresponds to the official Census intercensal estimates, which provide yearly population totals between decennial censuses. These values were matched to the corresponding analysis years (2019–2023) to maintain consistency with other data sources.

4.1.6.3 Demographic and Socioeconomic Variables

Demographic and socioeconomic information was drawn from both the U.S. Census Bureau (CENSUS, n.d.) and the County Health Rankings and Roadmaps (CHRR) program (CHRR, 2025). These data sources provide a wide range of indicators describing the population composition, health status, and social and economic conditions of each county.

From the U.S. Census Bureau, measures such as total population, age distribution, median household income, and percent of rural population were obtained. These indicators describe the basic demographic structure and economic capacity of each county.

The County Health Rankings and Roadmaps (CHRR) dataset contributed additional contextual variables related to community well-being. These include information on demographic characteristics, health outcomes, quality of life, physical and mental health, and health behaviors. These include frequent mental distress which measures the percentage of adults who report 14 or more days of poor mental health in the past 30 days, excessive drinking which shows percentage of adults reporting heavy drinking in the past 30 days. The dataset also includes social and economic measures, such as education levels, employment rates, income inequality, and access to health care. In addition, built environment and commuting indicators, such as the percentage of workers driving alone to work or experiencing long commutes, were included. While not all variables from CHRR were used in the final modeling stage, they were reviewed to select measures most relevant to roadway safety and travel exposure. These variables help describe broader county-level conditions that may influence driving patterns, travel demand, and vulnerability to crash risk.

One important consideration when using the County Health Rankings and Roadmaps data is that the publication year does not always correspond to the data year. The CHRR dataset compiles information from multiple underlying sources, each collected at different times. For example, a dataset released in 2025 may include certain measures representing conditions from 2022 or earlier. To address this, each variable was assigned to the year that reflects its actual data period, not its publication year. For instance, if a 2025 CHRR release reported a median income measure based on 2022 data, that value was applied to the 2022 observation in this dataset. This approach ensures that all variables represent the correct time period and maintain temporal consistency across counties.

4.1.6.4 Mental Health Variables

In addition to the variables described above, county-level mental health indicators were examined using data from Mental Health America's (MHA) State and County Data Dashboard (IIHS, n.d.). The MHA dataset compiles anonymized results from more than ten million online mental health screenings conducted nationwide between 2020 and 2025. The dashboard reports the number and percentage of individuals screening at risk for conditions such as depression, anxiety, post-traumatic stress, trauma, and psychosis, disaggregated by state, county, age group, and race/ethnicity.

While this data provided valuable insight into population-level mental health needs, substantial missingness at the county level and inconsistent temporal coverage limited the suitability for integration with other variables in the national panel dataset. Preliminary analyses also indicated no significant relationship between these measures and roadway fatality trends after accounting for demographic and socioeconomic factors. Consequently, the MHA data was excluded from the final modeling framework but is noted here for completeness.

4.1.6.5 Law Enforcement Data

Information on traffic enforcement was obtained from the Insurance Institute for Highway Safety (IIHS), which maintains detailed archives of communities using red light running and speed safety cameras across the United States (MHA, n.d.). The IIHS dataset compiles historical records identifying the presence of active enforcement programs, along with the dates of implementation, suspension, or termination.

For this study, community-level records were reviewed through the IIHS archives to identify every update to camera program activity from 2019 through 2023. Counties containing at least one community with an active camera program were coded as having automated enforcement in place for that month. This process produced county-level monthly indicators for the presence of red-light running cameras and speed cameras.

However, the analysis revealed no clear or statistically significant relationship between these enforcement indicators and monthly fatality counts after accounting for other factors. Consequently, these variables were excluded from the final model specification but are documented here to acknowledge the scope of data collection and evaluation efforts.

4.1.7 Michigan State Data

After developing the national county-monthly dataset to examine fatality trends and contributing factors across the United States, a more detailed dataset was created specifically for Michigan counties. The national analysis provided a broad understanding of how roadway fatalities evolved during and after the COVID-19 pandemic; however, Michigan's extensive crash data systems allow for a deeper exploration of underlying crash characteristics, severity patterns, and contributing circumstances. This state-level dataset enables more refined spatial and temporal analyses, supports comparisons across MDOT regions, and helps identify specific factors influencing safety outcomes within Michigan. The dataset follows the same monthly temporal structure but integrates more comprehensive local crash information available through the Michigan State Police (MSP) and Michigan Department of Transportation (MDOT).

Crash dataset for Michigan obtained from the Michigan State Police Traffic Crash Reporting System was provided by MDOT. In this dataset, each crash record contains detailed information on crash location and time, along with severity and contributing factors such as roadway condition, lighting, weather, driver sobriety, and whether roadway construction or maintenance was present. The annual number of crashes occurring in each county was calculated both overall and by the most severe level of injury sustained in the crash, according to the five-point KABCO scale, where K represents fatal crashes, A denotes serious injury crashes, B indicates minor injury crashes, C represents possible injury crashes, and O corresponds to property damage only (PDO) crashes. In addition to these severity-based classifications, separate variables were created for crashes involving pedestrians, bicyclists, alcohol, and drugs. These detailed classifications allow for focused examination of vulnerable road user crashes and behavior-related factors contributing to roadway fatalities.

The Michigan county-monthly dataset was developed to identify where crashes occurred most frequently and to evaluate how different MDOT regions and counties have experienced changes in crash outcomes over time. By integrating these detailed crash variables with demographic, roadway, and exposure data, the analysis supports spatial comparisons across counties and highlights regions that experienced the greatest increases in crashes and fatalities. This work complemented the national-level analysis by providing Michigan-specific insights to guide MDOT's safety planning and regional prioritization efforts.

4.2 Data Integration and Preparation

The integration and preparation process involved combining multiple datasets into a unified, analysis-ready panel at the county-monthly level. The goal was to merge fatality data, travel exposure, demographic and socioeconomic indicators, environmental conditions, and policy measures related to COVID-19 into a consistent structure that could support national analyses.

The process began with the national county-monthly dataset, which served as the foundation for all analyses. Each dataset was standardized using the five-digit Federal Information Processing Standards (FIPS) code to ensure consistent county-level matching across sources. Time-dependent variables such as fatalities, trips, estimated VMT, weather, and COVID-19 indicators were aggregated from daily to monthly format covering January 2019 through December 2023. Annual variables, including demographic and socioeconomic measures, were expanded to every month within the corresponding year to maintain temporal alignment.

Following aggregation, individual data sources were merged sequentially using county FIPS and month-year identifiers as the common keys. Each merge was followed by validation checks to confirm that record counts remained consistent across data sources and that no counties or time periods were lost during the process.

Quality control procedures were also implemented to ensure temporal and spatial completeness. Missing or anomalous values were identified and addressed using simple imputation or logical correction. For instance, missing monthly trip counts or weather values were replaced with the average for the corresponding county and adjacent months, while binary policy indicators were set to zero when no order or restriction was in effect. These steps ensured continuity across the full 2019–2023 period.

The final integrated national dataset contained consistent monthly records for more than 3,000 counties across all 50 states and the District of Columbia. This dataset provided the primary basis for national-level statistical analysis.

4.3 Aggregate Data Summary

This section summarizes the key characteristics of the county-monthly dataset and describes temporal trends, spatial variability, and distributions of the primary variables used in the analysis. Descriptive statistics and visualizations are presented to illustrate changes in fatalities, travel exposure, COVID-19 conditions, and policy measures across the pre-pandemic, pandemic, and recovery periods.

Figure 18 presents monthly national vehicle miles traveled and the corresponding percent change relative to the same month in 2019. Clear temporal shifts in travel behavior are evident across the study period, with the most pronounced reductions occurring during 2020.

National VMT declined substantially in early 2020, coinciding with the onset of the COVID-19 pandemic and the implementation of statewide stay-at-home orders and travel restrictions. The largest decrease occurred in April 2020, where VMT was approximately 40 percent lower than April 2019. Other months in 2020 also exhibited reductions, generally ranging from 5 to 15 percent below 2019 levels. Although traffic volumes began recovering during the summer and fall of 2020, VMT remained consistently below pre-pandemic conditions throughout the year. In 2021, travel demand rebounded considerably, with monthly VMT levels approaching those observed in 2019.

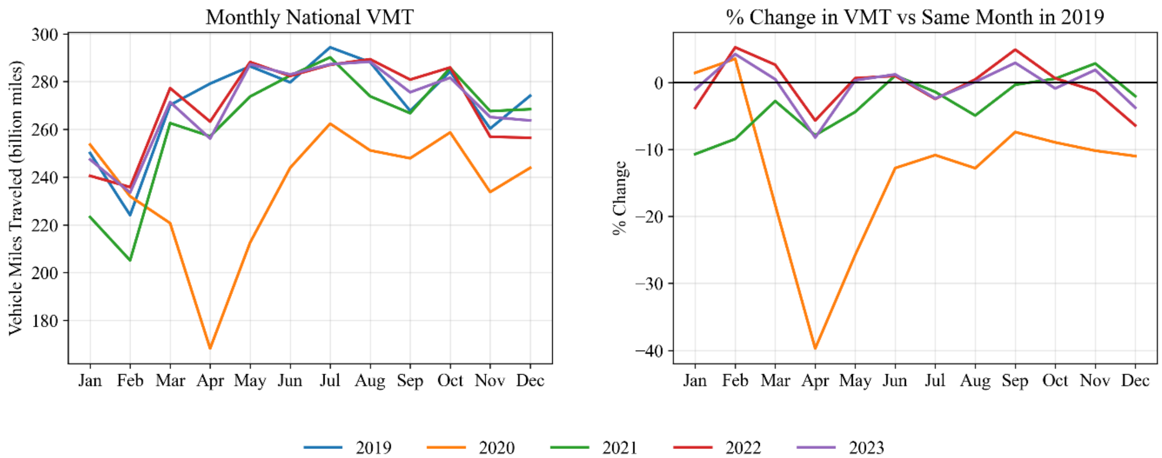

Figure 18: National Monthly VMT (2019–2023) and Percent Change Relative to Pre-Pandemic Levels

However, most months still remained slightly below the 2019 baseline. By 2022 and 2023, national VMT largely returned to pre-pandemic conditions, with many months closely matching or occasionally exceeding 2019 levels. Percent differences during these later years were generally small, indicating stabilization of travel behavior. Across all years, April consistently shows lower volumes relative to the 2019 baseline, while May and June demonstrate stronger recovery and values comparable to typical pre-pandemic levels. Outside of 2020, month-to-month fluctuations are modest, suggesting that national travel demand has largely normalized following the initial pandemic disruption.

Figure 19 presents national monthly trends in total fatalities and fatality rates per hundred million vehicle miles traveled for the period 2019–2023. Clear temporal shifts in travel behavior are evident across the study period, with the most pronounced reductions occurring during 2020.

In terms of total counts, fatalities declined during the early months of 2020, particularly in March and April, followed by a sharp increase beginning in late spring. From approximately May through October, monthly fatalities in 2020 exceeded corresponding values observed in 2019. The highest overall fatality counts occurred in 2021, with most months surpassing those of all other years. Elevated totals persisted in 2022, while 2023 showed modest reductions compared with 2021–2022 but remained above pre-pandemic (2019) levels.

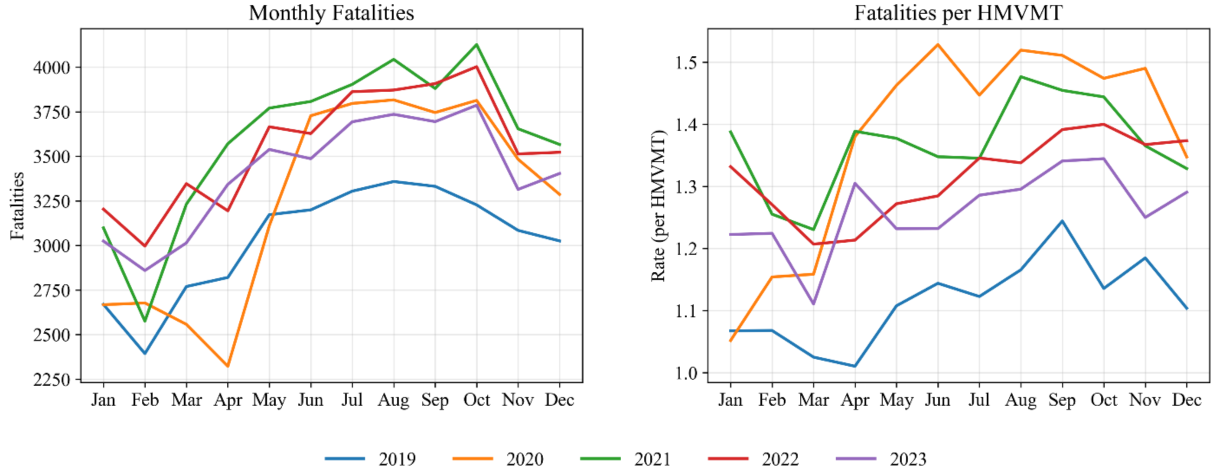

Figure 19: Monthly National Fatalities and Fatality Rates per HMVMT

When adjusting for exposure using vehicle miles traveled, a different pattern emerges. Despite not having the highest total fatalities, 2020 exhibits the highest fatality rates for most months. This reflects the substantial reduction in travel during the early pandemic period, which resulted in fewer vehicle miles but disproportionately higher fatalities per unit of travel. Fatality rates remain elevated in 2021 and 2022 relative to 2019, indicating persistently higher risk levels even as travel volumes recovered. Although rates in 2023 show some stabilization and slight declines compared with the immediate post-pandemic years, they continue to exceed pre-pandemic values.

Figure 20 illustrates the percent change in state-level fatality rates relative to 2019 for the period 2020 through 2023. In 2020, nearly all states experienced higher fatality rates compared with 2019, despite substantial reductions in travel demand. Wyoming was the only state that exhibited a decline in fatality rate during that year, while most other states recorded increases exceeding 10-30 percent. Elevated fatality rates persisted into subsequent years. In 2021, only Nebraska and Wyoming showed reductions relative to 2019, whereas the majority of states continued to experience positive deviations. Although some moderation is evident in 2022 and 2023, many states still remained above pre-pandemic levels, indicating that fatality risk did not fully return to baseline conditions even as traffic volumes recovered.

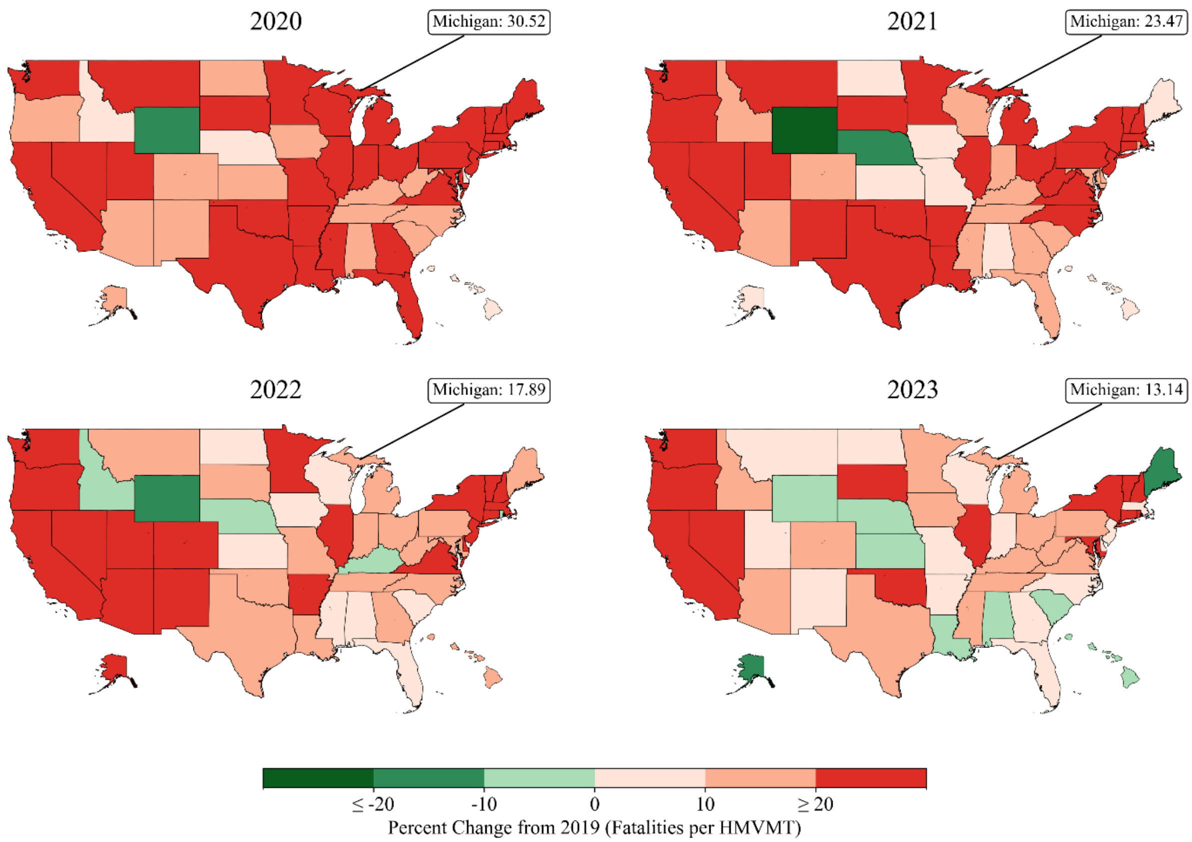

Figure 20: Percent Change in Fatality Rate Relative to 2019

Michigan followed the broader national pattern of increased fatality rates beginning in 2020. The state experienced a 30.5 percent increase in fatality rate in 2020 relative to 2019, placing it among the states with more pronounced early-pandemic increases. Although Michigan's fatality rate declined in each subsequent year, it remained elevated at 23.5 percent in 2021, 17.9 percent in 2022, and 13.1 percent in 2023. This pattern suggests gradual improvement but not a full return to baseline conditions during the study period.

To further contextualize Michigan's experience within its regional setting, Table 3 compares percentage changes in fatality rates for selected Midwestern states. In addition to changes relative to the 2019 baseline, the table also presents year-over-year percentage changes to illustrate the pace at which fatality rates increased or moderated across states. This comparison provides additional insight into whether Michigan's recovery trajectory was consistent with, faster than, or slower than that of neighboring states. Table 3 indicates that Michigan experienced one of the more persistent elevations in fatality risk among Midwestern states. While most neighboring states recorded substantial increases in 2020, several exhibited faster moderation in subsequent years.

For example, Wisconsin's fatality rate increase declined from 24.5 percent in 2020 to approximately 1 percent by 2023, effectively returning to near-baseline levels. Indiana and Missouri also showed steady reductions after 2020, with year-over-year decreases in most post-pandemic years.

Table 3: Percent Change in Fatality Rate for Selected Midwest States

State	Percentage change in Fatality Rate Compared to 2019				Percentage change in Fatality Rate Compared to Previous Year		
	2020 vs 2019	2021 vs 2019	2022 vs 2019	2023 vs 2019	2021 vs 2020	2022 vs 2021	2023 vs 2022
Michigan	30.52	23.47	17.89	13.14	-5.4	-4.52	-4.03
Illinois	39.3	40.17	29.23	30.52	0.62	-7.8	1
Indiana	24.92	15.14	17.33	9.62	-7.83	1.9	-6.57
Iowa	12.44	5.74	2.12	12.3	-5.96	-3.43	9.97
Minnesota	24.68	38.16	26.03	13.88	10.82	-8.78	-9.64
Missouri	23.88	9.81	12.8	5.18	-11.36	2.72	-6.75
Ohio	26.44	26.46	16.12	11.97	0.02	-8.18	-3.57
Wisconsin	24.45	11.9	8.99	0.99	-10.08	-2.59	-7.34

In contrast, Michigan's fatality rate, although gradually declining each year after 2020, remained elevated throughout the entire 2020–2023 period. Even in 2023, Michigan's fatality rate remained 13.1 percent above its 2019 level, exceeding the relative increases observed in several peer states. The year-over-year changes further illustrate that while Michigan experienced consistent annual reductions after 2020 (approximately 4-5 percent per year), the rate of improvement was gradual and insufficient to return to pre-pandemic conditions by 2023.

While the preceding discussion compared state-level fatality rate changes, state averages can mask substantial variation within individual states. To better understand the geographic distribution of these changes, Figure 21 presents county-level percent changes in fatality rates relative to 2019 across the United States. For each county, fatality rates were compared to that same county's rate in 2019 to maintain a consistent local baseline. Counties with zero fatalities in 2019 and zero fatalities in subsequent years are shown with hatching. If a county had zero fatalities in 2019 but recorded one or more fatalities in a later year, the change was displayed as +100 percent for visualization purposes.

Unlike the state-level summaries, these maps reveal substantial within-state variation. In 2020, increases were geographically widespread, with many counties across the Midwest, South, and West exhibiting fatality rate increases exceeding 20 percent. Although some counties show reductions (green shading), the dominant pattern in 2020 and 2021 reflects elevated fatality risk across much of the country.

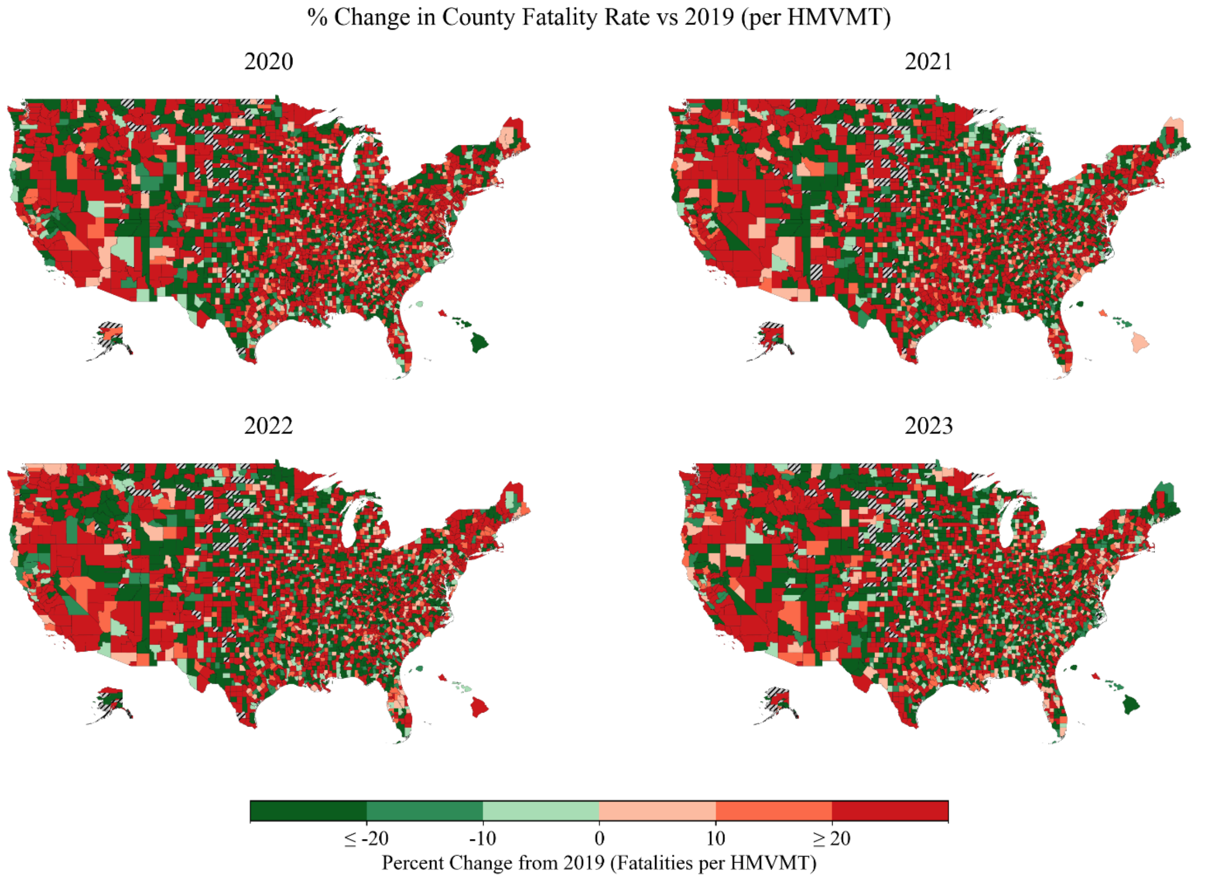

Figure 21: County-Level Percent Change in Fatality Rate (per HMVMT) Relative to 2019

In 2022 and 2023, the spatial pattern becomes more heterogeneous, with a greater mix of increases and decreases, though many counties remain above baseline levels. These results suggest that the pandemic-related shifts in fatality risk were not uniformly distributed and that recovery trajectories varied substantially across local jurisdictions.

Figure 22 presents county-level percentages of adults reporting frequent mental distress (14 or more days of poor mental health per month) for 2019 through 2022, based on County Health Rankings data. In 2019 and 2020, spatial patterns are relatively stable. Higher levels of reported mental distress are concentrated in parts of the Southeast, while many counties in the Upper Midwest and Northern Plains exhibit comparatively lower levels. The overall geographic distribution remains similar between 2019 and 2020, suggesting that early pandemic impacts were not immediately reflected in large-scale spatial shifts in this measure. In 2021 and particularly

2022, however, the maps show a noticeable increase in the proportion of counties with higher reported levels of frequent mental distress. The expansion of darker shading (higher percentages) across portions of the Midwest, South, and Western states indicates a broader rise in reported mental health challenges. By 2022, elevated levels appear more widespread compared to the pre-pandemic period.

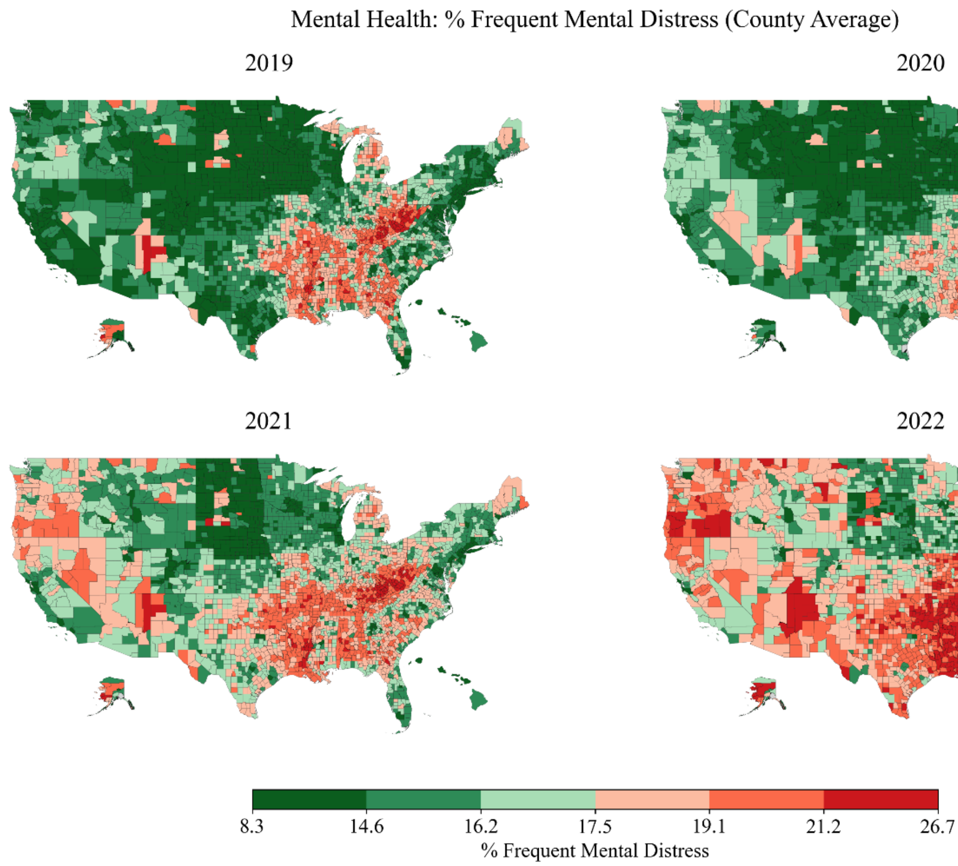

Figure 22: County-Level Percentage of Adults Reporting Frequent Mental Distress (≥14 Days in Past 30 Days)

This figure provides contextual evidence that broader population-level stress and distress increased during the same period in which fatality rates remained elevated. These spatial patterns support further statistical examination of whether county-level mental distress is associated with fatality outcomes after controlling for exposure and roadway characteristics.

Given that Michigan experienced relatively persistent increases in fatality rates compared to several Midwestern peers, a more detailed examination of county-level trends within Michigan is warranted. Figure 23 presents the percent change in fatality rates at the county level within Michigan relative to 2019. Several sparsely populated counties (e.g., Keweenaw, Luce, and

Montmorency) recorded zero fatalities in 2019 and also zero fatalities in certain subsequent years. These counties are hatched to indicate unchanged zero values. In cases where a county had zero fatalities in 2019 but recorded one or more fatalities in later years (e.g., Huron County), the percent change is reflected as a 100 percent increase for visualization purposes.

As shown, substantial within-state variation is evident across all years. In 2020, many counties experienced increases relative to 2019, with several southern and central counties exhibiting increases exceeding 20 percent. Although some counties show reductions, elevated fatality rates were geographically widespread during the early pandemic period.

In subsequent years (2021–2023), the spatial pattern becomes more mixed. Some counties show gradual movement toward pre-pandemic levels, while others continue to exhibit persistent increases. This heterogeneity suggests that recovery trajectories were not uniform across Michigan and that local factors likely influenced fatality risk patterns.

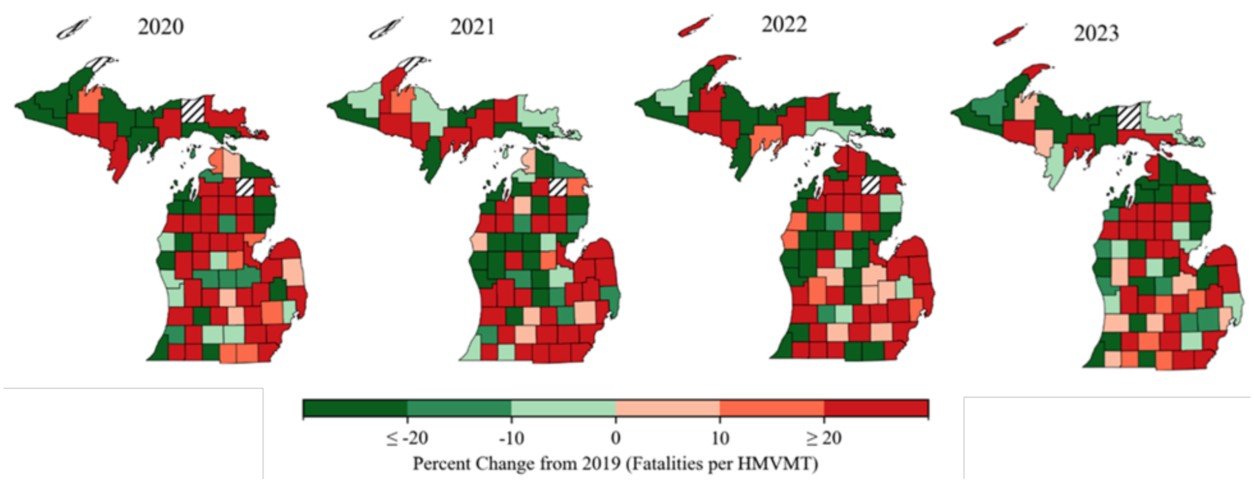

Figure 23: Michigan County-Level Percent Change in Fatality Rate (per HMVMT) Relative to 2019

Figure 24 presents the percent change in county-level fatality rates relative to the previous year, providing additional insight into how fatality risk evolved locally across Michigan. In 2020 (relative to 2019), several urban and high-population counties experienced notable increases. For example, Wayne County, Macomb County, and Kent County all recorded substantial increases, consistent with the broader statewide surge observed during the early pandemic period.

At the same time, several rural northern counties, such as Alger, Marquette, and Baraga, showed decreases or smaller changes, reflecting lower traffic volumes and smaller baseline fatality counts.

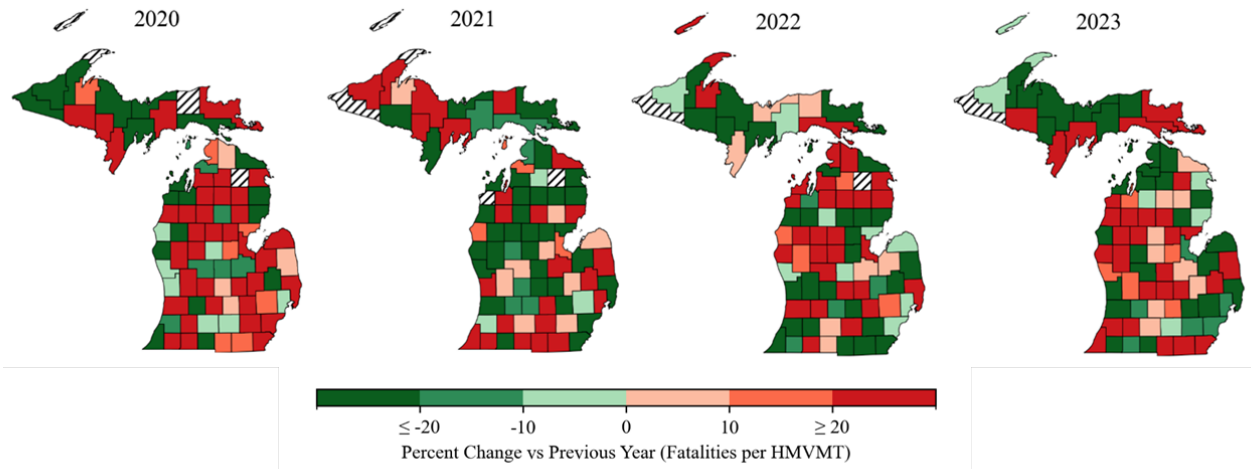

Figure 24: Michigan County-Level Percent Change in Fatality Rate (per HMVMT) Relative to Prior Year

In 2021 (relative to 2020), many counties that experienced sharp increases in 2020 exhibited reductions. For instance, Wayne County and Oakland County showed declines compared to 2020, even though their fatality rates remained elevated relative to 2019. This pattern suggests that the initial spike in fatality risk was not uniformly sustained. However, some rural counties, including Dickinson, Delta, and Houghton, displayed large percentage increases in certain years, which is partly attributable to small baseline counts where even a few additional fatalities result in large percentage changes.

By 2022 and 2023, the spatial pattern becomes increasingly heterogeneous. Urban counties such as Washtenaw and Oakland generally show more moderate year-to-year fluctuations, while several rural counties, such as Oscoda, Manistee, and Wexford, exhibit pronounced swings across years. These large fluctuations are characteristic of low-population rural counties where fatal crash counts are relatively small and therefore more volatile in percentage terms.

Importantly, no single county demonstrates a continuous increase in fatality rate from 2020 through 2023. Instead, both urban and rural counties exhibit alternating increases and decreases over time. This suggests that while the early pandemic period produced widespread increases in fatality risk, subsequent years reflect localized adjustments influenced by differences in traffic demand, roadway characteristics, and exposure conditions across Michigan’s diverse regions.

4.4 Statistical Analysis

This section addresses three primary objectives related to traffic safety and mobility patterns before and after onset of the pandemic.

The first objective is to examine how traffic fatalities varied across counties and over time. Monthly fatality counts were evaluated at the county level to assess how changes in travel demand, population characteristics, socioeconomic conditions, and COVID-19 related factors corresponded with fatal crash outcomes. Fatality trends during the pandemic period were shaped not only by reductions in traffic exposure but also by broader behavioral and policy shifts. Therefore, this analysis considers variation in demographic composition, economic indicators, public health measures (e.g., stay-at-home orders, mask requirements, and restaurant/bar restrictions), vaccination rates, and COVID-19 case prevalence.

The second objective is to evaluate changes in travel demand during the same period. Monthly vehicle miles traveled for each county were compared with the corresponding month in 2019 to establish a consistent pre-pandemic baseline.

The third objective focuses specifically on Michigan and examines how fatality outcomes and travel demand changed across different regions of the state. This objective aims to identify where the largest changes occurred geographically and to determine whether certain regions or counties experienced more pronounced shifts in fatalities and mobility patterns during and after the pandemic period. Understanding these spatial patterns provides additional context for interpreting statewide trends and helps identify locations where safety impacts were most substantial.

The following sections present the statistical analyses conducted to address these objectives.

4.4.1 Statistical Methods for Fatality Analysis

A series of regression models were estimated to evaluate the relationship between travel exposure, demographic characteristics, socioeconomic factors, COVID-19 conditions, policy measures, and monthly fatality counts at the county level. The number of fatalities occurring in county i during month t represents a discrete, non-negative integer outcome. Such count data are commonly analyzed using Poisson or negative binomial (NB) regression models. Under a Poisson specification, the probability of observing y_{it} fatalities in county i during month t is expressed as Equation (5):

$$P(y_{it}) = \frac{e^{-\lambda_{it}} \lambda_{it}^{y_{it}}}{y_{it}!} \quad (5)$$

Where λ_{it} denotes the expected number of fatalities in county i during month t. However, crash and fatality data typically exhibit overdispersion, wherein the variance exceeds the mean. To account for this, a negative binomial model was employed. In the NB framework, a gamma-distributed error term is incorporated into the conditional mean function, as in Equation (6):

$$\lambda_{it} = \exp(\beta X_{it} + \varepsilon_i) \times E_{it} \quad (6)$$

Where β is a vector of estimable parameters, X_{it} is a vector of explanatory variables, and E_{it} represents the exposure term. The term $\exp(\varepsilon_i)$ is gamma-distributed with mean equal to 1 and variance equal to α, where α is the overdispersion parameter.

Because fatality counts are influenced by traffic volume, the natural logarithm of estimated monthly VMT (MVMT) was incorporated as an offset term in the model. This ensures that predicted fatality counts scale proportionally with travel exposure and allows coefficients to be interpreted as multiplicative effects on fatality rates rather than raw counts.

The dataset consists of repeated monthly observations for each county over multiple years, forming a longitudinal panel structure. To account for within-county correlation and unobserved county-specific heterogeneity, a random-effects modeling framework was adopted. Specifically, a random intercept was specified for each county using the State-County FIPS identifier Equation (7):

$$\beta_{0i} = \beta_0 + \omega_i \quad (7)$$

Where ω_i represents a normally distributed random effect capturing unobserved time-invariant characteristics of county i. This specification accounts for persistent differences across counties in baseline fatality risk due to factors not explicitly included in the model.

The explanatory variables included demographic composition (age structure, race), socioeconomic conditions (income, unemployment, income variability), population density, weather conditions, regional indicators, mental health measures, COVID-19 incidence, vaccination rates, and policy variables (mask mandates, stay-at-home orders, restaurant/bar restrictions). Temporal indicators were also incorporated to capture seasonal and year-specific effects.

Models were estimated using maximum likelihood methods. The estimated coefficients reflect multiplicative effects on expected fatality rates. Parameter estimates, associated standard errors (in parentheses), and statistical significance at the 95% confidence level are presented in Table 5.

The same modeling framework was also applied to evaluate fatality patterns within Michigan specifically. For this purpose, as mentioned before a subset of the national dataset corresponding to Michigan counties was extracted, and equivalent model specifications were estimated.

4.4.2 Statistical Methods for Travel Demand Analysis

To evaluate the factors associated with changes in travel demand during and after the COVID-19 period, a Linear Regression (LR) model was estimated in which the dependent variable was the percentage change in monthly VMT for each county relative to the corresponding month in 2019. Specifically, for each county and month during the study period, monthly VMT was compared with the VMT observed in the same calendar month of 2019, thereby controlling for seasonal variation in travel patterns.

The dependent variable representing travel change was calculated as the percentage difference between monthly VMT in each county and the VMT observed for the same county and calendar month in 2019, as shown in Equation 8:

$$\%\ \text{Change in Monthly VMT}_{i,t} = \frac{\text{Monthly VMT}_{i,t} - \text{Monthly VMT}_{i,2019(m)}}{\text{Monthly VMT}_{i,2019(m)}} \times 100 \qquad (8)$$

where i represents the county and t denotes the observation month. This assessment provides insight into how mobility patterns evolved during the pandemic and recovery phases and how these changes varied across counties with different demographic, economic, and policy environments.

The resulting dependent variable is continuous and approximately normally distributed, making it suitable for estimation using linear regression techniques. The final dataset includes repeated monthly observations for each county over multiple years, forming a county-level panel dataset.

The repeated nature of observations within counties over time introduces potential temporal correlation and unobserved county-specific heterogeneity. Counties may differ systematically in baseline travel behavior, infrastructure characteristics, socioeconomic composition, or policy responsiveness, which may influence observed VMT changes. To account for this, a mixed-effects modeling framework was adopted, incorporating county-specific random intercepts based on the state-county FIPS code.

The general form of the model is expressed as Equation 9:

$$y_{it} = \beta X_{it} + u_i + \varepsilon_{it} \tag{9}$$

Where y_{it} represents the percentage change in monthly VMT for county i in month t relative to the same month in 2019; β is a vector of estimable parameters; X_{it} is a vector of explanatory variables, including sociodemographic characteristics, economic indicators, COVID-19 case prevalence, vaccination rates, public health policies, and temporal controls; u_i represents the county-specific random effect; and ε_{it} is the idiosyncratic error term.

The error components are assumed to follow normal distributions:

$$u_i \sim N(0, \sigma_u^2)$$
$$\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$$

The model was estimated using maximum likelihood methods. By incorporating county-level random effects, the specification accounts for within-county correlation across months and improves the efficiency and reliability of the parameter estimates.

4 provides descriptive statistics for the final county-month analysis dataset. The variables include fatality outcomes, traffic exposure measures, demographic and socioeconomic characteristics, weather conditions, regional indicators, mental health metrics, COVID-19 incidence, vaccination rates, and public health policy variables.

Table 4: Descriptive Statistics for Key Variables

Parameter	**Including 2023**		**Excluding 2023**	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Fatalities per county-month	1.07	2.94	2.08	4.18
Estimated monthly VMT	82,477,059	225,583,212	164,695,279	323,348,070
Population density (persons/sq. mi)	253.23	1559.51	524.91	2455.39
Percentage of population below 18 years	21.84	3.49	22.17	3.10
Percentage of population above 65 years	20.28	4.87	18.28	4.31
Percentage of non-Hispanic white population	75.24	20.23	67.16	20.14
Median income in $1,000	59.92	15.30	60.65	17.27
Normalized income variability [(80th percentile-20th percentile)/median income]	1.47	0.20	1.50	0.18
Percentage of unemployed people	4.52	2.03	5.12	2.20

COVID-19 data (new COVID cases per day per 1,000 people)	5.18	11.77	6.45	10.42
Percentage of fully vaccinated people	20.62	25.02	22.06	25.70
Percentage of the Month that Face Masks was Required in Public	0.12	0.32	0.16	0.36
Percentage of month with most restrictive stay-at-home order	0.02	0.11	0.02	0.13
Percentage of month with Less restrictive stay-at-home orders	0.02	0.13	0.03	0.15
Restaurant/bar closed (exclusive of mandatory orders)	0.04	0.18	0.06	0.22
Restaurant/bar open with restrictions (exclusive of Mandatory orders)	0.16	0.36	0.21	0.40
Mean monthly precipitation (in.)	3.35	2.50	3.84	2.60
Midwest Region	0.34	0.47	0.18	0.39
West Region	0.14	0.35	0.14	0.35
South Region	0.45	0.50	0.58	0.49
Northeast Region	0.07	0.25	0.09	0.29
Frequent mental distress	N/A	N/A	17.12	2.47
Homicide rate	N/A	N/A	7.48	6.27
Percentage of Adults reported excessive drinking in the past 30 days	N/A	N/A	18.05	2.96
Sample Size	187,572		64,752	

It should be noted that the analysis is conducted at the county-month level. Variables such as monthly VMT, COVID-19 cases per day per 1,000 people, vaccination rates, and policy indicators vary over time, while demographic and socioeconomic characteristics (e.g., age distribution, race, income) remain constant for each county during the study period.

Across all county-month observations, the average number of fatalities was 1.07 per month. The percentage change in VMT relative to baseline conditions averaged 0.86 percent but displayed substantial variability (SD = 19.83), reflecting sharp pandemic-related declines and subsequent rebounds in travel demand. Regionally, 45 percent of county-month observations were located in the South, 34 percent in the Midwest, 14 percent in the West, and 7 percent in the Northeast.

Demographic and socioeconomic characteristics exhibited meaningful variation across counties. On average, 21.8 percent of the population was under age 18 and 20.1 percent was aged 65 or older, values broadly consistent with national demographic patterns. The non-Hispanic White population share averaged 75.3 percent but ranged from 2.7 to 97.8 percent, reflecting significant demographic diversity across counties.

The average median household income was $58,780 (in thousands), somewhat lower than recent national medians. However, median income alone does not fully capture economic conditions within a county. To address this, a normalized income variability measure was created, defined as Equation 10:

$$Normalized\ Income = \frac{(\text{80th percentile income} \ - \ \text{20th percentile income})}{\text{median income}} \tag{10}$$

This variable distinguishes counties with relatively uniform income distributions from those exhibiting substantial income inequality. The mean normalized income variability was 1.46, with moderate dispersion across counties.

Mental health indicators were included to explore potential associations between behavioral health and traffic safety outcomes. The average number of mentally unhealthy days was 5.14 per month, and the percentage of adults reporting frequent mental distress averaged 16.9 percent, ranging from 8.3 to 26.7 percent across counties.

COVID-19 incidence varied dramatically over the study period. New COVID-19 cases per day per 1,000 people averaged 6.20 but reached values exceeding 1,500 during peak outbreak periods in certain counties. Vaccination rates increased over time, with the average percentage of fully vaccinated individuals equal to 20.3 percent across the full study period, though values ranged from 0 to 100 percent depending on month and county.

Policy variables reflect the proportion of each month during which specific interventions were in effect. On average, face mask requirements were active for 15 percent of county-months. Restaurant and bar closures (exclusive of stay-at-home orders) were present for approximately 5 percent of observations, while establishments operating with restrictions were observed in 18 percent of county-months. The most restrictive and less restrictive stay-at-home orders were active in approximately 2 percent of observations each, indicating that such measures were concentrated in limited time periods.

Overall, the descriptive statistics indicate substantial variation across counties and over time in fatality outcomes, exposure levels, demographic composition, socioeconomic conditions, public health measures, and pandemic severity. This heterogeneity provides the necessary variation to estimate statistically meaningful relationships within the regression modeling framework.

4.5 Model Results

This section presents the results of the statistical models developed to evaluate factors associated with monthly traffic fatalities and changes in travel demand. Separate models were estimated for fatality counts and percentage change in VMT at the county-month level. Results are first presented for the national dataset, followed by Michigan-specific models in the subsequent section.

4.5.1 National County Model Results

Table 5 presents the parameter estimates for the national county-level models for both traffic fatalities and changes in VMT. One objective of this study was to evaluate whether areas with higher levels of mental health challenges experienced different fatality and mobility patterns during the study period. Therefore, the presented model specification incorporated mental health related variables obtained from the County Health Rankings dataset. These variables were only available through 2022, which required exclusion of the 2023 monthly observations from this specification.

Separate analyses were conducted that used all 2023 data, excluding mental health information. However, as the results were generally consistent, those have been omitted here for the sake of space. The model specifications presented here includes demographic characteristics, socioeconomic indicators, COVID-19 incidence measures, vaccination rates, policy variables, weather conditions, regional indicators, and temporal controls. Monthly indicator variables capture time-specific effects relative to the baseline month. Parameter estimates are presented with corresponding standard errors in parentheses, and statistically significant estimates at the 95 percent confidence level are indicated with an asterisk. The fatality models were estimated using a negative binomial framework, while the travel demand models were estimated using linear mixed-effects regression.

Table 5: Model Results for Changes in Traffic Fatalities and Vehicle Miles Traveled

Parameter	**Parameter Estimates (Standard Errors)**	
	Negative Binomial Traffic Fatalities	**Linear Regression VMT Change**
Intercept	-17.36 (0.29)*	10.42 (3.94)*
Ln (VMT)	0.93 (0.01)*	N/A
Ln (Population Density)	-0.03 (0.01)*	-1.28 (0.18)*
Feb-19	-0.01 (0.04)	N/A
Mar-19	-0.02 (0.04)	N/A

Parameter	Parameter Estimates (Standard Errors)	
	Negative Binomial Traffic Fatalities	Linear Regression VMT Change
Apr-19	-0.04 (0.04)	N/A
May-19	0.05 (0.04)	N/A
Jun-19	0.06 (0.04)	N/A
Jul-19	0.08 (0.04)*	N/A
Aug-19	0.10 (0.04)*	N/A
Sep-19	0.16 (0.04)*	N/A
Oct-19	0.10 (0.04)*	N/A
Nov-19	0.11 (0.04)*	N/A
Dec-19	0.05 (0.04)	N/A
Jan-20	-0.05 (0.04)	2.87 (0.33)*
Feb-20	0.04 (0.04)	5.13 (0.33)*
Mar-20	0.09 (0.04)*	-14.17 (0.34)*
Apr-20	0.28 (0.06)*	-32.31 (0.54)*
May-20	0.30 (0.04)*	-19.48 (0.41)*
Jun-20	0.36 (0.04)*	-7.49 (0.39)*
Jul-20	0.30 (0.04)*	-4.48 (0.39)*
Aug-20	0.37 (0.04)*	-6.99 (0.39)*
Sep-20	0.35 (0.04)*	-0.29 (0.39)
Oct-20	0.32 (0.04)*	-1.91 (0.38)*
Nov-20	0.34 (0.04)*	-2.74 (0.40)*
Dec-20	0.21 (0.05)*	-2.93 (0.42)*
Jan-21	0.25 (0.04)*	-3.68 (0.38)*
Feb-21	0.11 (0.04)*	-2.27 (0.35)*
Mar-21	0.14 (0.04)*	4.18 (0.34)*
Apr-21	0.26 (0.04)*	-0.82 (0.35)*
May-21	0.24 (0.04)*	3.25 (0.35)*
Jun-21	0.19 (0.04)*	9.53 (0.36)*
Jul-21	0.19 (0.04)*	6.43 (0.36)*
Aug-21	0.26 (0.04)*	3.75 (0.39)*
Sep-21	0.26 (0.05)*	8.84 (0.42)*
Oct-21	0.25 (0.04)*	10.97 (0.40)*
Nov-21	0.17 (0.04)*	13.46 (0.41)*
Dec-21	0.16 (0.05)*	10.31 (0.43)*
Jan-22	0.06 (0.06)	8.77 (0.63)*
Feb-22	0.05 (0.05)	18.19 (0.48)*
Mar-22	0.03 (0.05)	10.47 (0.46)*
Apr-22	0.02 (0.05)	3.56 (0.46)*
May-22	0.06 (0.05)	11.06 (0.46)*
Jun-22	0.08 (0.05)	10.87 (0.47)*
Jul-22	0.15 (0.05)*	7.66 (0.47)*
Aug-22	0.13 (0.05)*	10.04 (0.47)*
Sep-22	0.16 (0.05)*	14.39 (0.46)*
Oct-22	0.18 (0.05)*	12.50 (0.47)*
Nov-22	0.15 (0.05)*	12.94 (0.47)*
Dec-22	0.11 (0.05)*	6.46 (0.47)*

Percentage of non-Hispanic white population	-0.00 (0.00)*	0.07 (0.01)*
Percentage of population below 18 years	0.01 (0.00)	0.39 (0.08)*
Percentage of population above 65 years	0.02 (0.00)*	0.08 (0.06)
Median income in $1,000	-0.01 (0.00)*	-0.12 (0.01)*
Normalized income variability [80th percentile-20th percentile)/median income]	-0.12 (0.05)*	-0.88 (0.64)
Percentage of Unemployed Adults	0.01 (0.00)	-0.47 (0.05)*
COVID-19 data (new COVID cases per day per 1,000 people)	0.00 (0.00)	-0.08 (0.01)*
Percentage of fully vaccinated people	0.001 (0.00)*	-0.09 (0.01)*
Percentage of the Month that Face Mask was Required in Public	0.001 (0.02)	-2.21 (0.20)*
Most restrictive stay-at-home order	-0.08 (0.06)	-4.39 (0.58)*
Less restrictive stay-at-home orders	0.01 (0.03)	1.07 (0.30)*
Restaurant/bar closed (exclusive)	-0.05 (0.02)*	-1.49 (0.24)*
Restaurant/bar open with restrictions (exclusive)	-0.02 (0.02)	1.42 (0.24)*
Mean Monthly precipitation (in)	-0.01 (0.00)*	-0.13 (0.02)*
Midwest	Baseline	Baseline
West	0.22 (0.03)*	-0.15 (0.81)
South	0.21 (0.02)*	2.13 (0.59)*
Northeast	0.02 (0.03)	1.32 (0.85)
Frequent Mental Distress	0.02 (0.00)*	-0.68 (0.05)*
Homicide Rate	0.01 (0.00)*	0.39 (0.03)*
Percentage of Adults Reported Excessive Drinking in the past 30 Days	0.01 (0.00)*	-0.04 (0.03)
Negative Binomial	0.13	N/A
Pseudo-R Square	N/A	0.607

4.5.1.1 Discussion of National County Results

4.5.1.1.1 Monthly Trends

Monthly indicator variables were included in the models to capture temporal changes in fatalities relative to January 2019, which represents the pre-pandemic baseline period. Results from the model, including the full study period through 2023, indicate clear seasonal patterns as well as substantial deviations associated with the pandemic period.

During 2019, warmer months generally exhibited higher fatality levels compared to January 2019, reflecting typical seasonal travel patterns. Among these months, September showed the largest relative increase in fatalities, followed by other late summer and early fall months. These findings are consistent with expected increases in travel exposure and roadway activity during warmer periods of the year.

In 2020, fatalities during January and February were similar to or lower than the baseline month; however, a substantial shift began in April 2020. Starting in April and continuing through December 2020, all months exhibited significantly higher fatality levels relative to January 2019. The largest increases were observed between May and September 2020, with August showing the highest relative increase. This period corresponds closely with the early stages of the pandemic, including widespread stay-at-home orders during March and April, followed by gradual reopening phases. Although travel volumes declined sharply during the early pandemic period, the results suggest that fatality risk increased substantially during the subsequent months of 2020.

For 2021, monthly indicators remained significantly elevated relative to the baseline month across most of the year, although the magnitude of increases was generally lower than those observed during 2020. Elevated levels persisted through much of the year, particularly during spring and summer months, indicating that fatality patterns had not returned to pre-pandemic levels despite partial recovery in travel demand.

In 2022, fatalities remained consistently higher than the baseline month beginning in late spring and continuing through the end of the year, with May through December showing statistically significant increases. These results suggest continued elevated fatality levels during the post-pandemic recovery period.

For 2023, monthly indicators for January through April were not statistically different from the baseline period, indicating conditions closer to pre-pandemic patterns during the early part of the year. However, fatalities were again significantly higher from late spring through the remainder of the year. Overall, the results indicate that the largest national increases in fatalities occurred between May and September 2020, with elevated levels persisting in subsequent years but gradually moderating over time.

Results from the model specification excluding 2023 and incorporating mental health variables show similar temporal patterns, including pronounced increases beginning in April 2020, peak effects during the summer of 2020, and sustained elevated levels through 2021 and 2022. This consistency across model specifications provides additional confidence in the observed monthly trends.

In addition to fatality outcomes, the VMT change models provide important context regarding monthly travel patterns relative to the corresponding months in 2019. Travel demand during

January and February 2020 was higher than the same months in 2019, with increases of approximately 6 to 10 percent depending on the month and model specification. A substantial decline began in March 2020, with reductions ranging from about 8 to 14 percent relative to March 2019. The largest reduction occurred in April 2020, when travel declined by approximately 25 to 32 percent compared to April 2019. These reductions coincide with the period during which most states implemented widespread stay-at-home orders and restrictions on non-essential activities, resulting in significant nationwide mobility reductions.

Travel demand began to recover during the summer of 2020, although levels remained below or near pre-pandemic conditions for several months. By late 2020, monthly travel volumes were generally within approximately 0 to 6 percent of 2019 levels, indicating a gradual normalization of mobility patterns.

Beginning in 2021, VMT levels were generally higher than the corresponding months in 2019 across much of the year. Several months exhibited increases exceeding 10 percent, with peak increases of approximately 13 to 15 percent observed during late 2021. This pattern continued through 2022, with multiple months showing increases between approximately 6 and 17 percent relative to 2019, suggesting sustained rebound and growth in travel demand beyond pre-pandemic levels.

For 2023, most months exhibited higher travel levels compared to 2019, with increases generally ranging from approximately 2 to 15 percent. April 2023 showed a small decline of approximately 1 percent relative to April 2019, representing the only month with a negative deviation during that year. This short-term decrease may reflect temporary economic conditions, fuel price fluctuations, or residual behavioral adjustments; however, overall travel demand remained elevated compared to pre-pandemic conditions.

The model specification incorporating mental health variables and excluding 2023 observations shows broadly similar temporal patterns, including substantial reductions during the early pandemic period followed by recovery in later months. However, the recovery in travel demand appears somewhat slower in this specification, with several months in early 2021 remaining below corresponding 2019 levels before exceeding the baseline beginning in spring 2021. These results remain consistent with the overall conclusion that travel demand declined sharply during the early pandemic period and subsequently rebounded in later years.

4.5.1.1.2 Sociodemographic and Economic Factors

Several demographic and socioeconomic variables were evaluated to examine how county characteristics were associated with fatality outcomes and changes in travel demand. These variables included the population density, percentage of the non-Hispanic White population, age distribution, median income, and income variability.

Population density exhibited negative associations across all model specifications, indicating that counties with higher population density tended to experience lower fatality levels and greater reductions in travel relative to baseline conditions. For the fatality models, the results suggest that fatalities decreased by approximately 0.03% to 0.05% for a 1% increase in population density, holding other factors constant. In the travel demand models, higher-density counties exhibited reductions in VMT change of approximately 1.3 to 2.4 percentage points compared to less dense counties. These findings likely reflect differences in mobility behavior, as more densely populated areas typically have lower operating speeds, greater congestion, and higher adoption of remote work or alternative travel patterns during the pandemic period.

Counties with a higher percentage of non-Hispanic White population were associated with slightly lower fatality levels. For the travel demand models, the results were mixed across specifications, although the full-period model indicated modest reductions in VMT as the proportion of the non-Hispanic White population increased. These findings may reflect differences in behavior across counties with differing demographic compositions.

The proportion of older adults was positively associated with fatality outcomes, with results indicating higher fatalities in counties with larger populations aged 65 years and older. This relationship may reflect increased vulnerability among older populations as well as differences in exposure patterns and roadway risk factors across counties with older demographic profiles. In contrast, the proportion of the population below 18 years of age did not show a consistent association with fatalities but was associated with increases in travel demand in the model excluding mental health variables.

Median income exhibited a consistently negative relationship with both fatalities and VMT change across model specifications. Specifically, counties with higher median income levels tended to experience lower fatality counts and smaller increases in travel demand. For the fatality models, the results suggest that fatalities decreased by approximately 0.4% to 1.0% for each $1,000 increase in median income. These findings are consistent with prior research indicating that higher-income populations may have greater access to safer vehicles, improved roadway infrastructure, and increased flexibility to modify travel behavior during disruptive events such as the pandemic.

Income variability, measured using a normalized index capturing differences between upper and lower income percentiles, was also negatively associated with fatality outcomes. Counties with greater income variability tended to exhibit lower fatality levels, although this variable was not statistically significant in the travel demand models. The relationship between income variability and safety outcomes may reflect complex interactions between economic diversity, land use patterns, and exposure differences across counties.

Unemployment levels were also correlated with both fatality outcomes and mobility patterns. Counties with higher percentages of unemployed adults tended to experience higher fatality levels in the primary model specification, with results indicating approximately a 1.4% increase in fatalities for each one percentage-point increase in unemployment, holding other factors constant. Although this relationship was not statistically significant in the specification including mental health variables, the direction of the association remained consistent.

For travel demand, higher unemployment corresponded to reductions in VMT change in both specifications. Specifically, VMT declined by approximately 0.5 to 1.4 percentage points for each one percentage-point increase in unemployment. These findings are consistent with expected reductions in commuting and work-related travel during periods of economic disruption, particularly during the early stages of the pandemic.

Overall, the results indicate that demographic composition and socioeconomic conditions were significant determinants of both fatality outcomes and mobility patterns during the study period. These relationships highlight the importance of considering underlying population characteristics when evaluating the impacts of large-scale disruptions on transportation safety and travel behavior.

The model results indicate that multiple COVID-19-related indicators and mitigation policies were statistically significant predictors of both fatalities and changes in VMT, although the direction and magnitude of effects varied across model specifications.

4.5.1.1.3 COVID-19 Conditions and Mitigation Policies

Several COVID-19-related indicators and mitigation policy variables were included in the models to examine how pandemic severity and public health interventions were related to fatality outcomes and changes in travel demand. These variables included new COVID-19 case rates, vaccination levels, mask requirements, stay-at-home orders, and restaurant and bar restrictions.

Higher COVID-19 case rates were statistically significant predictors of both fatality and VMT change outcomes, although the magnitude of the effects was relatively small. In the primary fatality specification, fatalities increased slightly as the number of new COVID-19 cases per month per 1,000 population increased, corresponding to approximately a 0.1% increase in fatalities for each additional monthly case per 1,000 people. This relationship was not statistically significant in the alternative fatality specification incorporating mental health variables. In contrast, the travel demand models showed a consistent negative relationship, with VMT declining by approximately 0.03 to 0.08 percentage points for each additional monthly case per 1,000 population relative to the corresponding month in 2019. These findings suggest that higher infection levels were associated with reductions in mobility, likely reflecting behavioral responses to perceived health risks and public health messaging.

Vaccination levels were statistically significant across all model specifications. In the fatality models, the positive parameter estimates indicate that a 1 percentage-point increase in the proportion of fully vaccinated individuals corresponded to approximately a 0.1% increase in fatalities, conditional on other variables. This relationship should be interpreted cautiously, as vaccination rates increased during later phases of the pandemic when mobility levels were also recovering, suggesting that the observed association may primarily reflect increased exposure rather than a direct causal effect. For travel demand, higher vaccination rates corresponded to lower VMT change relative to 2019, with reductions of approximately 0.06 to 0.09 percentage points for each 1 percentage-point increase in vaccination coverage.

Mask requirements did not show statistically significant relationships with fatalities in either model specification. However, mask requirements were associated with measurable reductions in travel demand. When mask requirements were in place for the full month, VMT declined by approximately 1.9 to 2.2 percentage points relative to the same month in 2019. This pattern suggests that periods with stronger mitigation measures corresponded to lower mobility levels, likely reflecting broader behavioral caution during periods of heightened public health concern.

Stay-at-home orders demonstrated more pronounced effects than other policy variables. The most restrictive stay-at-home orders were associated with reductions in fatalities in the primary specification, corresponding to approximately a 12% decrease in fatalities relative to periods without such orders. This effect was not statistically significant in the alternative fatality model. For travel demand, the most restrictive orders resulted in substantial reductions, with VMT declining by approximately 4.4 to 5.1 percentage points relative to the corresponding month in 2019. Less restrictive stay-at-home orders showed smaller and less consistent relationships with fatalities but were associated with modest increases in travel relative to the most restrictive conditions, with VMT increasing by approximately 1.1 percentage points. These findings indicate that the severity of restrictions played an important role in shaping mobility responses during the pandemic.

Restaurant and bar closures were statistically significant in both fatality and travel models. Full closures corresponded to approximately a 5% reduction in fatalities relative to periods without closures. For travel demand, closures reduced VMT by approximately 0.9 to 1.5 percentage points compared to the same month in 2019. Periods when restaurants and bars were open with restrictions showed less consistent relationships. In the fatality models, the primary specification indicated approximately 4% lower fatalities, although the alternative specification was not statistically significant. For travel demand, the effects varied across specifications, with one model showing no significant relationship and the other indicating an increase of approximately 1.4 percentage points. This variability likely reflects differences in timing, enforcement, and public response across jurisdictions during phased reopening periods.

Overall, the results indicate that pandemic severity indicators and mitigation policies were important determinants of both mobility patterns and safety outcomes. Reductions in travel were consistently observed during periods of higher infection rates and stronger mitigation measures, while increases in mobility during later pandemic phases coincided with elevated exposure and corresponding changes in fatality outcomes.

4.5.1.1.4 Monthly Precipitation

Weather conditions were also considered in the models through the inclusion of mean monthly precipitation. Monthly temperature variables were not included in the analysis because the models already incorporated month-specific indicator variables, which capture seasonal variation in temperature and other time-related effects. As a result, precipitation was included as the primary weather-related control variable to account for short-term environmental conditions that may influence travel behavior and crash risk.

The results indicate that higher precipitation levels were associated with reductions in both fatalities and travel demand across all model specifications. In the fatality models, a one-inch increase in mean monthly precipitation corresponded to approximately a 1% decrease in fatalities, holding other factors constant. Similarly, in the travel demand models, higher precipitation was associated with reductions in VMT change of approximately 0.06 to 0.13 percentage points relative to the corresponding month in 2019. These findings are consistent with expected behavioral responses to adverse weather conditions, as increased precipitation may lead to more cautious driving behavior, reduced travel demand, or trip postponement, thereby lowering overall exposure and crash risk.

4.5.1.1.5 Regions

Regional indicator variables were included to capture geographic differences in fatality outcomes and changes in travel demand relative to the Midwest region, which served as the reference category. The results indicate that fatalities were generally higher in other regions compared to the Midwest. Specifically, the fatality models show that counties in the West experienced approximately 23% to 25% higher fatality levels relative to comparable counties in the Midwest. Counties in the South exhibited even larger differences, with fatalities approximately 23% to 31% higher than those observed in the Midwest, depending on the model specification. The Northeast also showed modest increases, with fatalities approximately 6% higher in the primary model, although the alternative specification was not statistically significant.

For travel demand, regional differences were also evident. Counties in the South experienced significantly higher VMT levels relative to the Midwest, with increases of approximately 2.1 to 2.7 percentage points compared to the same month in 2019. Similarly, counties in the Northeast exhibited increases of approximately 3.2 percentage points relative to the Midwest baseline, although this increase was not significant when excluding 2023 data. In contrast, the West did not show statistically significant differences in VMT change compared to the Midwest.

These regional differences likely reflect variations in travel behavior, roadway characteristics, population distribution, and policy responses across geographic areas during the pandemic period. Regions with more dispersed development patterns and greater reliance on personal vehicle travel may have experienced higher mobility levels and corresponding exposure, contributing to the observed differences in both travel demand and fatality outcomes.

4.5.1.1.6 Behavioral and Mental Health Indicators

Several behavioral and community health indicators were evaluated to examine whether broader social and mental health conditions were related to fatality outcomes and travel patterns during the study period. Although multiple mental health related variables were initially considered, three measures were retained in the final model specification: frequent mental distress, homicide rate, and the percentage of adults reporting excessive drinking.

Frequent mental distress showed a statistically significant positive relationship with fatalities in the model including these variables. The results indicate that a one percentage-point increase in the share of adults reporting frequent mental distress corresponded to approximately a 2% increase in fatalities, holding other factors constant. In contrast, higher levels of frequent mental distress were associated with reductions in travel demand, with VMT declining by approximately 0.68 percentage points for each one percentage-point increase in this measure relative to the same month in 2019. These findings suggest that counties experiencing greater mental health challenges may also have experienced behavioral or mobility changes that influenced both exposure and safety outcomes.

The homicide rate also exhibited a positive association with fatalities. Specifically, a one-unit increase in the homicide rate corresponded to approximately a 1% increase in fatalities in the model specification incorporating mental health variables. For travel demand, higher homicide rates were associated with increases in VMT change, with travel increasing by approximately 0.39 percentage points for each unit increase in the homicide rate relative to the baseline month in 2019. This relationship may reflect broader social or environmental factors correlated with both mobility and safety conditions across counties.

The percentage of adults reporting excessive drinking was positively related to fatalities, with results indicating approximately a 1% increase in fatalities for each one percentage-point increase in excessive drinking prevalence. However, this variable was not statistically significant in the travel demand model, suggesting that its relationship with mobility patterns may be less direct than its relationship with safety outcomes. Overall, these results indicate that community health and behavioral factors were associated with variations in fatality outcomes during the study period, highlighting the importance of considering broader social context when examining transportation safety trends.

4.5.2 Michigan County Model Results

Table 6 presents the parameter estimates for the Michigan county-level models. Separate models were estimated for multiple crash outcomes, including total crashes, non-animal crashes, fatal and serious injury (KA) crashes, alcohol and drug involved crashes, and pedestrian and bicyclist involved crashes. Negative binomial regression models were estimated for each crash outcome, with the natural logarithm of monthly VMT included as an offset term to account for exposure differences across counties and time periods. In addition, a linear regression model was estimated to evaluate percentage change in VMT.

All model specifications include regional indicators corresponding to MDOT regions, temporal indicator variables representing monthly effects relative to the baseline month, and the logarithm of VMT where applicable. Parameter estimates are presented with corresponding standard errors in parentheses, and statistically significant estimates at the 95 percent confidence level are indicated with an asterisk.

Table 6: Analysis Results for Michigan Counties

Variable	Negative Binomial					Linear Regression
	Total Crash	Non-Animal	KA	Alc and drug	Ped& Bike	% Change in VMT
	Coefficient (SE)*					
Intercept	-8.14 (0.68)*	-13.22 (0.73)*	-11.35 (0.72)*	-15.12 (0.60)*	-23.92 (1.36)*	-2.10 (1.94)
Ln (VMT)	0.76 (0.04)*	1.02 (0.04)*	0.71 (0.04)*	0.96 (0.03)*	1.35 (0.08)*	N/A
Bay						
University	0.07 (0.12)	0.18 (0.12)	0.01 (0.11)	0.03 (0.09)	0.03 (0.20)	-2.11 (3.05)
Superior	-0.56 (0.11)*	-0.13 (0.12)	-0.08 (0.11)	0.04 (0.09)	0.03 (0.20)	7.45 (2.64)*
Southwest	0.04 (0.12)	0.20 (0.13)	0.13 (0.12)	0.04 (0.10)	0.15 (0.21)	0.46 (3.31)
North	-0.28 (0.10)*	-0.11 (0.10)	-0.20 (0.10)*	0.02 (0.08)	-0.03 (0.18)	3.46 (2.45)

Variable	Negative Binomial					Regression
	Total Crash	Non-Animal	KA	Alc and drug	Ped& Bike	% Change in VMT
	Coefficient (SE)*					
Metro	0.73 (0.20)*	0.66 (0.21)*	0.47 (0.19)*	0.06 (0.16)	-0.09 (0.34)	-3.71 (4.58)
Grand	0.07 (0.10)	0.21 (0.11)*	0.21 (0.10)*	0.14 (0.08)	0.10 (0.18)	1.31 (2.74)
Jan-19						
Feb-19	-0.10 (0.04)*	-0.10 (0.05)*	-0.07 (0.09)	-0.10 (0.07)	-0.34 (0.16)*	N/A
Mar-19	-0.41 (0.04)*	-0.71 (0.05)*	-0.27 (0.10)*	-0.23 (0.07)*	-0.36 (0.15)*	N/A
Apr-19	-0.56 (0.04)*	-0.85 (0.05)*	-0.27 (0.10)*	-0.31 (0.07)*	-0.28 (0.15)	N/A
May-19	-0.52 (0.04)*	-0.81 (0.05)*	0.07 (0.09)	-0.22 (0.07)*	-0.01 (0.14)	N/A
Jun-19	-0.35 (0.04)*	-0.68 (0.05)*	0.12 (0.09)	-0.11 (0.07)	0.30 (0.14)*	N/A
Jul-19	-0.41 (0.04)*	-0.58 (0.05)*	0.37 (0.09)*	-0.15 (0.07)*	0.28 (0.14)*	N/A
Aug-19	-0.53 (0.04)*	-0.68 (0.05)*	0.30 (0.09)*	-0.12 (0.06)	0.28 (0.14)*	N/A
Sep-19	-0.51 (0.04)*	-0.73 (0.05)*	0.13 (0.09)	-0.20 (0.07)*	0.33 (0.14)*	N/A
Oct-19	-0.03 (0.04)	-0.52 (0.05)*	0.21 (0.09)*	-0.03 (0.07)	0.47 (0.14)*	N/A
Nov-19	0.27 (0.04)*	-0.12 (0.05)*	-0.04 (0.09)	0.01 (0.07)	0.02 (0.15)	N/A
Dec-19	-0.04 (0.04)	-0.31 (0.05)*	-0.14 (0.09)	-0.08 (0.07)	0.09 (0.15)	N/A
Jan-20	-0.11 (0.04)*	-0.30 (0.05)*	-0.15 (0.10)	-0.04 (0.07)	-0.15 (0.15)	-4.26 (2.11)*
Feb-20	-0.19 (0.04)*	-0.31 (0.05)*	-0.08 (0.09)	-0.06 (0.07)	-0.42 (0.16)*	9.44 (2.11)*
Mar-20	-0.73 (0.04)*	-1.08 (0.05)*	-0.47 (0.10)*	-0.25 (0.07)*	-0.63 (0.16)*	-12.12 (2.11)*
Apr-20	-0.90 (0.05)*	-1.12 (0.05)*	-0.37 (0.11)*	-0.08 (0.07)	-0.42 (0.18)*	-41.58 (2.11)*
May-20	-0.64 (0.04)*	-0.88 (0.05)*	0.16 (0.09)	0.04 (0.07)	-0.35 (0.16)*	-23.73 (2.11)*
Jun-20	-0.32 (0.04)*	-0.58 (0.05)*	0.51 (0.09)*	0.20 (0.06)*	0.45 (0.14)*	-15.59 (2.11)*
Jul-20	-0.42 (0.04)*	-0.51 (0.05)*	0.48 (0.09)*	0.08 (0.06)	0.36 (0.14)*	-13.15 (2.11)*
Aug-20	-0.54 (0.04)*	-0.62 (0.05)*	0.44 (0.09)*	0.07 (0.06)	0.32 (0.14)*	-9.55 (2.11)*
Sep-20	-0.39 (0.04)*	-0.59 (0.05)*	0.40 (0.09)*	0.13 (0.06)*	0.40 (0.14)*	-13.14 (2.11)*
Oct-20	-0.06 (0.04)	-0.55 (0.05)*	0.21 (0.09)*	0.16 (0.06)*	0.10 (0.15)	-3.48 (2.11)
Nov-20	0.00 (0.04)	-0.58 (0.05)*	0.13 (0.09)	0.04 (0.07)	0.27 (0.15)	0.05 (2.11)
Dec-20	-0.29 (0.04)*	-0.51 (0.05)*	-0.19 (0.10)	-0.24 (0.07)*	-0.25 (0.15)	2.08 (2.11)
Jan-21	-0.25 (0.04)*	-0.43 (0.05)*	-0.03 (0.09)	-0.13 (0.07)	-0.31 (0.16)*	-5.16 (2.11)*
Feb-21	-0.30 (0.04)*	-0.33 (0.05)*	-0.20 (0.10)*	-0.07 (0.07)	-0.52 (0.16)*	3.62 (2.11)
Mar-21	-0.68 (0.04)*	-0.99 (0.05)*	-0.22 (0.09)*	-0.21 (0.07)*	-0.54 (0.16)*	-0.38 (2.11)
Apr-21	-0.73 (0.04)*	-0.95 (0.05)*	0.00 (0.09)	-0.15 (0.07)*	-0.32 (0.15)*	-5.86 (2.11)*
May-21	-0.50 (0.04)*	-0.71 (0.05)*	0.23 (0.09)*	-0.02 (0.06)	-0.25 (0.15)	-7.68 (2.11)*
Jun-21	-0.32 (0.04)*	-0.53 (0.05)*	0.28 (0.09)*	0.10 (0.06)	0.16 (0.14)	-8.55 (2.11)*
Jul-21	-0.43 (0.04)*	-0.59 (0.05)*	0.35 (0.09)*	-0.04 (0.06)	0.06 (0.14)	-2.49 (2.11)
Aug-21	-0.44 (0.04)*	-0.48 (0.05)*	0.50 (0.09)*	0.03 (0.06)	0.31 (0.14)*	-13.67 (2.11)*
Sep-21	-0.28 (0.04)*	-0.49 (0.05)*	0.40 (0.09)*	-0.02 (0.07)	0.50 (0.14)*	-14.25 (2.11)*
Oct-21	-0.12 (0.04)*	-0.62 (0.05)*	0.14 (0.09)	0.04 (0.06)	0.37 (0.14)*	10.05 (2.11)*
Nov-21	0.00 (0.04)	-0.46 (0.05)*	-0.07 (0.09)	-0.18 (0.07)*	-0.15 (0.15)	26.47 (2.11)*
Dec-21	-0.24 (0.04)*	-0.44 (0.05)*	-0.10 (0.09)	-0.18 (0.07)*	-0.10 (0.15)	29.99 (2.11)*
Jan-22	-0.14 (0.04)*	-0.28 (0.05)*	-0.02 (0.09)	-0.04 (0.07)	-0.63 (0.16)*	9.98 (2.11)*
Feb-22	-0.24 (0.04)*	-0.27 (0.05)*	-0.10 (0.10)	-0.14 (0.07)*	-0.35 (0.16)*	1.82 (2.11)
Mar-22	-0.40 (0.04)*	-0.57 (0.05)*	-0.18 (0.10)	-0.06 (0.07)	-0.33 (0.16)*	-14.08 (2.11)*
Apr-22	-0.51 (0.04)*	-0.81 (0.05)*	-0.08 (0.09)	-0.17 (0.07)*	-0.27 (0.15)	-14.94 (2.11)*
May-22	-0.45 (0.04)*	-0.74 (0.05)*	0.28 (0.09)*	-0.13 (0.07)*	-0.10 (0.15)	-6.58 (2.11)*
Jun-22	-0.32 (0.04)*	-0.68 (0.05)*	0.37 (0.09)*	-0.14 (0.07)*	0.32 (0.14)*	-6.59 (2.11)*
Jul-22	-0.44 (0.04)*	-0.64 (0.05)*	0.35 (0.09)*	-0.13 (0.07)*	0.16 (0.14)	-5.38 (2.11)*

Variable	Negative Binomial					Regression
	Total Crash	Non-Animal	KA	Alc and drug	Ped& Bike	% Change in VMT
	Coefficient (SE)*					
Aug-22	-0.49 (0.04)*	-0.63 (0.05)*	0.28 (0.09)*	-0.15 (0.07)*	0.33 (0.14)*	-11.35 (2.11)*
Sep-22	-0.39 (0.04)*	-0.68 (0.05)*	0.23 (0.09)*	-0.22 (0.07)*	0.20 (0.14)	-4.99 (2.11)*
Oct-22	-0.04 (0.04)	-0.60 (0.05)*	0.20 (0.09)*	-0.09 (0.07)	0.39 (0.14)*	6.85 (2.11)*
Nov-22	0.17 (0.04)*	-0.34 (0.05)*	-0.02 (0.09)	-0.12 (0.07)	0.05 (0.15)	15.42 (2.11)*
Dec-22	-0.15 (0.04)*	-0.43 (0.05)*	-0.27 (0.10)*	-0.16 (0.07)*	-0.23 (0.15)	20.71 (2.11)*
Jan-23	-0.26 (0.04)*	-0.46 (0.05)*	-0.14 (0.09)	-0.20 (0.07)*	-0.18 (0.15)	8.23 (2.11)*
Feb-23	-0.34 (0.04)*	-0.47 (0.05)*	-0.19 (0.10)*	-0.29 (0.07)*	-0.19 (0.15)	7.92 (2.11)*
Mar-23	-0.38 (0.04)*	-0.63 (0.05)*	-0.23 (0.10)*	-0.27 (0.07)*	-0.45 (0.16)*	-5.94 (2.11)*
Apr-23	-0.55 (0.04)*	-0.84 (0.05)*	-0.19 (0.10)	-0.22 (0.07)*	-0.14 (0.15)	-11.54 (2.11)*
May-23	-0.45 (0.04)*	-0.69 (0.05)*	0.29 (0.09)*	-0.23 (0.07)*	0.12 (0.14)	-7.27 (2.11)*
Jun-23	-0.33 (0.04)*	-0.64 (0.05)*	0.37 (0.09)*	-0.13 (0.07)	0.29 (0.14)*	-7.09 (2.11)*
Jul-23	-0.52 (0.04)*	-0.71 (0.05)*	0.35 (0.09)*	-0.24 (0.07)*	0.05 (0.14)	0.89 (2.11)
Aug-23	-0.53 (0.04)*	-0.68 (0.05)*	0.28 (0.09)*	-0.27 (0.07)*	0.24 (0.14)	-3.50 (2.11)
Sep-23	-0.49 (0.04)*	-0.74 (0.05)*	0.15 (0.09)	-0.31 (0.07)*	0.28 (0.14)*	-0.80 (2.11)
Oct-23	-0.07 (0.04)	-0.63 (0.05)*	0.05 (0.09)	-0.16 (0.07)*	0.37 (0.14)*	10.02 (2.11)*
Nov-23	0.10 (0.04)*	-0.54 (0.05)*	-0.10 (0.09)	-0.29 (0.07)*	0.09 (0.15)	15.90 (2.11)*
Dec-23	-0.30 (0.04)*	-0.66 (0.05)*	-0.22 (0.10)*	-0.10 (0.07)	-0.15 (0.15)	10.61 (2.11)*
Negative Binomial	0.06	0.08	0.08	0.05	0.17	N/A
Pseudo-R Square	N/A	N/A	N/A	N/A	N/A	0.36

The results provide estimates of temporal variation across the study period as well as regional differences in crash outcomes and travel demand across Michigan counties. Detailed interpretation and discussion of these findings are presented in the following section.

4.5.2.1 Discussion of Michigan County Results

4.5.2.1.1 Regional Differences

To further investigate temporal and spatial patterns within Michigan, a series of negative binomial regression models were estimated for multiple crash outcomes at the county level. The crash types examined included total crashes, non-animal crashes, fatal and serious injury (KA) crashes, alcohol- and drug-involved crashes, and pedestrian- and bicyclist-involved crashes. In addition, a linear regression model was estimated to examine percentage changes in VMT relative to the corresponding month in 2019. The primary objective of this analysis was to identify whether certain regions of Michigan consistently experienced higher crash levels across outcomes and whether specific months exhibited recurring increases in crash frequency or severity during the study period.

All crash models incorporated the natural logarithm of VMT as an exposure variable to account for differences in travel demand across counties and months. The results indicate that travel exposure was a significant predictor across all crash types. Specifically, a 1% increase in VMT corresponded to approximately a 0.71% to 1.35% increase in crashes, depending on the crash type. The strongest relationship was observed for pedestrian- and bicyclist-involved crashes, suggesting that vulnerable road user crashes were particularly sensitive to changes in travel exposure levels.

Regional indicator variables were included to evaluate differences across Michigan Department of Transportation (MDOT) regions relative to the Bay region, which served as the reference category. The results indicate that regional differences were present for several crash outcomes. The Metro region exhibited consistently higher crash levels across multiple models. Compared to the Bay region, total crashes were approximately 108% higher in the Metro region, while non-animal crashes were approximately 93% higher, and KA crashes were approximately 60% higher. These findings likely reflect higher traffic volumes, greater roadway density, and increased urban exposure in the Metro region.

In contrast, some regions exhibited lower crash levels relative to the Bay region. The Superior region showed significantly lower total crashes, with reductions of approximately 43% compared to the reference region. The North region also exhibited lower crash levels for both total crashes and KA crashes, with reductions of approximately 24% and 18%, respectively. These reductions may reflect lower traffic exposure, rural roadway environments, and differences in population density compared to more urbanized regions.

The Grand region exhibited moderately higher non-animal and KA crash levels relative to the Bay region, with increases of approximately 23% for both outcomes. Other regions, including University and Southwest, did not show statistically significant differences across most crash types, indicating relatively similar patterns compared to the reference region.

For the VMT change model, regional differences were generally smaller and less consistent. However, the Superior region exhibited significantly higher VMT relative to 2019 levels compared to the Bay region, with increases of approximately 7.5 percentage points. Other regions did not show statistically significant differences in VMT change, suggesting that temporal factors played a larger role than regional differences in shaping mobility patterns within Michigan.

4.5.2.1.2 Monthly Trends

Monthly indicator variables were included to capture seasonal and pandemic-related temporal patterns relative to January 2019. Across crash types, the results indicate strong seasonal effects as well as substantial deviations during the early pandemic period. The most pronounced reductions occurred during March through May 2020, with April 2020 showing the largest decreases across nearly all crash types. For example, total crashes declined by approximately 59% in April 2020 relative to January 2019, while non-animal crashes declined by approximately 67%. These reductions coincide with the period during which Michigan implemented widespread stay-at-home orders and mobility restrictions.

Following the early pandemic period, crash frequency began to increase during summer 2020, with several crash types exceeding baseline levels by mid-year, particularly for KA crashes and pedestrian- and bicyclist-involved crashes. Elevated levels persisted across portions of 2021 and 2022, although the magnitude of deviations varied across months and crash types. Seasonal patterns remained evident throughout the study period, with warmer months generally exhibiting higher crash levels compared to winter months.

The VMT change model showed patterns consistent with statewide travel trends observed during the pandemic. Travel demand declined sharply during spring 2020, with April 2020 exhibiting the largest reduction of approximately 42% relative to April 2019. Travel gradually recovered during late 2020 and 2021, with several months in 2021 and 2022 exceeding 2019 levels. By 2023, most months showed positive deviations relative to 2019, indicating sustained recovery in mobility patterns across Michigan counties.

Overall, the Michigan county analysis identified clear regional differences in crash occurrence as well as strong seasonal and pandemic-related temporal patterns. The results indicate that urban regions, particularly the Metro region, consistently experienced higher crash levels across multiple outcomes, while northern regions generally exhibited lower crash frequencies. Temporal patterns were strongly influenced by pandemic-related mobility disruptions during 2020, followed by gradual recovery and stabilization in subsequent years.

4.6 Summary

The COVID-19 pandemic substantially altered traffic safety and mobility patterns both nationally and within Michigan. To better understand these changes, crash and travel data before, during, and after the pandemic were analyzed at a monthly county level, allowing for direct comparison of temporal and regional trends across the United States and within Michigan.

At the national level, fatalities exhibited clear seasonal patterns prior to the pandemic, with higher levels during warmer months in 2019, peaking in late summer and early fall. A sharp deviation emerged beginning in April 2020, when fatalities increased markedly and remained elevated through the remainder of the year despite significant reductions in travel. Elevated fatality levels persisted through 2021 and 2022, although with somewhat smaller increases, suggesting a gradual return toward pre-pandemic conditions. By early 2023, fatality levels were similar to baseline conditions but rose again from late spring onward. Models incorporating mental health indicators showed similar temporal patterns, reinforcing the robustness of these findings.

Mobility trends help explain these patterns. Nationally, VMT increased slightly in early 2020, declined sharply during March and April with the implementation of stay-at-home orders, and then recovered steadily through late 2020. From 2021 onward, travel demand exceeded pre-pandemic levels, indicating a sustained rebound in exposure.

Within Michigan, temporal patterns closely mirrored national trends but with sharper short-term declines. Crash levels fell dramatically during March through May 2020, with April showing reductions of about 59% for total crashes and 67% for non-animal crashes, corresponding to statewide restrictions. Similar to national patterns, crash frequency increased during summer 2020 and remained elevated through portions of 2021 and 2022, particularly for severe and vulnerable road user crashes. Michigan VMT followed a comparable trajectory, with a roughly 42% reduction in April 2020, followed by steady recovery and sustained increases above 2019 levels by 2022–2023.

Socioeconomic and demographic factors influenced both national and Michigan outcomes in similar ways. Higher population density and higher median income were associated with lower fatality levels and reduced travel growth, while a larger proportion of older adults and higher unemployment were associated with higher fatalities and reduced mobility. Behavioral and community health factors such as mental distress, homicide rates, and excessive drinking were also positively associated with fatalities, highlighting the broader influence of issues related to public health on traffic safety.

Regional differences were evident both nationally and in Michigan, as shown in Figure 25 and Figure 26.

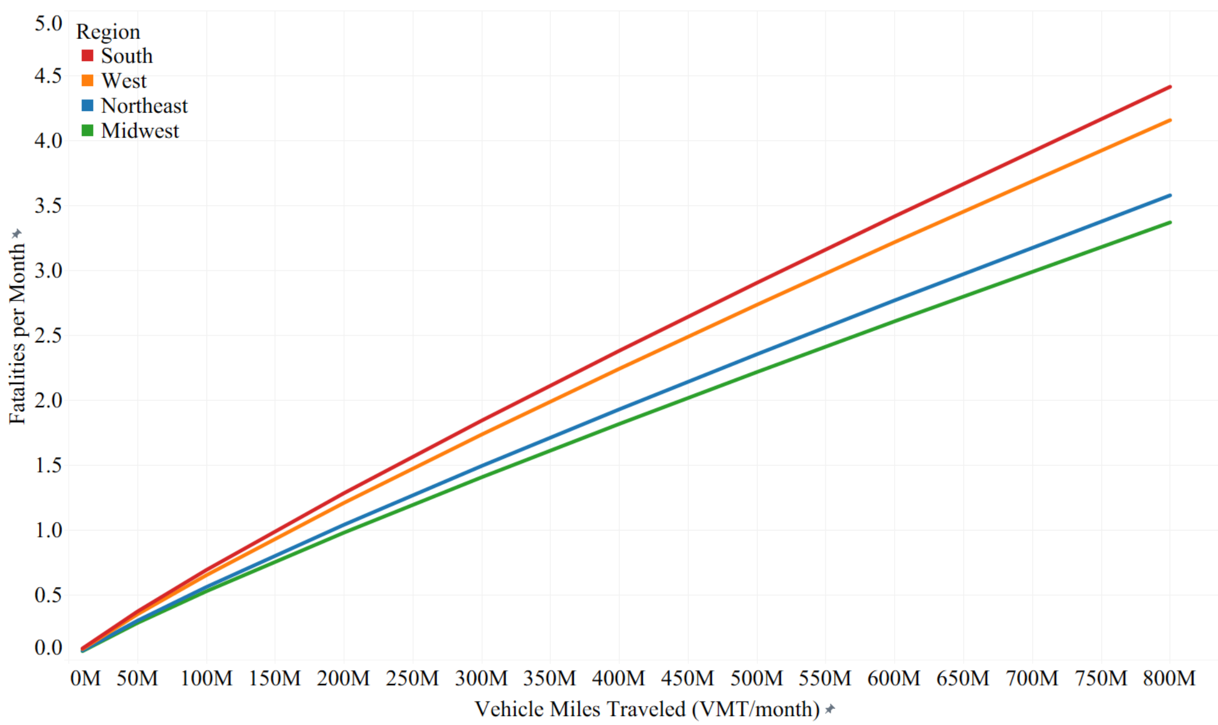

Figure 25: Expected Number of Fatalities per County-Month by National Region

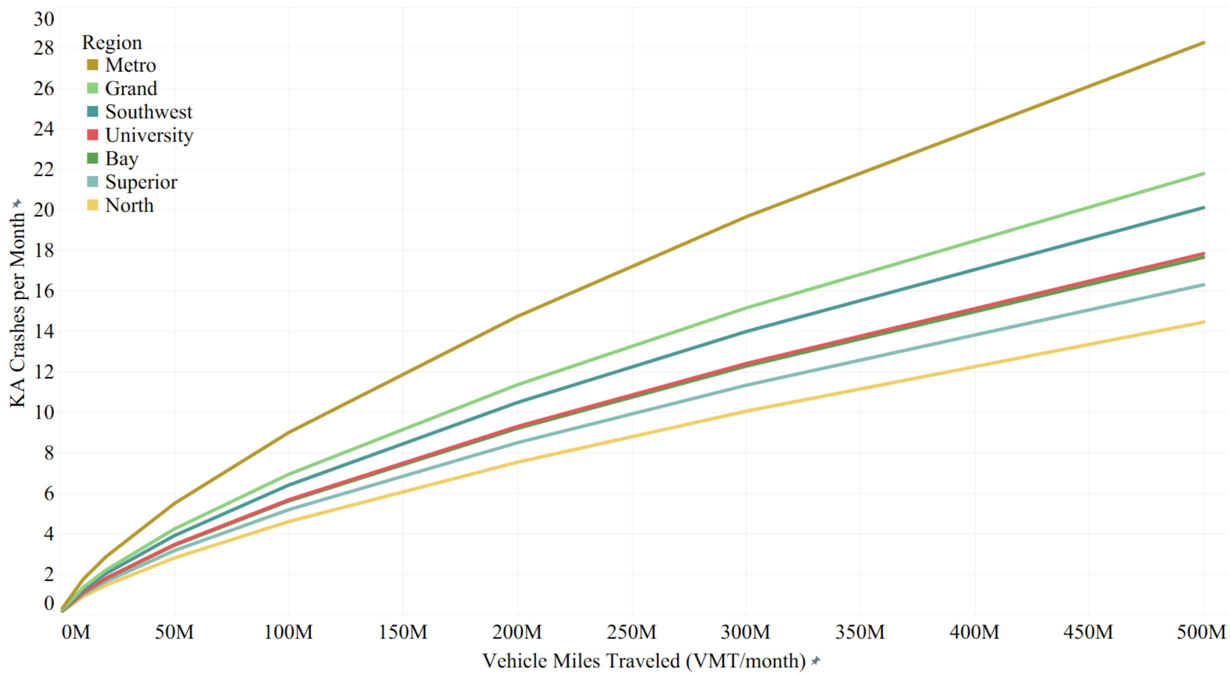

Figure 26 Expected Number of KA Crashes per County-Month by Michigan Region

Nationally, fatalities were highest in the South and West and slightly higher in the Northeast compared to the Midwest. In Michigan, urban regions showed the highest crash exposure. For instance, the Metro region had substantially higher crash levels across outcomes, while northern regions such as Superior and North experienced significantly lower crash levels, reflecting differences in density, exposure, and roadway environments.

Overall, both national and Michigan results indicate that pandemic-related disruptions significantly altered mobility and safety patterns, with strong seasonal effects, pronounced early pandemic declines in travel, and sustained elevated risk levels in subsequent years.

5 MICHIGAN SEGMENT-LEVEL ANALYSIS

Following the COVID-19 pandemic in 2020, the number of crashes, fatalities, and severe injuries were affected substantially due to COVID-19 and the implementation of different policies. However, changes in total crashes and fatalities varied across roadway facility types and varied by month. The following sections provide a comprehensive assessment of the changes in the number of crashes, fatalities, severe injuries, and injury severity across different facility types at the segment-level.

5.1 Data Collection

To support the evaluation of crash trends, a comprehensive segment-level dataset was developed for limited-access freeways, multilane divided highways, multilane undivided highways, two-lane rural highways, and two-lane urban highways using information from multiple sources. Probe vehicle speed data was obtained and integrated with crash records, traffic volume measures, and detailed roadway inventory data to capture both temporal and spatial variation in roadway conditions. The following subsections describe the data sources used in this study and summarize the procedures employed for data collection, quality control, and integration to develop analysis-ready datasets.

5.1.1 Roadway Geometry Data

The Michigan Department of Transportation (MDOT) maintains an annual roadway inventory database for all state-maintained roads in Michigan, which is referred to as the sufficiency file. The sufficiency file is organized into homogeneous segments of varying lengths, and segments are divided whenever roadway characteristics change. Each segment is assigned a physical road (PR), beginning mile point (BMP), and ending mile point (EMP), which can be combined to uniquely identify each roadway segment. The sufficiency file includes detailed information on roadway geometry and other segment characteristics, including the number of lanes, lane width, median type and median width, left and right shoulder width, speed limit, presence of signals, passing lanes, turn lanes, sight restrictions, and other attributes. This sufficiency file was provided by MDOT to the research team.

The posted speed limit information in the sufficiency file was not current for this study because the most recent version available for use reflected conditions through 2015. Following the 2017

Michigan legislation, posted speed limits were increased from 70 mph to 75 mph (and from 60 mph to 65 mph for trucks) on 614 miles of freeways, and from 55 mph to 65 mph on 943 miles of non-freeways. These increases were not reflected in the original sufficiency file. Therefore, using shapefiles of the affected segments, posted speed limits were updated for the study network, and these updated speed limits were used in subsequent analyses.

5.1.2 Horizontal Curves

In addition, information on horizontal curves was prepared for each segment. This process was applied to a broader Michigan road network using geographic information system (GIS) tools to extract curve-related attributes. Curve information was organized into cumulative categories based on decreasing radii, ranging from 0.75-mile radii to 0.008-mile radii. Curve attributes were then merged with the roadway inventory data for the corresponding segment. To account for segment breaks across curves, curve data were compiled for each radius threshold at the segment-level, including the length of curved roadway, the proportion of the segment on a curve, and the average curve radius.

Horizontal curve characteristics were summarized at the roadway segment-level using three complementary measures: average radius, proportion of the segment that is curved, and weighted average degree of curvature. These measures were derived using curve-level information extracted from the roadway network and aggregated to the segment-level to account for segments containing multiple horizontal curves.

5.1.2.1 Average Radius of Curvature

The average radius of curvature represents a simple descriptive measure of curve geometry within a segment. For each segment (a segment could have curved and tangent sections), all horizontal curves located within that segment were identified. If a segment contained only one horizontal curve, the average radius was set equal to the radius of that curve. If a segment contained multiple horizontal curves, the average radius was calculated as the arithmetic mean of the individual curve radii within the segment.

This measure does not apply weighing by curve length and is intended solely to provide a general summary of the radii of curves present on the segment.

5.1.2.2 Proportion of Segment That Is Curved

The proportion of the segment that is curved quantifies the extent to which a roadway segment consists of horizontal curvature. For segments containing one or more curves, the total length of all curved portions within the segment was first calculated by summing the lengths of individual curves. This total curved length was then divided by the total segment length using Equation 11:

$$\text{Proportion Curved} = \frac{\text{Total length of curved portions of the segment}}{\text{Total segment length}} \tag{11}$$

Segments with no horizontal curves were assigned a value of zero. This variable represents the fraction of each segment that is exposed to horizontal curvature and is treated separately from curvature magnitude.

5.1.2.3 Weighted Average Degree of Curvature

The weighted average degree of curvature was developed to represent the overall sharpness of horizontal curves within a segment while accounting for the relative lengths of individual curves.

First, the degree of curvature for each individual curve within a segment was calculated from its radius using the standard arc definition of curvature. Because radii was measured in miles, the degree of curvature was computed using Equation 12:

$$D_i = \frac{1.085}{R_i} \tag{12}$$

Where R_i is the radius of the curve in miles and D_i is the degree of curvature in degrees.

Next, a curve-length–weighted average degree of curvature was calculated using Equation 13:

$$\text{Weighted Avg. Degree of Curvature} = \frac{\sum(L_i \times D_i)}{\sum L_i} \tag{13}$$

Where L_i is the length of curve i, and D_i is the degree of curvature of curve i.

The summation is taken over all curves within the segment. This ensures that longer and sharper curves contribute more to the degree of curvature measure. Segment length is not included in this calculation, as tangential sections have zero curvature. Segments with no horizontal curves were assigned a weighted average degree of curvature equal to zero.

5.1.3 Traffic Volume Data

Traffic volume information was also obtained from MDOT. MDOT provides annual average daily traffic (AADT) volume data for the statewide trunkline network in the form of GIS shapefiles. These AADT data can be integrated with the sufficiency file using the "IDENTITY" tool in GIS. However, manual review of the AADT shapefile data indicated considerable year-to-year variability in AADT values on some segments. As a result, AADT data was reviewed in greater detail. Segments exhibiting substantial variability were examined, and AADT values were compared with raw traffic count data available through the MDOT Transportation Data Management System (TDMS). Based on this review, AADT values for selected segments were replaced through a manual process to ensure volumes were consistent over the study period (2019 to 2024).

5.1.4 Speed Data from Probe Vehicles

Probe vehicle data are collected from global positioning systems (GPS) that are installed in a wide variety of vehicles, including commercial vehicle fleets and connected vehicles, as well as devices such as cell phones. These GPS devices send and receive signals from earth-orbiting satellites, and these signals are processed to generate real-time vehicle location and speed information for probe vehicles.

In Michigan, probe vehicle data are available from INRIX through the Regional Integration Transportation Information System (RITIS) (RITIS, n.d.). RITIS is a secure data platform that integrates operational data from transportation agencies and provides speed and travel time information, among other datasets, at multiple levels of fidelity. This data is used by transportation officials, first responders, planners, and researchers. Probe vehicle data through RITIS for Michigan is available back to January 1, 2016, and includes speed information at multiple time intervals (5-minutes, 15-minutes, 1-hour, and 24-hours). RITIS uses the eXtreme Definition (XD) segmentation system as the identification scheme for each roadway segment.

Initially, this study aimed to compare speed trends across 2018–2019 (pre-COVID), 2020–2021 (COVID), and 2022–2024 (post-COVID). However, quality control review of the probe vehicle data identified a notable inflection point in June 2019, where speeds increased substantially across locations. This change was attributable to changes in the fleet composition contributing to probe vehicle data. Specifically, a significant reduction in the proportion of heavy vehicles in the fleet resulted in increases of 5 mph or more in the reported speeds across locations, especially on limited-access freeways.

Consequently, before-and-after comparisons using probe vehicle data focused only on data beginning in January 2019. For January 2019 to May 2019, speed trends were adjusted by comparing the average speed between 2019 and 2018 from July to December of each year. The resulting differences between this month represent a shift that can be attributed to the change in probe vehicle data composition rather than the change in travel speed behavior. These differences are then averaged by speed limit to obtain a representative bias estimate for each speed limit category. The estimated bias is then applied to 2019 using a phased transition approach. For January 2019 to May 2019, the full estimated speed difference is added to the observed mean speed, while June 2019 is adjusted using 50 percent of the estimated speed difference, thereby avoiding an artificial spike in June 2019. From July 2019 to December 2019, no adjustment was applied, and the observed speeds were retained. It should be noted that this adjustment was applied only to limited-access freeways, as the change in probe data composition did not have a significant effect on other road facility types.

Following data collection and subsequent adjustment, the 15-minute speed observations were then aggregated to monthly averages for each roadway segment included in the dataset.

5.2 Data Integration and Preparation

Probe vehicle speed data was integrated with roadway geometry, traffic volume, and crash data to develop analysis-ready datasets. First AADT data was spatially joined with the MDOT sufficiency file using GIS tools. A unique segment identifier was created for each segment using the PR number, BMP, and EMP. Probe vehicle speed data were then joined to the sufficiency file using this identifier, allowing roadway geometry and operational characteristics to be associated with each speed observation.

The sufficiency file was prepared for six years of analysis, including one year before COVID (2019), two years during the COVID period (2020 and 2021), and three years after the COVID period (2022 through 2024). Crash data was obtained from the Michigan State Police (MSP) and included information on crash location, time of occurrence, injury severity, and additional driver, roadway, and environmental factors, such as weather conditions, driver sobriety, and roadway conditions at the time of the crash.

Using the sufficiency file, probe vehicle speed data, and crash data, a dataset was created at the segment-month level, where the monthly number of crashes occurring on each segment was calculated. Annual traffic volumes were converted to monthly average daily traffic (MADT) using MDOT seasonal adjustment factors (MDOT, 2025b).

MDOT provides seasonal adjustment factors for multiple roadway groupings. After evaluating the availability and consistency of these classifications across the statewide network, urban and rural seasonal adjustment factors were selected for use in this study. Segments located within the Adjusted Census Urban Boundary (ACUB) (MDOT, 2025a) were classified as urban, while segments outside the ACUB were classified as rural for the purpose of applying seasonal factors. Monthly adjustment factors were computed using MDOT day-of-week factors and the distribution of weekdays within each calendar month and were applied to annual AADT values to estimate MADT for each segment and month.

Following dataset development, roadway segments were categorized into five facility types: (1) freeways, (2) multilane divided highways, (3) multilane undivided highways, (4) rural two-lane highways, and (5) urban two-lane highways. Freeways and multilane facilities were identified using the Road Type variable in the sufficiency file. Urban two-lane facilities were identified using the same variable for segments located within the SEMCOG region (Livingston, Macomb, Monroe, Oakland, St. Clair, Washtenaw, and Wayne counties). Rural two-lane segments were identified through manual GIS review and verification using satellite imagery. Approximately 1,000 miles of roadway located outside MDOT-defined community boundaries were selected and classified as rural two-lane highways. Community boundaries were identified using MDOT-provided village shapefiles (MDOT, 2025c), which are part of the Michigan Geographic Framework (MGF).

5.3 Data Summary

This section summarizes the characteristics of the analysis datasets developed for this study. This involves descriptive statistics and coverage information for the segment-month dataset.

5.3.1 Dataset Coverage Segment Monthly

The segment-month dataset covers five roadway facility types (freeways, divided multilane highways, undivided multilane highways, and rural two-lane and urban two-lane highways) for the 2019–2024 study period. Table 7 summarizes the dataset coverage by facility type, including the number of segments, total mileage, total segment-month observations, total crashes, and crash rates expressed as crashes per million vehicle miles traveled.

The final segment-month dataset represents a comprehensive statewide coverage of the MDOT trunkline network across all five facility types. In total, the dataset includes 3,748 roadway segments spanning approximately 6,939 centerline miles. With 84 months of observations for each segment, this corresponds to more than 300,000 segment-month records. Over the study period, a total of 426,730 crashes were observed across these facilities. Crash rates over the 2019–2024 study period varied across facility types, ranging from 1.14 crashes per million VMT on freeways to 5.02 crashes per million VMT on undivided multilane highways.

Table 7: Segment-Month Dataset Coverage and Crash Summary by Facility Type

Variable	Freeway	Divided Multilane	Undivided Multilane	Rural Two-Lane	Urban Two-Lane
Total mileage	3736	789	483	1661	270
Total segment-months	169657	54553	43104	29016	15169
Total crashes	199649	79541	99014	35841	12685
Crash Rate (per million VMT)	1.14	3.36	5.02	2.47	2.46
Study Period			2019–2024		

Table 8 summarizes the average monthly crash frequency and key exposure characteristics across facility types. On average, freeway segments experienced approximately 1.18 crashes per month per segment and carried the highest traffic volumes, with an average MADT of 26,040 vehicles. Divided and undivided multilane highways exhibited higher average crash frequencies (1.46 and 2.31 crashes per month per segment, respectively), despite serving lower traffic volumes than freeways. Rural two-lane highways carried substantially lower traffic volumes and exhibited an average of 1.21 crashes per month per segment, but were characterized by longer average segment lengths. Urban two-lane highways exhibited lower average crash frequencies (0.84 crashes per month per segment) and moderate traffic volumes (8,596 vehicles), with shorter segment lengths relative to rural two-lane facilities.

These differences highlight substantial variation in traffic exposure, segment geometry, and crash occurrence across facility types.

Table 8: Average Monthly Crash Frequency and Segment Exposure Characteristics by Facility Type

Facility Type	Average Total Crash	Average MADT	Average Segment Length
Freeway	1.18	26,040	1.58
Divided Multilane	1.46	13,062	1.03
Undivided Multilane	2.31	18,185	0.81
Rural Two-Lane	1.20	4,461	3.99
Urban Two-Lane	0.84	8,596	1.34

Figure 27 compares monthly average daily traffic and average monthly crash totals by facility type. Data from 2019 and 2021–2024 are combined to represent a typical-year profile, while 2020 is shown separately due to its distinct temporal pattern. Across all facilities, 2020 exhibits a pronounced reduction in both traffic volumes and crash totals during the spring months, with the lowest values observed in April. This decline corresponds with the period of statewide stay-at-home orders and travel restrictions implemented in Michigan during early 2020. Following this period, both MADT and crash totals increase through the summer as travel activity resumes.

For the typical-year profiles (2019 and 2021–2024), MADT generally increases into the summer months and declines toward late fall and winter. In contrast, crash totals do not peak during the highest-volume summer months and instead tend to increase during the fall, particularly in October and November, across multiple facility types. These late-fall increases coincide with seasonal conditions historically associated with elevated crash risk, including reduced daylight hours and increased wildlife-related conflicts on roadways. Overall, while traffic exposure influences crash frequency, the differing seasonal patterns suggest that additional roadway and environmental factors contribute to monthly crash variation.

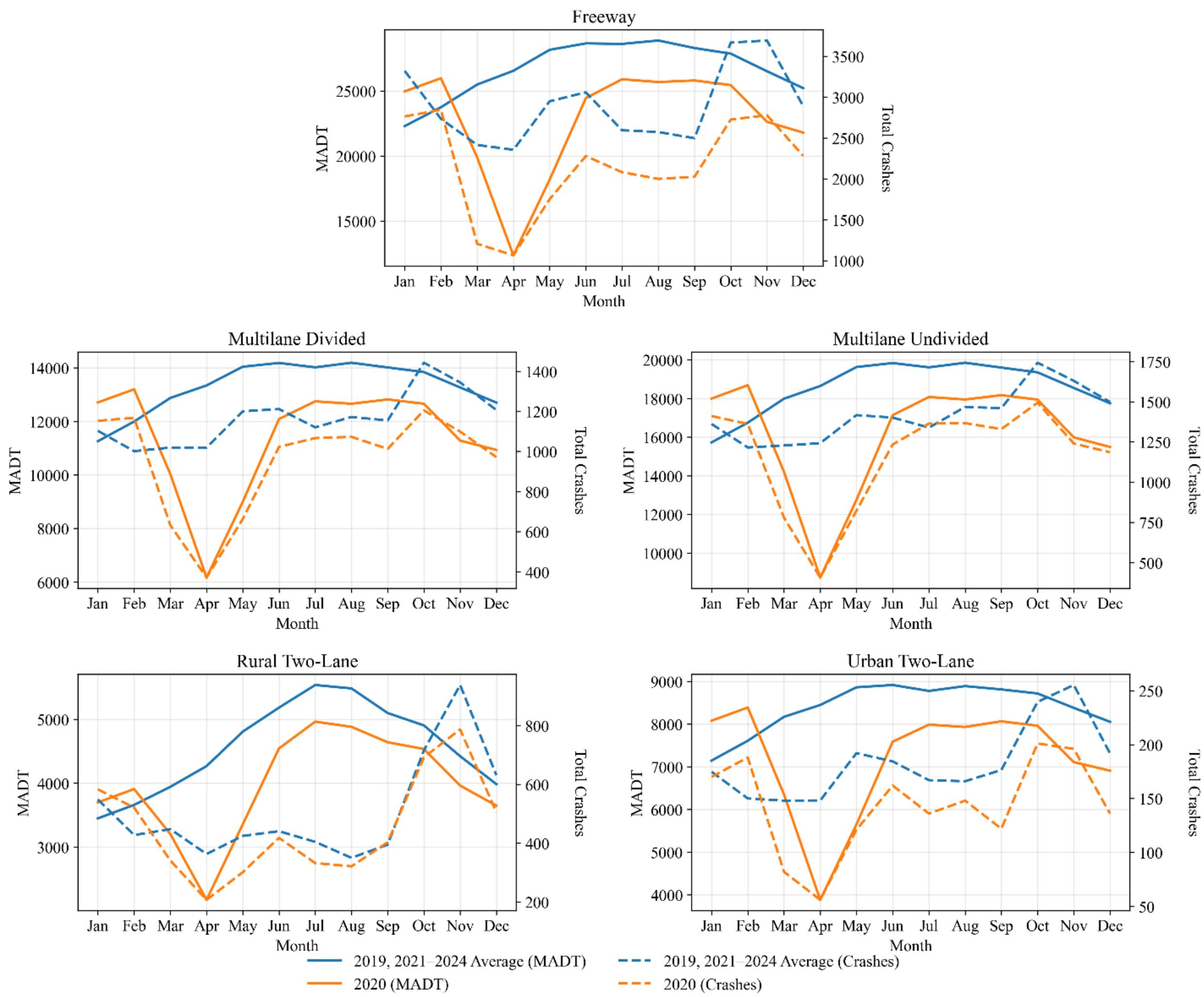

Figure 27: MADT and Average Monthly Crash Totals by Facility Type: Typical Years (2019, 2021–2024) Compared with 2020

Figure 28 presents MADT and average monthly non-deer crash totals by facility type. Similar to the total-crash trends, 2020 exhibits a pronounced reduction in both traffic volumes and non-deer crashes during the spring months, with the lowest values observed in April. This indicates that the 2020 decline is not limited to wildlife-related crashes but reflects broader reductions in overall crashes.

For the typical-year profiles (2019 and 2021–2024), excluding deer-related crashes reduces the magnitude of the late-fall crash increases, particularly for rural two-lane highways where October-November peaks are noticeably pronounced. These comparisons suggest that wildlife-related crashes contribute substantially to late-fall crash totals, especially on rural roadways, while other seasonal factors continue to influence crash frequency throughout the year.

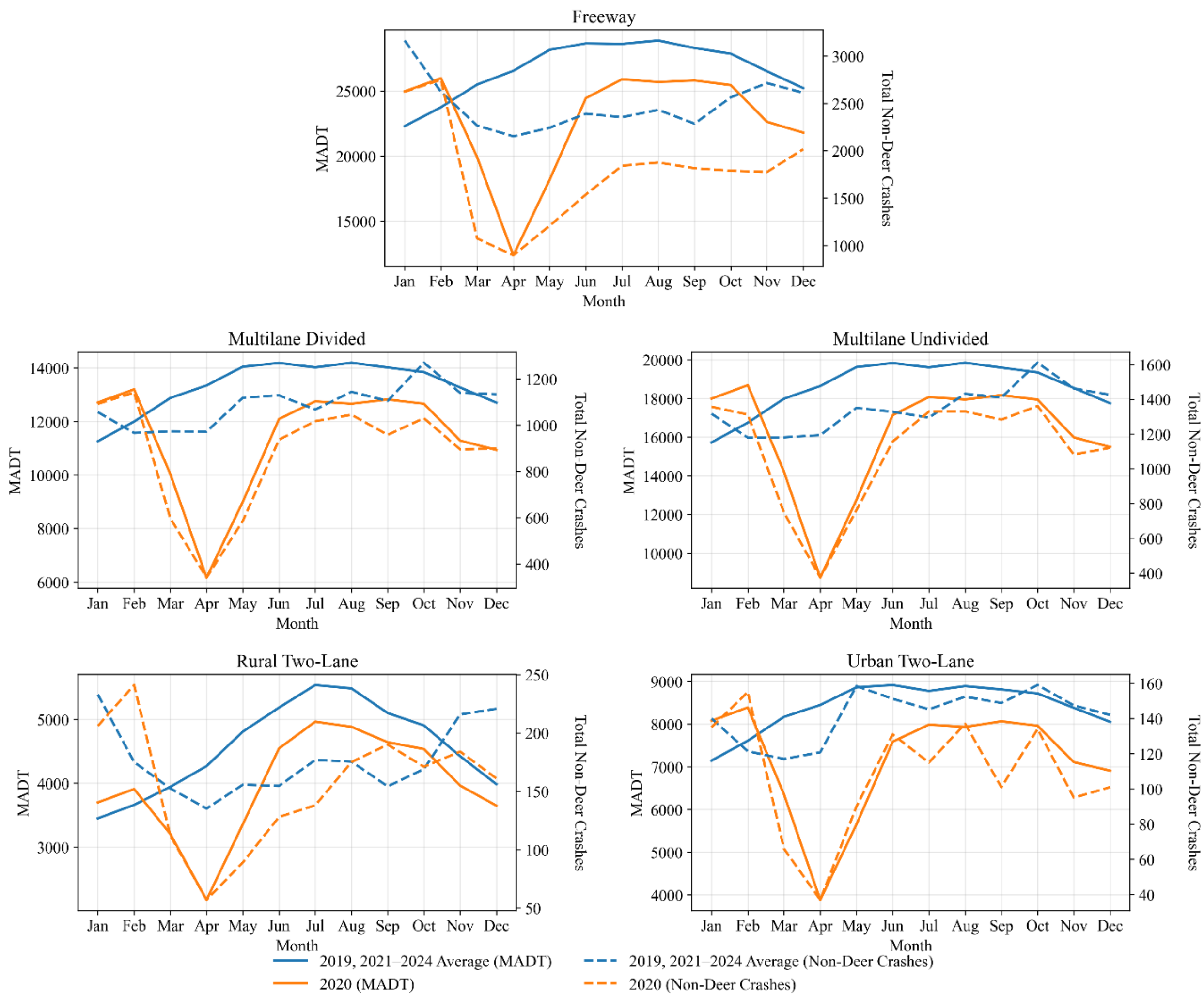

Figure 28: MADT and Average Monthly Non-Deer Crash Totals by Facility Type: Typical Years (2019, 2021–2024) Compared with 2020

To account for differences in traffic exposure, monthly fatality rates were computed as the number of fatalities divided by estimated vehicle miles traveled (MADT × days × segment length), expressed per hundred million vehicle miles traveled. Percent changes were then calculated relative to the corresponding month in 2019 to control for seasonal effects and provide a consistent pre-period baseline (Figure 29). In two instances, the 2019 baseline fatality rate was zero (April for multilane divided highways and April for rural two-lane highways), resulting in an undefined percent-change value. For visualization purposes only, these points were assigned a nominal value of +100 percent to indicate the presence of fatalities relative to a zero baseline. Preliminary examination of monthly fatality rate trends for each year indicated that several years exhibited comparable seasonal patterns, while 2020 displayed a distinct and atypical profile with substantially larger deviations from baseline. For clarity and to reduce visual redundancy, years with similar trends were grouped.

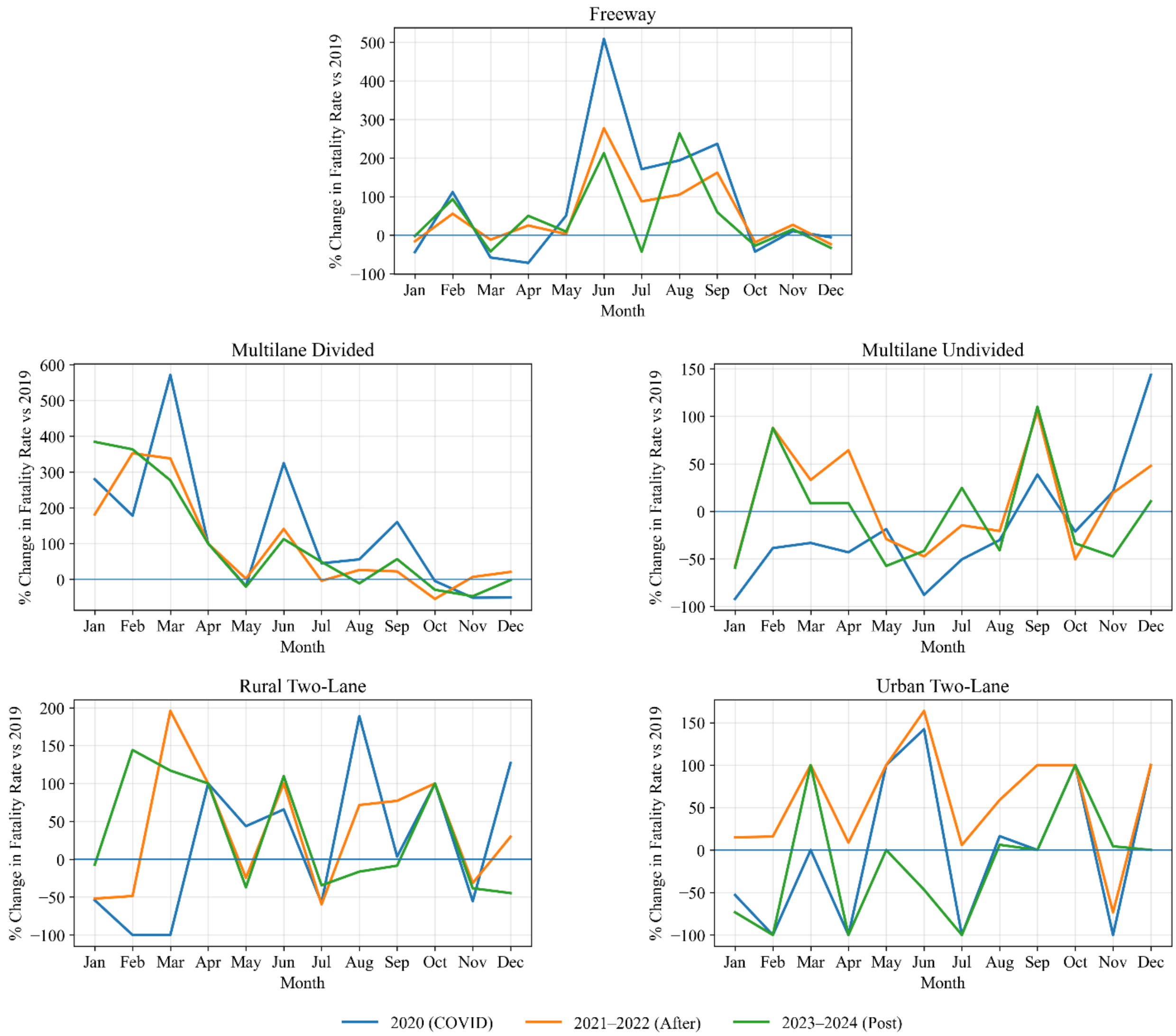

Figure 29: Monthly Percent Change in Fatality Rate Relative to 2019 Baseline by Facility Type

Across facilities, the largest deviations from baseline occur in 2020, where several months exhibit substantial increases in fatality rate despite lower traffic volumes. Freeways and divided multilane highways show particularly pronounced mid-year increases during 2020, with multiple months exceeding 200 percent above baseline levels. In contrast, post-2020 years generally exhibit smaller fluctuations than 2020, but fatality rates remain elevated in many months and are frequently above the 2019 baseline rather than fully returning to pre-period levels.

Multilane undivided highways display more moderate changes over time, while rural two-lane facilities show greater month-to-month variability, reflecting the smaller number of fatal crashes and lower traffic volumes on these segments. Urban two-lane facilities show multiple months in 2021–2022 with fatality rates above baseline levels, though the magnitude of these increases is generally smaller than that observed on freeways and divided multilane highways.

Overall, these results indicate that changes in fatal outcomes were not solely proportional to changes in traffic exposure, with certain periods exhibiting elevated fatality risk relative to 2019 conditions.

Probe vehicle speed data was not available for all roadway segments and months included in the segment-month crash dataset. Consequently, the result of the analyses presented in this report may be based on a subset of segment-month observations for which both crash and speed information were available. Table 9 summarizes the number of segment-month observations with available speed data by facility type and the corresponding coverage percentages relative to the full dataset.

Speed data coverage was complete for freeways (100 percent) and remained high for the remaining facilities, exceeding 80 percent for multilane divided, multilane undivided, and rural two-lane roadways. Therefore, while some observations were excluded from speed-related analyses, the retained data represent the substantial majority of the study network and are expected to provide a representative characterization of operating speed patterns.

Table 9: Availability of Probe Vehicle Speed Data

Facility Type	Speed Coverage (%)
Freeway	100.00
Multilane Divided	88.85
Multilane Undivided	85.31
Rural Two-Lane	83.55
Urban Two-Lane	77.02

Figure 30 presents the average monthly operating speed by facility type and year. Because these values represent average operating speeds across all traffic conditions rather than free-flow or uncongested speeds, they reflect overall system operating conditions rather than unconstrained travel speeds.

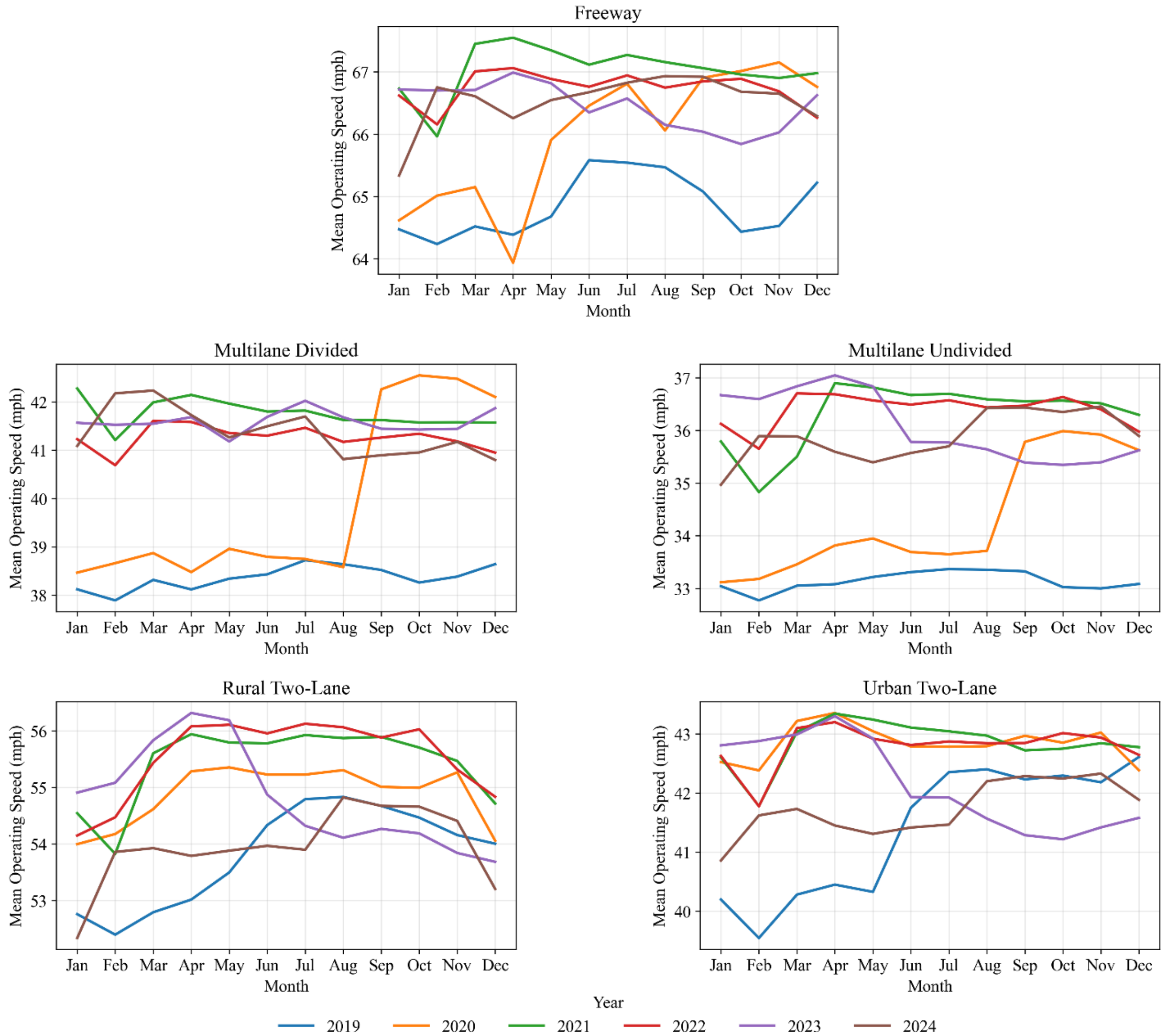

Figure 30: Average Monthly Operating Speed by Facility Type: 2019–2024

Across most facility types, operating speeds increased during 2020 and remain elevated relative to 2019 for several subsequent years, indicating a systemwide shift in traffic operating conditions during the pandemic period. On freeways, mean speeds decline slightly between March and April 2020, coinciding with the initial implementation of stay-at-home policies. However, speeds increase sharply beginning in late spring, particularly between April and May, and continue rising through the remainder of the year, reaching their highest levels in November 2020. Following this period, freeway operating speeds remain consistently higher than pre-pandemic levels throughout 2021–2023. Although some moderation is observed in 2024, speeds remain above the levels observed during 2019.

Multilane divided facilities exhibit a similar pattern but with a particularly pronounced increase later in 2020. While speeds during the early months of the year remain relatively close to pre-pandemic levels, a sharp increase occurs between August and September 2020, with operating speeds reaching their highest values in October 2020. After this shift, speeds remain elevated relative to 2019 for the remainder of the study period.

For multilane undivided facilities, mean operating speeds during most of 2020 remain relatively close to 2019 levels, indicating a smaller immediate change in operating conditions compared with other facilities. However, similar to multilane divided facilities, a noticeable increase occurs beginning in August 2020, reflecting a late-year increase in travel speeds during the pandemic period.

Rural two-lane facilities display somewhat different behavior. Operating speeds increased beginning in early 2020 and remain higher than 2019 levels throughout that year. However, beginning around May 2023, speeds begin to decline, and by July 2023 average speeds fall below those observed in 2020, gradually returning to levels similar to the pre-pandemic period. A similar pattern is observed in 2024, where speeds remain above 2019 levels through approximately June before declining to values comparable with pre-pandemic conditions during the latter part of the year. In general, the results indicate that operating speeds increased across most facilities during the pandemic period, particularly during 2020, and while some moderation occurs in later years, speeds generally remain elevated relative to pre-pandemic conditions across much of the study period.

Two-lane facilities in 2019 exhibit a distinct seasonal pattern compared to other roadway facility types. Average travel speeds were approximately 2.5 mph lower during the early part of the year (January–February) relative to the remaining months. Speeds then increased steadily from early spring through late summer, reaching peak levels during this period, before gradually declining toward the end of the year.

It should be noted that the trends observed in 2019 reflect true travel speed behavior rather than differences in fleet composition, as discussed in Chapter 5.1.4. Although speeds were adjusted using 2018 data as described in that section, the resulting changes in average speed were negligible and did not materially affect the observed trends.

Beginning in early 2020, operating speed increased and remained consistently higher than 2019 levels throughout that year, indicating a notable shift in drivers' speed selection behavior. However, beginning around May 2023, speeds began to decline, and by July 2023, average speeds fell below those observed in 2020, gradually returning to levels similar to the pre-pandemic period.

A similar pattern is observed in 2024, where speeds remain above 2019 levels through approximately June before declining to values comparable with pre-pandemic conditions during the latter part of the year. In general, the results indicate that operating speeds increased across most facilities during the pandemic period, particularly during 2020, and while some moderation occurs in later years, speeds generally remain elevated relative to pre-pandemic conditions across much of the study period.

Figure 31 presents the average monthly operating speed and the corresponding standard deviation in operating speed by facility type. Prior to aggregation, monthly trends were examined individually for each year and facility. Because operating speed patterns were highly consistent across the post-2020 years, these years were combined and averaged to simplify visualization and highlight systematic differences relative to 2020, which exhibited distinct traffic conditions associated with the pandemic period.

Across all facilities, mean operating speeds in 2020 generally exceed those observed during the post-2020 period, particularly on freeway and multilane facilities. These higher speeds coincide with reduced traffic demand during the early pandemic months and reflect lower congestion levels. In contrast, post-2020 years show slightly lower and more stable speeds, suggesting a return toward typical operating conditions as travel demand recovered.

Speed variability, represented by the monthly standard deviation, exhibits complementary trends. Periods with higher traffic demand tend to show greater dispersion in speeds, while lower demand periods are associated with more uniform speeds. The elevated mean speeds and reduced variability observed in portions of 2020 are consistent with lighter traffic and fewer interactions among vehicles. Conversely, post-2020 conditions generally display modestly higher variability, reflecting more heterogeneous traffic streams.

Seasonal effects are present but relatively small compared with the year-to-year differences. Monthly speed patterns remain broadly consistent within each facility type, indicating that broader system conditions, rather than seasonal fluctuations, primarily explain the observed differences.

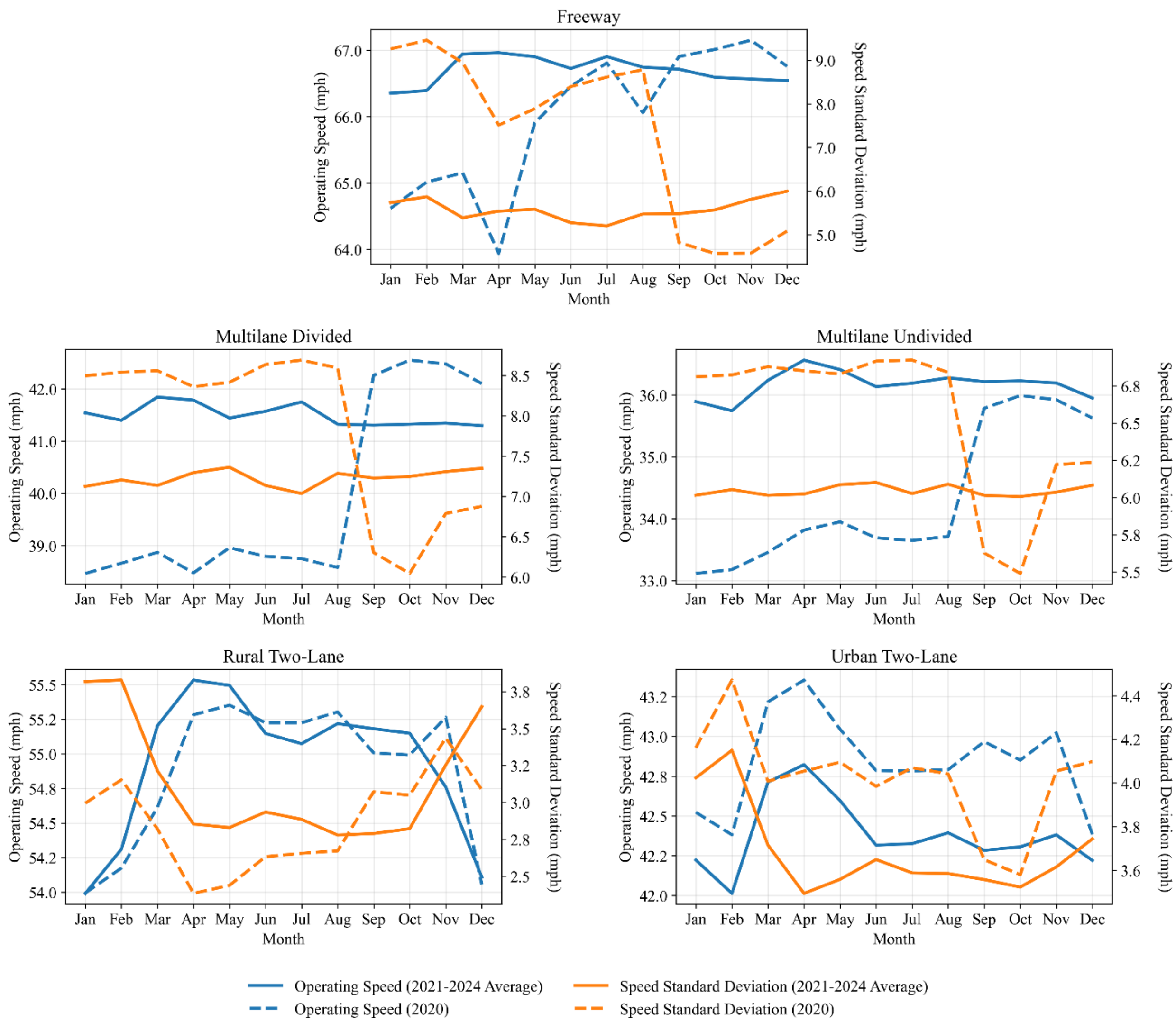

Figure 31: Average Monthly Operating Speed and Speed Variability by Facility Type: 2020 vs 2021–2024

Collectively, these results illustrate that operating speed metrics are closely linked to traffic demand conditions. Therefore, analyses examining relationships between speed and safety outcomes should explicitly account for exposure and traffic volume to avoid confounding effects.

Figure 32 compares monthly operating speeds with corresponding traffic exposure (MADT) for each facility type, with separate curves shown for 2020 and the average of 2021–2024. The relationship between traffic demand and operating speed is clearly evident across all facilities. Periods characterized by lower traffic volumes, most notably during the early pandemic months of 2020, correspond to higher operating speeds. Conversely, months with higher traffic volumes generally exhibit modest reductions in average speeds.

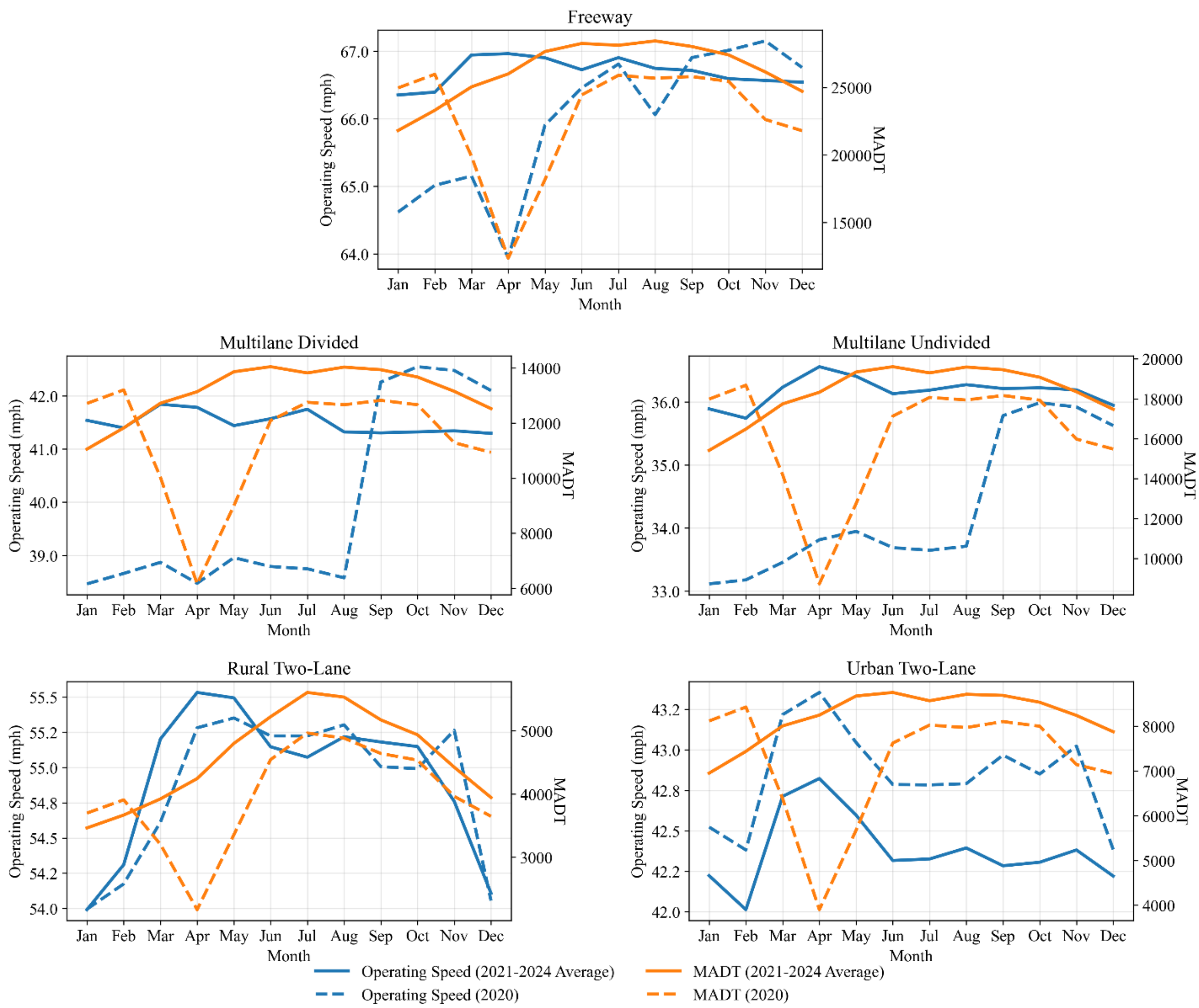

Figure 32: Average Monthly Operating Speed and Average MADT by Facility Type: 2020 vs 2021–2024

This inverse relationship between speed and volume is particularly pronounced on freeway and multilane facilities, where the substantial drop in traffic during spring 2020 coincides with noticeable increases in operating speed. As volumes recover in later months and in post-2020 years, speeds moderate and return toward more typical levels. Rural two-lane facilities display similar but smaller-magnitude changes, reflecting lower overall traffic density and reduced congestion effects.

These findings are consistent with earlier results showing that periods of higher traffic demand are associated not only with lower mean speeds but also with greater speed variability. During higher volume periods, increased vehicle interactions and traffic friction lead to both reduced average speeds and larger dispersion in speeds, whereas lighter traffic conditions produce higher and more uniform operating speeds. Collectively, these patterns highlight the strong influence of traffic exposure on observed speed metrics and reinforce the importance of accounting for volume when interpreting relationships between speed and safety outcomes.

Figure 33 presents monthly percent changes in crash frequencies by severity category and facility type relative to corresponding months in 2019, which serves as the baseline (pre-pandemic) year. For each facility type (freeway, multilane divided, multilane undivided, rural two-lane, and urban two-lane), crash counts were aggregated by month and severity group and compared with the same month in 2019 using Equation 14:

$$\text{Percentage Change in Crash} = \frac{C_{y,m-}\ C_{2019,m}}{C_{2019,m}} \times 100 \tag{14}$$

Where $C_{y,m}$ represents the number of crashes in year y and month m, and $C_{2019,m}$ represents the corresponding count in the same month of 2019.

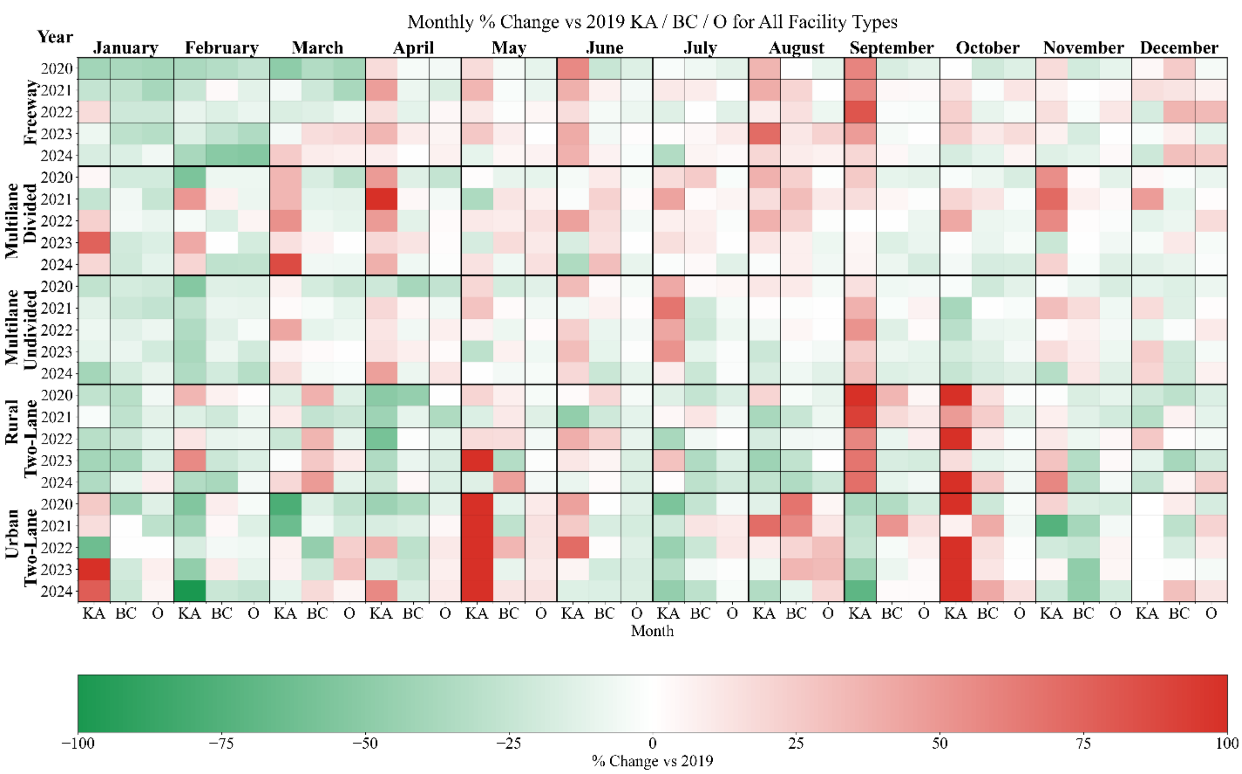

Figure 33: Monthly Percent Change in Crash Frequency by Severity and Facility Type Relative to 2019

Within each month, three columns are shown representing fatal and suspected serious injury crashes (KA), minor and possible injury crashes (BC), and property-damage-only crashes (O).

Rows correspond to individual years (2020–2024), grouped by facility type. The color scale illustrates the magnitude and direction of change. Green shades indicate reductions relative to 2019, red shades indicate increases, and values near zero are shown in white. Darker colors reflect larger deviations from the baseline. To enhance visual comparability and prevent extreme outliers from compressing the color range, the legend scale was capped at ±100 percent; values exceeding this range are displayed using the maximum or minimum color intensity. This visualization facilitates identification of temporal patterns, seasonal differences, and shifts in crash severity across facility types over time, enabling direct comparison of how crash trends evolved during and after the pandemic period.

Across facilities, several consistent temporal patterns are evident. Increases in fatal and suspected serious injury (KA) crashes are more frequently observed during late summer and early fall months relative to the 2019 baseline. In particular, September exhibits consistently higher KA crash frequencies across multiple years, with the largest and most persistent increases occurring on rural two-lane facilities. Elevated KA crash levels are also visible on rural two-lane facilities during October, indicating sustained increases into the fall season. Multilane divided facilities display notable increases during selected spring and late-fall months, most prominently in April and November, where KA crash counts exceed baseline levels across multiple years. Additionally, several of the earliest post-baseline increases are observed during 2020, including June, August, and September, and these same months continue to exhibit higher KA crash frequencies in subsequent years, suggesting recurring seasonal effects rather than isolated deviations.

5.4 Analysis of Crash Frequency

The objective of this analysis was to examine how crash frequency varied across roadway segments and over time. Monthly crash counts were evaluated at the segment-level to quantify the influence of changes in travel demand and driving behavior observed during and after the COVID-19 period while accounting for differences in segment length and other geometric features.

5.4.1 Statistical Analysis

A series of regression models were estimated to evaluate the relationship between roadway characteristics, operating speeds, traffic exposure, and crash frequency. The monthly crash count on any given roadway segment represents a discrete, non-negative integer outcome. Such count data are commonly analyzed using Poisson or negative binomial (NB) regression models. Under a Poisson model, the probability of observing y_{it} crashes on segment i during month t is expressed as Equation 15:

$$P(y_{it}) = \frac{e^{-\lambda_{it}}\lambda_{it}^{y_{it}}}{y_{it}!} \tag{15}$$

Where λ_{it} denotes the average number of crashes for segment i during month t. The NB model is preferred over Poisson model as it accounts for overdispersion generally found in the crash data. Thus, in a NB model, a gamma-distributed error term is included in estimating λ_{it} as shown in Equation 16:

$$\lambda_{it} = EXP(\beta X_{it} + \varepsilon_i) \times L_{it} \tag{16}$$

Where β is a vector of estimable parameters X_{it} is a vector of explanatory variables and L_{it} denotes the exposure associated with segment length. The term $EXP(\varepsilon_i)$ is gamma distributed with mean and variance equal to 1 and α, respectively, where α is the overdispersion parameter.

As stated previously, the analysis dataset combines cross-sectional and longitudinal data to form a panel dataset wherein roadway segments are repeated for each month for six years. Thus, a random-effects modeling framework is adopted to account for correlation among observations and unobserved segment-specific characteristics. The random-effects model allows the constant term to vary across segments, as shown in Equation 17:

$$\beta_{0i} = \beta_0 + \omega_i \tag{17}$$

Where, ω_i is a randomly distributed random effect for segment i and all other variables are as defined previously. To account for differences in roadway exposure, the natural logarithm of segment length was incorporated in the model as an offset term. This ensures that predicted crash counts scale proportionally with segment length and allows coefficients to be interpreted as effects on crash rates rather than raw crash counts. Models were estimated using maximum likelihood methods, and the estimated coefficients reflect multiplicative effects on expected crash frequency.

5.4.2 Analysis Results and Discussion

Separate random-effects negative binomial models were estimated for crash frequency across five facility types, including freeways, multilane divided, multilane undivided, rural two-lane, and urban two-lane highways. Due to the high frequency of deer-involved crashes and their distinct crash mechanisms relative to typical traffic and roadway conditions, these crashes were excluded from the analysis. Accordingly, the models focus only on non-deer-involved crashes.

An initial model specification included indicator variables for each month-year combination (e.g., January 2019, February 2019, …, December 2024) to fully account for potential temporal variation in crash frequency. However, these disaggregated indicators produced highly similar and consistent patterns across months and years while substantially increasing the number of parameters to be estimated. To improve model interpretability, the final specification instead incorporated separate month indicators to capture seasonal effects and year indicators to capture broader period-specific changes. These temporal controls were included alongside traffic exposure, speed-related measures, geometric characteristics, and regional variables. Table 10 presents the results of the final models. For each variable, the estimated coefficient and corresponding standard error (in parentheses) are reported. Parameters statistically significant at the 95 percent confidence level are denoted with an asterisk.

Table 10 summarizes the estimated random-effects negative binomial models for non-deer-involved crashes by facility type. Positive parameter estimates indicate higher crash occurrence, whereas negative estimates indicate reductions relative to the reference category. The following subsections discuss the results by groups of related variables.

Table 10: Regression Results for Non-deer Crashes by Facility Type

Parameter	Estimate (Std. Error)				
	Freeway	Divided Multilane	Undivided Multilane	Rural Two-Lane	Urban Two-Lane
Intercept	-5.94 (0.17)*	-6.25 (0.31)*	-7.70 (0.38)*	-9.79 (0.34)*	-9.82(0.65)*
Ln (MADT)	0.53 (0.02)*	0.58 (0.03)*	0.88 (0.04)*	0.96 (0.04)*	1.05(0.08)*
Month					
January	Baseline	Baseline	Baseline	Baseline	Baseline
February	-0.21 (0.02)*	-0.13 (0.03)*	-0.14 (0.03)*	-0.24 (0.05)*	-0.16 (0.06)*
March	-0.50 (0.02)*	-0.26 (0.03)*	-0.26 (0.03)*	-0.53 (0.05)*	-0.31 (0.06)*
April	-0.57 (0.02)*	-0.28 (0.03)*	-0.30 (0.03)*	-0.72 (0.06)*	-0.30 (0.06)*
May	-0.55 (0.02)*	-0.16 (0.03)*	-0.20 (0.03)*	-0.71 (0.05)*	-0.07 (0.06)
June	-0.50 (0.02)*	-0.11 (0.03)*	-0.20 (0.03)*	-0.76 (0.05)*	-0.10 (0.06)
July	-0.48 (0.02)*	-0.15 (0.03)*	-0.19 (0.03)*	-0.73 (0.05)*	-0.12 (0.06)*
August	-0.45 (0.02)*	-0.10 (0.03)*	-0.12 (0.03)*	-0.66 (0.05)*	-0.12 (0.06)*
September	-0.51 (0.02)*	-0.13 (0.03)*	-0.14 (0.03)*	-0.70 (0.05)*	-0.16 (0.06)*
October	-0.42 (0.02)*	0.02 (0.03)	<0.01 (0.03)	-0.62 (0.05)*	-0.04 (0.06)
November	-0.28 (0.02)*	-0.07 (0.03)*	-0.06 (0.03)*	-0.28 (0.05)*	-0.12 (0.06)*
December	-0.26 (0.02)*	-0.05 (0.03)*	-0.03 (0.03)	-0.20 (0.05)*	-0.10 (0.06)
Year					
2019	Baseline	Baseline	Baseline	Baseline	Baseline

Parameter	Estimate (Std. Error)				
	Freeway	Divided Multilane	Undivided Multilane	Rural Two-Lane	Urban Two-Lane
Intercept	-5.94 (0.17)*	-6.25 (0.31)*	-7.70 (0.38)*	-9.79 (0.34)*	-9.82(0.65)*
Ln (MADT)	0.53 0.02)*	0.58 0.03)*	0.88 0.04)*	0.96 (0.04)*	1.05(0.08)*
Year					
2020	-0.33 (0.01)*	-0.22 (0.02)*	-0.15 (0.02)*	-0.18 (0.04)*	-0.15 (0.04)*
2021	-0.09 (0.01)*	-0.07 (0.02)*	-0.06 (0.02)*	-0.17 (0.04)*	0.03 (0.04)
2022	-0.06 (0.01)*	-0.06 (0.02)*	-0.05 (0.02)*	-0.11 (0.04)*	0.03 (0.04)
2023	-0.06 (0.01)*	-0.06 (0.02)*	-0.07 (0.02)*	-0.26 (0.04)*	<0.01(0.04)
2024	-0.05 (0.01)*	-0.12 (0.02)*	-0.10 (0.02)*	-0.20 (0.04)*	-0.03 (0.04)
Region					
Bay	Baseline	Baseline	Baseline	Baseline	Baseline
Superior	-0.57 (0.13)*	0.12 (0.17)	-0.39 (0.11)*	-0.35 (0.10)*	NA
North	-0.11 (0.07)	0.17 (0.23)	-0.01 (0.14)	-0.12 (0.08)	NA
Grand	0.66 (0.04)*	0.56 (0.13)*	0.26 (0.10)*	0.17 (0.08)*	NA
Southwest	0.25 (0.05)*	0.18 (0.14)	0.23 (0.10)*	0.16 (0.09)	NA
University	0.32 (0.04)*	0.44 (0.13)*	0.28 (0.09)*	0.11 (0.08)	0.27 (0.14)
Metro	0.86 (0.04)*	0.67 (0.13)*	0.29 (0.08)*	0.41 (0.32)	0.60 (0.19)*
Standard Deviation of Speed	0.01 (0.00)*	0.02 (0.00)*	0.03 (0.01)*	0.03 (0.01)*	0.07 (0.01)*
Road Geometry					
Percent Curved Segment	0.50 (0.07)*	0.28 (0.13)*	N/A	0.74 (0.20)*	N/A
Median type					
Graded with ditch	Baseline	Baseline	N/A	N/A	N/A
Concrete Barrier	0.65 (0.03)*	NA	N/A	N/A	N/A
Raised Island	N/A	0.85 (0.07)*	N/A	N/A	N/A
Median width (ft)					
≤75	Baseline	N/A	N/A	N/A	N/A
>75	-0.47 (0.03)*	N/A	N/A	N/A	N/A
Right shoulder width (ft)					
>0	NA	NA	-0.94 (0.07)*	NA	NA
>6	NA	NA	NA	NA	-0.45(0.13)*
>9	NA	-0.16 (0.07)*	NA	NA	NA
>10	-0.20 (0.03)*	NA	NA	NA	NA
Random Effects					
Variance of Intercept	0.52	0.34	0.37	0.35	0.12

5.4.2.1 Traffic Exposure

Across all facility types, traffic exposure was strongly associated with crash frequency. The estimated coefficients for monthly average daily traffic were positive and statistically significant for all models, indicating that higher traffic volumes correspond to increased crash occurrence. The larger effect observed on two-lane facilities indicates that these roadways may be more sensitive to changes in traffic demand compared to freeways.

5.4.2.2 Monthly Trends

Monthly indicators revealed consistent seasonal patterns across all facility types. Relative to January (baseline), crash frequencies were generally lower during early spring to early summer months. The largest reductions were observed between March and July, particularly on freeways and rural two-lane highways, where expected crash counts decreased by approximately 40-70 percent.

Seasonal effects were less pronounced for multilane facilities, though most months still exhibited statistically significant reductions relative to January. October and December showed comparatively smaller or nonsignificant differences on several facility types, suggesting that crash frequencies during these months were closer to baseline levels. Overall, the similarity in monthly patterns across roadway classes indicates that seasonal variation in crash occurrence was consistent statewide rather than facility-specific.

5.4.2.3 Year-to-Year Trends

Year indicators captured clear temporal changes associated with the pandemic period. Compared with 2019, crash frequencies decreased substantially in 2020 across all facility types, with the largest reductions observed on freeways. Two-lane and multilane facilities also exhibited meaningful declines, though the magnitude was somewhat smaller.

Crash counts remained below pre-pandemic levels in subsequent years (2021–2024), but the magnitude of these reductions gradually diminished over time, suggesting a partial recovery toward typical traffic conditions. This pattern is consistent with reduced travel demand during the early stages of the pandemic followed by a progressive return of traffic activity in later years.

5.4.2.4 Speed Variability

The standard deviation of operating speed was positively associated with crash frequency across all facility types. Higher speed variability, reflecting greater heterogeneity in vehicle speeds and increased interactions between faster and slower vehicles, corresponded to elevated crash occurrence. This relationship aligns with earlier descriptive analyses and supports the hypothesis that more turbulent or unstable traffic streams increase safety risk, even when average speeds remain similar.

5.4.2.5 Roadway Geometry

Several geometric characteristics were significantly related to crash frequency. The proportion of each segment that was curved exhibited positive effects, indicating that greater curvature is associated with increased crash risk. In contrast, wider medians and shoulders generally corresponded with lower crash frequencies, suggesting that additional lateral clearance provides safety benefits. Conversely, more restrictive or complex median configurations were associated with higher crash occurrence. These findings are consistent with established relationships between roadway design features and safety performance.

5.4.2.6 Regional Effects

Regional indicators demonstrated systematic differences in crash frequency across the state. Relative to the reference region, several regions exhibited higher crash occurrence, particularly in more urbanized or higher-traffic areas. These differences likely reflect variations in land use, traffic demand, and operational conditions that are not fully captured by other explanatory variables.

5.4.3 Summary

This chapter developed and analyzed a comprehensive segment-level, month-by-month crash and operating speed database for five roadway facility types in Michigan (freeways, multilane divided, multilane undivided, rural two-lane, and urban two-lane highways) over the 2019–2024 study period. The dataset was assembled by integrating MDOT roadway inventory (sufficiency) data, updated posted speed limits reflecting the 2017 statutory changes, horizontal-curve characteristics derived from GIS-based curve extraction, MDOT traffic volumes converted from AADT to MADT using seasonal adjustment factors, Michigan State Police crash records, and INRIX/RITIS probe vehicle speeds aggregated from 15-minute intervals to monthly segment values.

From a big-picture perspective, the descriptive analyses show clear and consistent temporal patterns in both traffic demand and safety outcomes. Across all facilities, 2020 exhibited a pronounced reduction in traffic volumes and crash totals during the spring months, with the sharpest decline occurring in April, consistent with Michigan's early-pandemic travel restrictions. Traffic volumes rebounded rapidly thereafter, and crash totals increased as travel activity returned. For typical-year conditions (2019 and 2021–2024), MADT generally peaked in summer months, while crash totals did not follow the same profile and instead tended to increase during the fall, particularly in October and November. Comparisons excluding deer-involved crashes indicate that wildlife-related crashes contribute meaningfully to late-fall peaks, especially on rural two-lane facilities; however, seasonal variation remains evident even after removing deer crashes, suggesting that broader seasonal and environmental factors also influence crash occurrence.

Probe vehicle operating speed analyses show a persistent shift in travel speeds relative to pre-pandemic conditions. Across freeways and multilane facilities, operating speeds in 2020 and subsequent years were consistently closer to posted speed limits than in 2019. Rural two-lane highways exhibited the greatest variability and were the only facility type where average operating speeds occasionally exceeded posted limits. When speeds were compared across periods, the early post-period (2021–2022) generally exhibited the highest operating speeds, followed by modest moderation in 2023–2024; however, speeds remained elevated relative to pre-pandemic conditions. Speed variability patterns were consistent with expected traffic-flow dynamics, where higher-volume periods tended to correspond with lower mean speeds and higher dispersion in speeds. Collectively, these results reinforce the importance of explicitly accounting for traffic volume when interpreting relationships between speed and safety outcomes.

Finally, random-effects negative binomial crash frequency models were estimated separately for each facility type to quantify relationships between crash occurrence and traffic exposure, temporal effects, operating conditions, roadway geometry, and regional context. Due to the high frequency and distinct nature of deer-involved crashes, the regression analyses focused on non-deer-involved crashes. Model results indicate that traffic exposure (ln(MADT)) is a strong and consistent predictor of crash frequency across all facility types, while monthly and yearly indicators capture substantial seasonal variation and the distinct reduction in crash occurrence during 2020 relative to 2019. Given the strong correlation between mean speeds and traffic volume, speed variability (standard deviation of operating speed) was retained as the primary speed-related metric and was positively associated with crash frequency across all facilities. Roadway geometry effects were also evident, with a higher proportion of segments being curved associated with increased crash occurrence and wider shoulders/medians generally associated with reduced crash frequency. Regional indicators further showed systematic spatial differences in crash frequency across Michigan. Collectively, these findings demonstrate that crash occurrence during the study period was strongly shaped by changes in traffic exposure and operating conditions during and after the pandemic, with additional contributions from roadway design and regional context.

6 MICHIGAN PERSON-LEVEL ANALYSIS

In addition to the segment-month crash dataset described in the previous chapter, a separate party-involved dataset was developed to support analyses of injury severity and driver-level risk factors. Whereas the segment-month dataset aggregates crashes to the roadway segment-level to evaluate crash frequency and exposure effects, the party-involved dataset disaggregates each crash into the individual roadway users involved. This structure enables examination of how operating conditions, driver characteristics, and roadway features influence injury outcomes at the individual level.

6.1 Data Collection and Preparation

6.1.1 Person-Level Data and Crash Data

Person-level data for the state of Michigan were obtained from the Michigan State Police (MSP) Traffic Crash Reporting System, which contains detailed information on injury severity, crash circumstances, restraint use, impairment, demographic, vehicle characteristics, and behavioral and environmental factors at the time of the crash. The dataset was disaggregated at the individual roadway user level, meaning that each record represents a single party involved in a crash, including drivers, passengers, pedestrians, bicyclists, and other roadway users. Each party record has a crash identification number (crsh_id), which was used to link party-level information to the corresponding crash-level data, However, it should be noted that parties such as “Owner”, “Engineer”, and “Witness” were excluded from the dataset.

As described in Chapter 5, the crash dataset provides information on the location and time of each crash occurrence, injury severity outcomes, and numerous contributing factors related to drivers, vehicles, roadway conditions, and the surrounding environment. Injury severity for each crash is coded using the five-level KABCO injury scale, where K represents fatal injuries, A denotes incapacitating injuries, B denotes non-incapacitating injuries, C denotes possible injuries, and O represents property damage only (PDO) crashes.

To support the person-level analysis, each party-crash record was assigned to the corresponding roadway segment using the available location referencing information. The roadway segment dataset contained roadway characteristics and operating information for five facility types: freeways, multilane divided highways, multilane undivided highways, rural two-lane highways, and urban two-lane highways. Segment-level attributes, including roadway geometry, traffic exposure, and speed measures, were subsequently linked to each party-crash record. This approach ensures that all roadway users associated with a given crash share consistent location-specific characteristics while allowing injury outcomes and behavioral factors to vary at the individual party level.

6.1.2 Roadway geometry

Roadway geometry variables were incorporated into the party-involved dataset using the segment-level roadway inventory prepared for the monthly segment analysis described in the previous chapter. The roadway geometry data was originally obtained from the Michigan Department of Transportation (MDOT) sufficiency file and included variables such as number of lanes, lane width, shoulder width, median characteristics, speed limit, horizontal curvature measures, and other roadway attributes.

The procedures used to extract, process, and integrate roadway geometry data was identical to those described previously for the segment-level dataset. Each crash was spatially matched to the corresponding roadway segment using the unique segment identifier (PR, BMP, and EMP), and the associated roadway characteristics were then assigned to all involved parties within that crash. Roadway geometry remains constant within a crash event; therefore, identical geometric attributes were assigned to each party associated with a given segment location.

This approach ensures consistency between the segment-level and person-level analyses while allowing roadway characteristics to be incorporated as explanatory variables in injury severity modeling.

6.1.3 Speed and Exposure Data Integration

Probe vehicle speed data obtained from the Regional Integration of Transportation Information System (RITIS) was linked to the party-involved records to characterize operating conditions immediately preceding each crash. For the party-involved dataset, speed observations were extracted at a finer temporal resolution. Specifically, for each crash, speed observations from the 15-minute interval immediately prior to the recorded crash time on the corresponding roadway segment were identified and assigned to all involved parties. This approach provides a measure of prevailing traffic speed and variability immediately before the event, rather than relying solely on posted speed limits or long-term averages.

6.1.4 Dataset Preparation

Following the assignment of crashes to roadway segments and the integration of speed, traffic exposure, and roadway geometry data, several quality control and data filtering procedures were applied to ensure consistency and reliability of the analytical dataset. These procedures included verification of temporal alignment, segment matching, and completeness of key explanatory variables.

As part of the data preparation process, observations from January through June 2019 were excluded for all facility types due to known inconsistencies in probe-based speed measurements associated with changes in vehicle fleet composition. This step was implemented to ensure comparability of operating speed measures across the study period.

In addition, records with missing or unknown values for key explanatory variables, including driver characteristics, behavioral indicators, roadway attributes, and operating speed measures, were excluded from the final analytical dataset. The injury severity models require complete information for all included variables; therefore, only observations with valid and consistent data were retained for analysis. The resulting dataset reflects a filtered subset of the original person-level data and provides a consistent basis for evaluating injury severity outcomes across facility types and over time.

6.1.5 Data Summary

This section summarizes the coverage and key characteristics of the party-involved dataset used for injury severity modeling across five facility types (freeways, multilane divided, multilane undivided, rural two-lane highways, and urban two-lane highways) over the 2019–2024 study period. Each record represents an individual party involved in a crash (drivers, passengers, pedestrians, bicyclists, and other involved parties), with injury outcome coded using the KABCO scale. Segment-level roadway attributes, posted speed limit, and traffic exposure measures were linked to each party based on the crash location.

Before presenting the descriptive statistics and modeling dataset characteristics, it is important to note that several data quality filters were applied during dataset preparation. The initial person-level dataset included all crashes that could be spatially matched to roadway segments during the 2019–2024 study period. However, some records contained missing or unknown values for key explanatory variables, including driver characteristics, behavioral indicators, and roadway attributes. In addition, probe vehicle speed observations were not available for all segments during the 15-minute interval preceding the recorded crash time.

Descriptive figures were developed using a broader dataset, where only records with missing or unknown values for the specific variables shown in each figure were excluded. Summary statistics reported for the modeling dataset, however, reflect only those records with complete information after quality control procedures were applied. This distinction ensures that the descriptive figures provide a comprehensive overview of observed crash characteristics, while the analytical dataset supports reliable statistical estimation.

Figure 34 presents trends in seatbelt use and impaired driving among drivers involved in fatal crashes across five facility types from 2019 through 2024. Seatbelt use was determined using reported restraint-use codes, with drivers classified as restrained when shoulder belt only, lap belt only, or combined shoulder and lap belt use was indicated. Records with unknown restraint use were excluded from the seatbelt use calculations.

Alcohol and drug involvement were identified using contributing factor indicators recorded in the crash database. Specifically, binary indicators were defined based on whether alcohol or drug involvement of the involved party was reported as a contributing factor to the crash. A value of one indicates that the respective factor was identified as contributing to the crash, and zero otherwise. Records with unknown or missing contributing factor information were excluded from the analysis. Across facility types, the proportion of impaired drivers involved in fatal crashes generally increased during the early pandemic period relative to 2019 levels. On freeways, impaired driving increased from 2020 to 2021 before declining in subsequent years. Multilane divided highways exhibited impairment levels peaking in 2022 before decreasing in 2023 and 2024. On multilane undivided highways, impairment peaked in 2021, followed by a notable decline in 2022 and relatively lower levels thereafter. Rural two-lane highways experienced their highest impairment levels in 2022, followed by substantial reductions in 2023 and 2024. Urban two-lane facilities showed a sharp increase in impaired driving in 2020 relative to 2019, followed by a gradual decline through 2022, with a subsequent increase in 2023 and a slight decrease in 2024. Overall, impaired driving proportions declined across most facility types in the later years, indicating some recovery from the elevated levels observed during the pandemic period. Seatbelt use among drivers involved in fatal crashes showed notable variability and several substantial declines relative to pre-pandemic levels. On freeways, seatbelt use declined in 2020 before gradually increasing in later years.

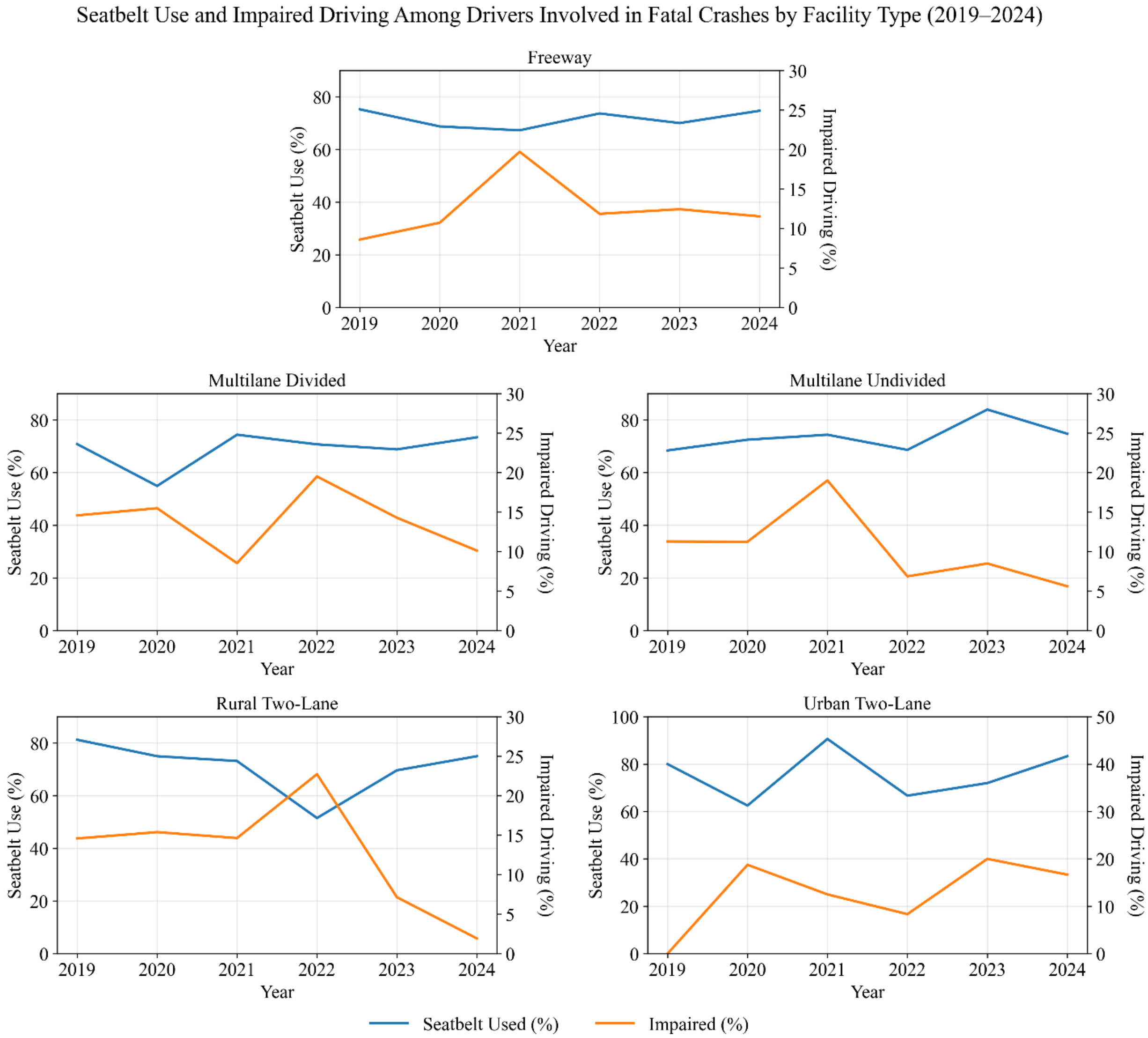

Figure 34: Seatbelt Use and Impaired (Alcohol or Drug) Driving Among Fatal Crash Involved Drivers by Facility Type (2019–2024)

Multilane divided highways experienced a substantial reduction in 2020, followed by a rebound in 2021 and relatively stable levels thereafter. Multilane undivided highways did not exhibit a comparable decline; instead, seatbelt use remained consistently higher than pre-pandemic levels, with particularly elevated values observed in 2023. Rural two-lane highways showed a pronounced reduction in 2022, with seatbelt use declining sharply before partially recovering in subsequent years, though remaining below pre-pandemic levels. Urban two-lane facilities exhibited considerable fluctuation, with a notable increase in 2021 followed by a decline in 2022 and a gradual recovery through 2024; overall, seatbelt use on this facility type remained generally comparable to or higher than pre-pandemic levels in most years after 2020. Figure 34 highlights substantial temporal variation in both impairment involvement and restraint use among drivers in fatal crashes, with increased impairment during the pandemic period and notable reductions in seatbelt use on several facility types. Figure 35 presents the percentage of drivers involved in fatal and severe injury crashes by age group across five facility types from 2019 through 2024.

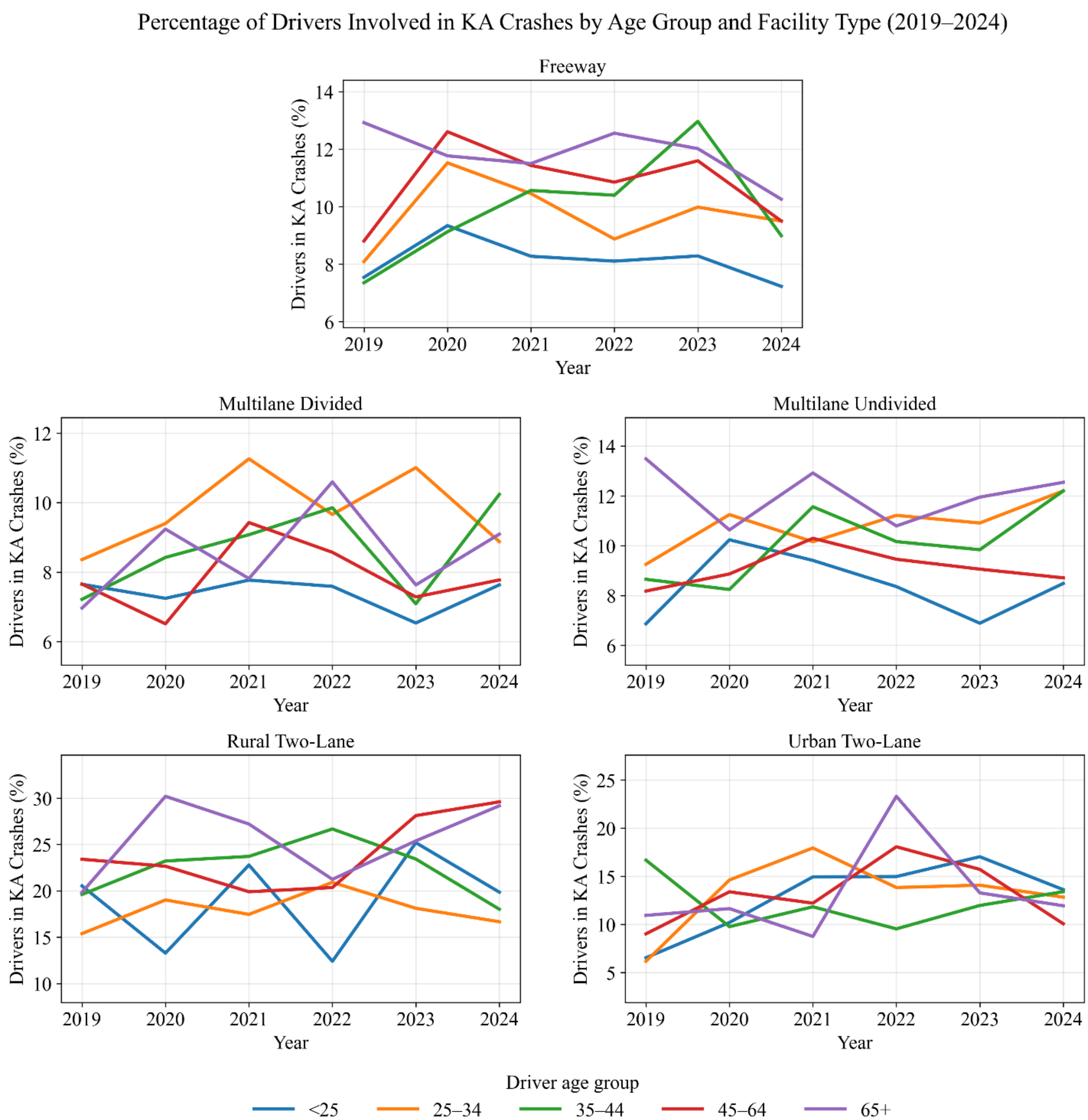

Figure 35: Percentage of Drivers with KA Injury Severity by Age Group and Facility Type (2019–2024)

Across all facility types and years, drivers involved in KA crashes were generally older on average. Temporal patterns varied somewhat by facility type. On freeways, KA injury severity for the 65+ group declines from a peak in 2019, stabilizes between 2021 and 2023, and decreases again in 2024. Middle-aged groups (35–64) show moderate variability, with a noticeable increase around 2023 before declining in 2024. Younger drivers (less than 34) exhibit relatively smaller fluctuations, indicating more stable severity patterns over time. For multilane divided facilities, temporal variation is more pronounced. Most age groups show an increase in KA severity around 2022, followed by a decline in 2023 and a partial increase in 2024. The 25–34 age group exhibited the highest levels, peaking in 2022. Younger groups (<25) remained comparatively stable but followed the same general temporal pattern. On multilane undivided facilities, trends are somewhat more stable, though the 65+ group consistently exhibits elevated severity levels with mild fluctuations. Younger age groups show moderate increases around 2021 and 2024, but the overall variation is less pronounced compared to multilane divided facilities.

The most substantial temporal variability is observed on rural two-lane facilities, where KA severity levels are significantly higher across all age groups compared to other facility types. All age groups exhibit pronounced fluctuations over time, with particularly high values observed for the 65+ group around 2020 and for middle-aged groups in later years.

Urban two-lane facilities also exhibit notable variability, though at lower overall severity levels compared to rural two-lane facilities. The 65+ group shows a sharp increase in 2022 followed by a decline in subsequent years. Younger and middle-aged groups (less than 65) display moderate fluctuations, with increases around 2020–2022 and slight decreases thereafter. Overall, while variability is evident across all age groups on urban two-lane facilities, severity levels remain more moderate relative to rural two-lane roads.

Figure 36 shows the mean operating speed during the 15-minute interval preceding crashes by injury severity level across five facility types from 2019 through 2024. Operating speed values were assigned based on probe vehicle observations corresponding to the crash location and time. Injury severity includes fatal and severe injury (KA), minor injury (B), possible injury (C), and property-damage-only (PDO) outcomes. For all facilities, observations from January through June

2019 were excluded due to known inconsistencies in probe-based speed measurements associated with changes in vehicle fleet composition, ensuring comparability across years.

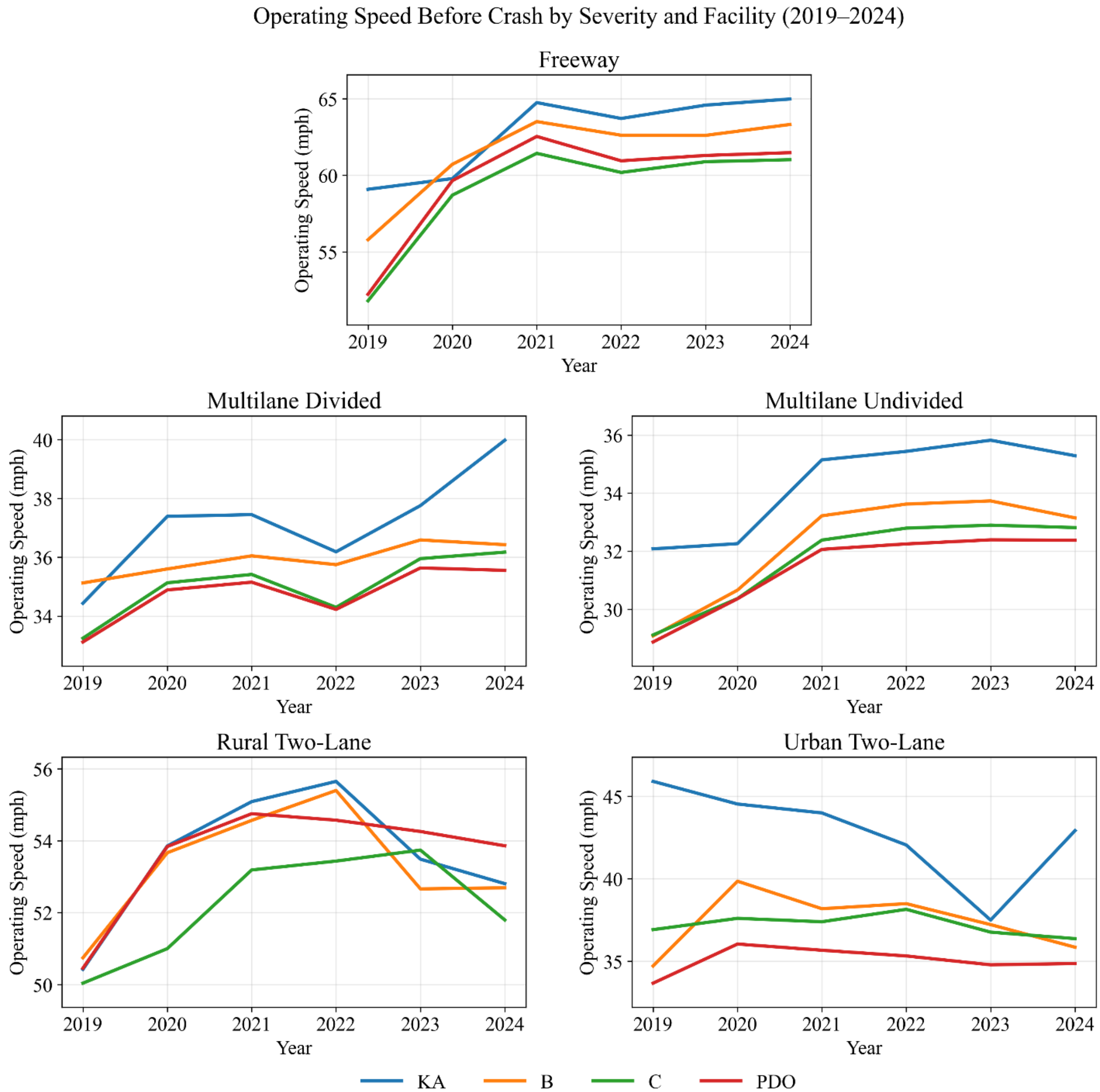

Figure 36: Average Operating Speed Before Crash by Severity and Facility Type (July 2019– December 2024)

Across all facility types, operating speeds increased noticeably from 2019 to 2020 and generally rose further in 2021, consistent with changes in traffic conditions during the early pandemic period. After 2021, speeds either stabilized or declined slightly, depending on facility type, although in several cases they remained comparable to or above pre-pandemic levels.

Within each facility type, operating speed trends were generally consistent across injury severity categories, however, differences in magnitude across severity levels were observed. In particular, crashes resulting in KA severity were typically associated with higher mean operating speeds compared to B, C, and PDO outcomes across most facility types and years. PDO crashes consistently exhibited the lowest operating speeds. Overall, the figure illustrates the temporal increase in operating speeds during the pandemic period and the consistent association between higher operating speeds and more severe injury outcomes.

Table 11 presents descriptive statistics for the person-level dataset. Most variables are indicator variables; therefore, the reported means represent the proportion of observations associated with each category. After excluding observations with missing or unknown values for key explanatory variables and operating speed measures, the final analytical dataset includes 188,901 party observations for freeways, 147,283 for undivided multilane facilities, 120,297 for divided multilane facilities, 16,933 for urban two-lane facilities, and 6,908 for rural two-lane facilities. For each variable, the mean and corresponding standard deviation (in parentheses) are reported.

Table 11: Descriptive statistics for key variables

Parameter	Mean (Standard Deviation)				
	Freeway	Divided Multilane	Undivided Multilane	Rural Two-lane	Urban Two-lane
Severity					
O	0.83 (0.37)	0.86 (0.35)	0.85 (0.36)	0.61 (0.49)	0.85 (0.36)
C	0.11 (0.31)	0.09 (0.29)	0.10 (0.30)	0.17 (0.38)	0.09 (0.29)
B	0.04 (0.20)	0.04 (0.19)	0.04 (0.19)	0.13 (0.34)	0.05 (0.21)
KA	0.01 (0.12)	0.01 (0.09)	0.01 (0.11)	0.09 (0.28)	0.02 (0.13)
Party Type					
Driver	0.94 (0.24)	0.89 (0.09)	0.89 (0.31)	0.90 (0.30)	0.88 (0.32)
Passenger/Ped/Bike	0.06 (0.24)	0.11 (0.31)	0.11 (0.31)	0.10 (0.30)	0.12 (0.32)
Age					
<25	0.24 (0.43)	0.24 (0.43)	0.26 (0.44)	0.25 (0.43)	0.26 (0.44)
25-34	0.25 (0.43)	0.21 (0.41)	0.20 (0.40)	0.19 (0.39)	0.18 (0.38)
35 - 44	0.17 (0.38)	0.16 (0.36)	0.15 (0.36)	0.14 (0.35)	0.15 (0.36)
45 - 64	0.27 (0.44)	0.27 (0.44)	0.26 (0.44)	0.26 (0.44)	0.29 (0.45)
>64	0.08 (0.27)	0.12 (0.32)	0.13 (0.34)	0.16 (0.36)	0.13 (0.34)
Gender					
Female	0.37 (0.48)	0.46 (0.50)	0.47 (0.50)	0.41 (0.49)	0.44 (0.50)
Male	0.63 (0.48)	0.54 (0.48)	0.53 (0.50)	0.59 (0.49)	0.56 (0.50)
Restraint Use	0.95 (0.21)	0.93 (0.26)	0.93 (0.26)	0.95 (0.22)	0.95 (0.22)

Impairment					
Alcohol Involved	0.02 (0.12)	0.01 (0.09)	0.01 (0.09)	0.02 (0.13)	0.01 (0.10)
Drug Involved	0.01 (0.07)	<0.01 (0.05)	<0.01 (0.05)	0.01 (0.08)	<0.01 (0.06)
Day of the week					
Weekday	0.77 (0.42)	0.79 (0.41)	0.80 (0.40)	0.77 (0.42)	0.79 (0.41)
Weekend	0.23 (0.42)	0.21 (0.41)	0.20 (0.40)	0.23 (0.42)	0.21 (0.41)
Lighting Condition					
Daylight	0.71 (0.46)	0.77 (0.42)	0.78 (0.41)	0.79 (0.41)	0.73 (0.44)
Dark	0.24 (0.43)	0.19 (0.39)	0.18 (0.39)	0.16 (0.36)	0.22 (0.41)
Dawn/Dusk	0.05 (0.22)	0.03 (0.18)	0.04 (0.19)	0.06 (0.23)	0.05 (0.22)
Presence of Traffic Control	NA	0.57 (0.49)	0.51 (0.5)	0.28 (0.45)	0.38 (0.48)
Driveways per Mile	NA	15.38 (11.4)	41.5 (20.07)	3.61 (5.88)	20.38 (30.47)
% of Curved Segment	NA	NA	NA	0.07 (0.20)	0.14 (0.18)
Degree of Curvature					
Tangent (0%)	0.61 (0.49)	NA	0.73 (0.44)	NA	NA
< 40%	0.28 (0.45)	NA	0.24 (0.43)	NA	NA
≥ 40%	0.11 (0.31)	NA	0.02 (0.15)	NA	NA
Mid-Block	NA	0.63 (0.48)	0.55 (0.5)	0.62 (0.48)	0.65 (0.48)
Intersection	NA	0.37 (0.48)	0.45 (0.5)	0.38 (0.48)	0.35 (0.48)
Median Type					
Guardrail	0.03 (0.16)	NA	NA	NA	NA
Concrete Barrier	0.51 (0.5)	NA	NA	NA	NA
Graded Ditch	0.46 (0.5)	NA	NA	NA	NA
Raised island with curb	NA	0.78 (0.41)	NA	NA	NA
Crash Type					
Rear End	0.40 (0.49)	0.48 (0.50)	0.41 (0.49)	0.33 (0.47)	0.43 (0.50)
Sideswipe	0.28 (0.45)	0.23 (0.42)	0.17 (0.38)	0.13 (0.33)	0.11 (0.32)
Angle	NA	0.19 (0.39)	0.25 (0.43)	0.21 (0.41)	0.18 (0.38)
Head On	NA	NA	0.08 (0.27)	0.07 (0.25)	0.07 (0.26)
Single Motor Vehicle	0.24 (0.43)	NA	NA	NA	0.17 (0.38)
Other	0.08 (0.27)	0.10 (0.28)	0.09 (0.28)	0.27 (0.44)	0.03 (0.18)
Sample Size	188,901	120,297	147,283	6,908	16,933

Table 11 illustrate clear differences in crash severity distributions, driver characteristics, roadway environments, and operating conditions across facility types. All facility types are dominated by property-damage-only crashes; however, rural two-lane facilities exhibit substantially higher proportions of injury and KA-severity outcomes compared to other facilities.

Across all facility types, the majority of involved parties are drivers, with relatively similar age distributions characterized by substantial representation of parties under age 25 and those between ages 45 and 64. Male parties account for slightly more than half of the involved parties across facility types and reported restraint use exceeds 90% across all facility types. Alcohol involvement and drug involvement indicators represent relatively small proportions of observations.

Environmental conditions show that most crashes occur during daylight. Differences in roadway characteristics are more pronounced across facility types. Freeways are access-controlled facilities and therefore do not include driveway access or at-grade intersections. In contrast, multilane and two-lane facilities exhibit substantially higher intersection involvement and driveway density. Divided multilane facilities also show a greater proportion of traffic control presence and mid-block crash occurrence compared to undivided facilities. Crash type distributions also vary by facility, with rear-end and sideswipe crashes more common on freeways and multilane facilities, and higher proportions of angle and head-on crashes on two-lane and undivided facilities.

For crash types, it should be noted that crash-type groupings varied slightly by facility due to differences in the number of observations. For urban two-lane facilities, the “Other” category was limited to backing and crashes originally coded as “Other.” For rural two-lane and undivided multilane facilities, the “Other” category additionally included single motor vehicle crashes. For divided multilane facilities, the “Other” category further included head-on crashes. On freeways, however, the “Other” category also included angle crashes due to the relatively small number of these crash types on access-controlled facilities.

The descriptive statistics demonstrate meaningful variation in crash and roadway characteristics across facility types, supporting the use of facility-specific modeling approaches in the injury severity analysis.

6.2 Analysis of Injury Severity

The objective of this analysis was to examine how injury severity outcomes varied across roadway facilities and operating conditions to identify factors associated with increased injury risk among crash-involved parties. Person-level injury outcomes were evaluated to quantify the influence of roadway characteristics, operating speeds, crash attributes, and behavioral factors observed during and after the COVID-19 period. Because injury severity reflects ordered levels of harm sustained by involved parties, an ordered discrete outcome modeling framework was employed.

6.2.1 Statistical Analysis

A series of ordered probit models were estimated to evaluate the relationship between party characteristics, roadway conditions, operating speeds, and injury severity outcomes. Injury severity represents an ordinal outcome with increasing levels of severity ranging from property-damage-only crashes to fatal or incapacitating injury outcomes. Such ordered categorical data are commonly analyzed using ordered response models, including ordered logit or ordered probit formulations. In this analysis, an ordered probit model was adopted.

The ordered probit model assumes the existence of an unobserved continuous latent variable representing the propensity for injury severity for party i, expressed as Equation 18:

$$y_i^* = \beta X_i + \varepsilon_i \tag{18}$$

Where y_i^* denotes the latent injury severity propensity, $\beta$is a vector of estimable parameters, X_i is a vector of explanatory variables, and $\varepsilon_i$is a normally distributed random error term with mean zero and unit variance.

The observed injury severity outcome $y_i$is determined by threshold parameters that partition the latent severity scale into ordered categories, as shown in Equation 19:

$$y_i = \begin{cases} 1 & \text{if } y_i^* \le \mu_1 \\ 2 & \text{if } \mu_1 < y_i^* \le \mu_2 \\ 3 & \text{if } \mu_2 < y_i^* \le \mu_3 \\ 4 & \text{if } y_i^* > \mu_3 \end{cases} \tag{19}$$

Where μ_1, μ_2, μ_3 represent threshold parameters to be estimated and satisfy the condition $\mu_1 < \mu_2 < \mu_3$.

The dependent variable was defined using four ordered categories derived from the KABCO injury scale: No Injury (O), possible injury (C), minor injury (B), and fatal or serious injury (KA). Fatal and serious injury outcomes were combined into a single category to ensure sufficient observations in the highest severity level and to improve model stability.

Within this modeling framework, explanatory variables influence injury severity through shifts in the latent injury propensity. Positive parameter estimates indicate an increased likelihood of more severe injury outcomes, whereas negative estimates indicate a reduced likelihood of severe outcomes.

Separate models were estimated for each facility type (freeways, multilane divided highways, multilane undivided highways, rural two-lane, and urban two-lane highways) to account for differences in roadway environments, traffic conditions, and operating characteristics across facility classes. This approach allows the effects of explanatory variables to vary across roadway contexts and improves the interpretability of results.

The explanatory variables included party characteristics (e.g., age, gender, restraint use, alcohol involvement, and drug involvement), crash characteristics (e.g., crash type, lighting condition, weather condition, month, and year indicators), roadway characteristics (e.g., curvature category, shoulder width indicators, and median type), and operating speed measures derived from probe vehicle data corresponding to the 15-minute interval preceding the crash. Speed variables were categorized relative to posted speed limits to capture differences between prevailing operating speeds and regulatory speed environments. Records with missing or unknown values for key explanatory variables or operating speed measures were excluded from the analytical dataset.

6.2.2 Analysis Results and Discussion

The results shown in Table 12 consolidate five separate facility-specific models into a single table to facilitate comparison across roadway contexts. Parameter estimates are presented with standard errors in parentheses, and statistically significant estimates at the 95% confidence level are denoted by an asterisk. Variables that were not included in a given facility model (because they were not applicable to that facility type or did not improve model performance), are denoted as "N/A" (not applicable).

Speed-related variables were specified using facility-specific categories to account for differences in posted speed limits and operating environments across facility types. Operating speed was categorized relative to the posted speed limit (average speed minus speed limit) using posted-speed groupings appropriate to each roadway class.

In an ordered probit model, coefficient signs indicate whether a factor is associated with a higher or lower likelihood of more severe injury outcomes (toward KA). The coefficients are not directly interpreted as odds ratios (odds ratios are a logit-based quantity). Accordingly, results are discussed in terms of the direction of association with injury severity.

Table 12: Ordered Probit Results for Crash Severity by Facility Type

	Estimate (Std. Error)				
Parameter	Freeway	Divided Multilane	Undivided Multilane	Rural Two-Lane	Urban Two-Lane
C	0.46 (0.03)*	0.65 (0.04)*	0.93 (0.03)*	-0.13 (0.11)	0.69 (0.10)*
B	1.16 (0.03)*	1.30 (0.04)*	1.63 (0.03)*	0.45 (0.11)*	1.27 (0.10)*
KA	1.83 (0.04)*	2.08 (0.04)*	2.37 (0.03)*	1.16 (0.11)*	1.96 (0.10)*
Person type					
Driver	Baseline	Baseline	Baseline	Baseline	Baseline
Passenger	1.15 (0.01)*	0.51 (0.01)*	0.65 (0.01)*	0.85 (0.05)*	0.47 (0.03)*
Ped/Bike	N/A	1.65 (0.05)*	1.71 (0.04)*	1.10 (0.22)*	1.97 (0.14)*
Age					
<25	-0.15 (0.01)*	-0.23 (0.02)*	-0.24 (0.01)*	-0.18 (0.05)*	-0.28 (0.04)*
25-34	-0.12 (0.01)*	-0.10 (0.02)*	-0.12 (0.01)*	-0.11 (0.05)*	-0.19 (0.04)*
35 - 44	-0.11 (0.02)*	-0.09 (0.02)*	-0.11 (0.02)*	-0.16 (0.05)*	-0.17 (0.04)*
45 - 64	-0.11 (0.01)*	-0.05 (0.02)*	-0.06 (0.01)*	-0.08 (0.05)	-0.10 (0.04)*
> 64	Baseline	Baseline	Baseline	Baseline	Baseline
Year					
2019	-0.04 (0.01)*	-0.07 (0.02)*	<0.01 (0.02)	0.05 (0.07)	0.00 (0.05)
2020	0.01 (0.01)	<0.01 (0.02)	0.03 (0.01)	0.05 (0.06)	-0.04 (0.05)
2021	0.05 (0.01)*	0.03 (0.01)	0.04 (0.01)*	-0.03 (0.05)	-0.03 (0.05)
2022	0.01 (0.01)	<0.01 (0.01)	0.01 (0.01)	0.02 (0.05)	-0.09 (0.05)
2023	-0.01 (0.01)	0.01 (0.02)	0.01 (0.01)	-0.08 (0.06)	-0.09 (0.05)
2024	Baseline	Baseline	Baseline	Baseline	Baseline
Month					
January	Baseline	Baseline	Baseline	Baseline	Baseline
February	-0.02 (0.02)	0.04 (0.03)	0.03 (0.02)	-0.20 (0.08)*	0.02 (0.07)
March	0.04 (0.02)*	0.10 (0.03)*	0.07 (0.02)*	-0.07 (0.08)	0.09 (0.07)
April	0.07 (0.02)*	0.08 (0.03)*	0.08 (0.02)*	-0.02 (0.08)	-0.01 (0.07)
May	0.10 (0.02)*	0.11 (0.02)*	0.12 (0.02)*	0.19 (0.08)*	-0.01 (0.06)
June	0.12 (0.02)*	0.13 (0.02)*	0.11 (0.02)*	-0.03 (0.08)	0.06 (0.06)
July	0.10 (0.02)*	0.15 (0.02)*	0.16 (0.02)*	0.06 (0.08)	0.09 (0.06)
August	0.07 (0.02)*	0.14 (0.02)*	0.14 (0.02)*	0.11 (0.07)	0.14 (0.06)*
September	0.07 (0.02)*	0.10 (0.02)*	0.12 (0.02)*	0.04 (0.07)	0.02 (0.06)
October	0.04 (0.02)*	0.05 (0.02)*	0.06 (0.02)*	0.00 (0.07)	-0.06 (0.06)
November	0.00 (0.02)	0.01 (0.02)	0.00 (0.02)	-0.12 (0.07)	-0.12 (0.06)*
December	-0.03 (0.02)	<0.01 (0.02)	-0.03 (0.02)	-0.21 (0.08)*	-0.18 (0.06)*
Day of the week					
Weekday	Baseline	Baseline	Baseline	Baseline	Baseline
Weekend	0.05 (0.01)*	0.05 (0.01)*	0.02 (0.01)	0.10 (0.03)*	0.06 (0.03)*
Gender					
Female	Baseline	Baseline	Baseline	Baseline	Baseline

Parameter	Freeway	Divided Multilane	Undivided Multilane	Rural Two-Lane	Urban Two-Lane
Male	-0.21 (0.01)*	-0.16 (0.01)*	-0.18 (0.01)*	<0.01 (0.03)	-0.18 (0.02)*
Restraint Use	-0.59(0.01)*	-0.38 (0.02)*	-0.44 (0.01)*	-0.69 (0.06)*	-0.54 (0.05)*
Impairment					
Alcohol Involved	0.56 (0.02)*	0.49 (0.04)*	0.49 (0.04)*	0.38 (0.11)*	0.77 (0.10)*
Drug Involved	0.69 (0.04)*	0.80 (0.07)*	0.72 (0.06)*	0.61 (0.17)*	1.17 (0.16)*
Lighting Condition					
Daylight	Baseline	Baseline	Baseline	Baseline	Baseline
Dark	0.15 (0.01)*	0.10 (0.01)*	0.09 (0.01)*	0.07 (0.04)	-0.03 (0.03)
Dawn/Dusk	0.00 (0.02)	0.03 (0.02)	0.05 (0.02)*	-0.02 (0.07)	-0.13 (0.06)*
Traffic Control					
Absence	N/A	Baseline	Baseline	Baseline	Baseline
Presence	N/A	<0.01 (0.01)	-0.01 (0.01)	-0.15 (0.05)*	-0.12 (0.03)*
Driveway per Mile	N/A	<0.01 (<0.01)	<0.01 (<0.01)*	-0.01 (<0.01)*	<0.01 (<0.01)*
Segment type					
Mid-Block	N/A	Baseline	Baseline	Baseline	Baseline
Intersection	N/A	0.08 (0.01)*	0.05 (0.01)*	0.10 (0.04)*	0.05 (0.03)
Curved % of Segment	N/A	N/A	N/A	0.30 (0.07)*	0.24 (0.07)*
Tangent (0%)	Baseline	N/A	Baseline	N/A	N/A
< 40%	0.02 (0.01)*	N/A	-0.01 (0.01)	N/A	N/A
≥ 40%	0.03 (0.01)*	N/A	0.09 (0.03)*	N/A	N/A
Shoulder width (ft)					
> 10	-0.04 (0.01)*	N/A	N/A	N/A	N/A
Median Type					
Raised island with curb	N/A	-0.04 (0.02)	N/A	N/A	N/A
Guardrail	Baseline	N/A	N/A	N/A	N/A
Concrete Barrier	0.01 (0.02)	N/A	N/A	N/A	N/A
Graded Ditch	-0.09 (0.02)*	N/A	N/A	N/A	N/A
Crash Type					
Rear End	Baseline	Baseline	Baseline	Baseline	Baseline
Single Vehicle	0.26 (0.01)*	N/A	N/A	N/A	-0.22 (0.04)*
Sideswipe	-0.29 (0.01)*	-0.81 (0.01)*	-0.40 (0.01)*	-0.36 (0.05)*	-0.35 (0.05)*
Angle	N/A	-0.37 (0.01)*	0.38 (0.01)	0.53 (0.05)*	0.42 (0.03)*
Head On	N/A	N/A	0.70 (0.01)*	1.03 (0.06)*	0.90 (0.04)*
Other	0.14 (0.01)*	-0.20 (0.02)*	0.14 (0.02)*	-0.14 (0.04)*	-0.07 (0.07)

Speed Limit: Average Speed - Speed Limit

Freeway

Parameter	Freeway	Divided Multilane	Undivided Multilane	Rural Two-Lane	Urban Two-Lane
55-65: ≤ 0	Baseline	N/A	N/A	N/A	N/A
55-65: > 0	0.12 (0.02)*	N/A	N/A	N/A	N/A
70:< -5	-0.01 (0.01)	N/A	N/A	N/A	N/A
70: -5 to 0	0.07 (0.02)*	N/A	N/A	N/A	N/A
70: > 0	0.07 (0.02)*	N/A	N/A	N/A	N/A
75	0.14 (0.02)*	N/A	N/A	N/A	N/A
Divided Multilane					
35: ≤ 0	N/A	Baseline	N/A	N/A	N/A
35: > 0	N/A	0.27 (0.09)*	N/A	N/A	N/A
40: ≤ -15	N/A	0.11 (0.04)*	N/A	N/A	N/A
40: -15 to 0	N/A	0.31 (0.03)*	N/A	N/A	N/A
40: > 0	N/A	0.37 (0.06)*	N/A	N/A	N/A
45: ≤ -15	N/A	0.12 (0.03)*	N/A	N/A	N/A
45: -15 to 0	N/A	0.22 (0.02)*	N/A	N/A	N/A
45: > 0	N/A	0.31 (0.05)*	N/A	N/A	N/A
50: ≤ -20	N/A	0.28 (0.03)*	N/A	N/A	N/A
50: -20 to -15	N/A	0.26 (0.03)*	N/A	N/A	N/A
50: -15 to -10	N/A	0.26 (0.03)*	N/A	N/A	N/A
50: -10 to -5	N/A	0.39 (0.03)*	N/A	N/A	N/A
50: -5 to 0	N/A	0.35 (0.04)*	N/A	N/A	N/A
50: > 0	N/A	0.34 (0.07)*	N/A	N/A	N/A
55: ≤ -5	N/A	0.17 (0.03)*	N/A	N/A	N/A
55: -5 to 0	N/A	0.26 (0.04)*	N/A	N/A	N/A
55: 0 to +5	N/A	0.28 (0.04)*	N/A	N/A	N/A
55: > +5	N/A	0.31 (0.06)*	N/A	N/A	N/A
Undivided Multilane					
30-35: < -5	N/A	N/A	Baseline	N/A	N/A
30-35: -5 to 0	N/A	N/A	0.12 (0.02)*	N/A	N/A
30-35: > 0	N/A	N/A	0.12 (0.03)*	N/A	N/A
40: < -5	N/A	N/A	-0.04 (0.01)*	N/A	N/A
40: -5 to 0	N/A	N/A	0.09 (0.03)*	N/A	N/A
40: > 0	N/A	N/A	0.19 (0.05)*	N/A	N/A
45: < -5	N/A	N/A	0.05 (0.01)*	N/A	N/A
45: -5 to 0	N/A	N/A	0.14 (0.03)*	N/A	N/A
45: > 0	N/A	N/A	0.13 (0.05)*	N/A	N/A
50: < -5	N/A	N/A	0.13 (0.02)*	N/A	N/A
50: -5 to 0	N/A	N/A	0.15 (0.04)*	N/A	N/A
50: > 0	N/A	N/A	0.21 (0.05)*	N/A	N/A
55: < -5	N/A	N/A	0.15 (0.02)*	N/A	N/A
55: -5 to 0	N/A	N/A	0.26 (0.04)*	N/A	N/A
55: > 0	N/A	N/A	0.22 (0.04)*	N/A	N/A

Parameter	Freeway	Divided Multilane	Undivided Multilane	Rural Two-Lane	Urban Two-Lane
Rural Two-Lane					
55: ≤ -5	N/A	N/A	N/A	Baseline	N/A
55: -5 to 0	N/A	N/A	N/A	0.16 (0.04)*	N/A
55: 0 to +5	N/A	N/A	N/A	0.24 (0.04)*	N/A
55: > +5	N/A	N/A	N/A	0.13 (0.06)*	N/A
65: ≤ 0	N/A	N/A	N/A	-0.15 (0.11)	N/A
65: >0	N/A	N/A	N/A	0.41 (0.16)*	N/A
Urban Two-Lane					
25-30-35: ≤ -5	N/A	N/A	N/A	N/A	Baseline
25-30-35: ≤ -5 to 0	N/A	N/A	N/A	N/A	0.27 (0.08)*
25-30-35: > 0	N/A	N/A	N/A	N/A	0.14 (0.07)*
40-45: ≤ -5	N/A	N/A	N/A	N/A	0.08 (0.06)
40-45: -5 to 0	N/A	N/A	N/A	N/A	0.17 (0.07)*
40-45: > 0	N/A	N/A	N/A	N/A	0.36 (0.08)*
50: ≤ -5	N/A	N/A	N/A	N/A	0.26 (0.07)*
50: -5 to 0	N/A	N/A	N/A	N/A	0.32 (0.08)*
50: > 0	N/A	N/A	N/A	N/A	0.43 (0.08)*
55: ≤ -5	N/A	N/A	N/A	N/A	0.47 (0.06)*
55: -5 to 0	N/A	N/A	N/A	N/A	0.47 (0.06)*
55: > 0	N/A	N/A	N/A	N/A	0.52 (0.06)*
Log Likelihood	-100085.98	-57234.73	-73284.37	-6845.13	-8926.56
AIC	200259.96	114581.47	146678.74	13780.26	17957.12

6.2.2.1 Person Type

Relative to drivers (baseline), pedestrians and bikes are associated with higher injury severity on all facility types. The results indicate that crashes involving pedestrians and bicyclists are more likely to result in more severe injuries compared to those involving drivers and passengers. This finding is as expected, as pedestrians and bicyclists lack the physical protection afforded by motor vehicles.

6.2.2.2 Age

Across all facility types, younger age groups are associated with lower injury severity relative to the 65+ category (baseline). Specifically, parties under 25, 25–34, and 35–44 show consistent negative associations with injury severity across all facility types. These results indicate that older parties, particularly those 65 and above, are more likely to experience more severe injury outcomes across facility types.

6.2.2.3 Year Effects

Temporal effects vary by facility type. For freeways and undivided multilane facilities, injury severity was generally higher in 2021 relative to 2024, while 2019 shows a lower or comparable severity propensity relative to the baseline. This suggests that severity patterns shifted during the early pandemic period, with a modest peak effect observed in 2021. However, these effects are relatively small in magnitude and not consistently significant across all facility types. For rural two-lane facilities, year effects are minimal and not statistically significant, with no clear temporal pattern observed. For urban two-lane facilities, injury severity appears higher in earlier years (2019 and 2020) relative to 2024. Overall, year effects are generally modest and inconsistent across facility types.

6.2.2.4 Month Effects

Monthly effects indicate seasonal variability in injury severity, with the magnitude and consistency varying across facility types. Freeways and multilane facilities show higher injury severity propensity from March through October relative to January (baseline), indicating elevated severity during warmer-month travel periods.

Rural and urban two-lane facilities show different and less consistent seasonal patterns compared to other facilities. For rural two-lane facilities, February and December exhibit lower injury severity propensity relative to January, while May shows a higher propensity. For urban two-lane facilities, August exhibits higher injury severity propensity, whereas November and December exhibit lower propensity. However, most monthly effects for both facility types are not statistically significant.

6.2.2.5 Day-of-Week Effects

Weekend crashes are generally associated with higher injury severity propensity relative to weekdays on freeways, divided multilane, and rural two-lane facilities, while the effect is smaller and not statistically significant for undivided multilane facilities.

6.2.2.6 Gender and Restraint Use

Gender effects are generally consistent across facility types, with male parties associated with lower injury severity relative to female parties (baseline). However, this effect is small in magnitude and not statistically significant on rural two-lane facilities.

Restraint use is consistently associated with lower injury severity across all facility types, with statistically significant negative effects in each facility-specific model. This finding aligns with expected safety benefits of restraint use and indicates a robust association between restraint use and reduced likelihood of severe injury outcomes across roadway contexts.

6.2.2.7 Alcohol, Drug, and Distraction Indicators

Alcohol and drug involvement are consistently associated with higher injury severity across all facility types and exhibit comparatively large positive effects, indicating a strong relationship with more severe injury outcomes.

6.2.2.8 Lighting Conditions

Lighting conditions show consistent results across facility types. Relative to daylight (baseline), dark conditions are associated with higher injury severity across all facility types and are statistically significant in each model. Dawn/dusk conditions show smaller and less consistent effects, with a positive effect observed on undivided multilane facilities.

6.2.2.9 Roadway Geometry and Access Characteristics

Geometry and access-related factors show facility-specific relevance, consistent with the different operating and design environments across roadway classes.

For freeways and undivided multilane facilities, higher curvature (≥ 40% curved segment) is associated with higher injury severity propensity relative to tangent segments. On freeways, the presence of a graded ditch is associated with lower injury severity, and wider shoulders (>10 ft) are also associated with lower injury severity, suggesting that greater lateral clearance may reduce injury risk.

For two-lane and multilane facilities, intersection crashes are associated with higher injury severity propensity relative to mid-block crashes, whereas the presence of traffic control is associated with reduced injury severity.

Driveway density is associated with slightly lower injury severity on two-lane facilities and slightly higher injury severity on undivided multilane facilities (statistically significant but small in magnitude). These results suggest that access density may influence injury severity differently across facility environments, potentially through changes in speed, conflict type, and crash composition.

6.2.2.10 Crash Type

Crash type effects are strong and consistent across facility types. Relative to rear-end crashes (baseline), sideswipe crashes are associated with lower injury severity propensity across all facility types. More severe crash configurations exhibit substantially higher injury severity propensity:

Head-on crashes show the largest positive effects on rural two-lane and both multilane facilities, indicating markedly higher likelihood of severe injury outcomes compared to rear-end crashes.

Angle crashes are associated with higher injury severity on rural two-lane and multilane facilities.

Single motor vehicle crashes are associated with higher injury severity on freeways, whereas on urban two-lane facilities they are associated with lower injury severity.

"Other" crash types are associated with modest positive effects on freeways and multilane facilities, indicating higher injury severity propensity relative to rear-end crashes.

6.2.2.11 Operating Speed Relative to Posted Speed Limit

Across all facility types, speed-related categories show consistent patterns relative to their respective baseline conditions. Categories in which operating speeds are closer to or exceed the posted limit are generally associated with higher injury severity. Similarly, segments with higher posted speed limits tend to exhibit increased injury severity. While the magnitude of these effects varies across facility types and speed regimes, the overall pattern indicates that higher operating speeds, particularly those approaching or exceeding the posted limit, are associated with greater injury severity. Taken together, these results highlight the importance of incorporating operating speed measures into injury severity modeling and indicate that higher operating speeds, relative to posted limits and speed regimes, are generally associated with more severe injury outcomes, although the magnitude and pattern of effects vary by facility type.

6.2.3 Summary

Crash injury severity is an important aspect of roadway safety as it reflects the consequences of crashes for roadway users and society. Thus, this chapter seeks to understand the factors that elevate or reduce injury severity, which is imperative to developing safety countermeasures and advancing the broader goals of Vision Zero and Safe System approaches.

Across all facility types, party type, age, temporal factors, behavioral factors, roadway characteristics, crash type, and operating speed are key determinants of injury severity, although their magnitude and consistency vary by roadway environment.

Pedestrians and bicyclists experience higher injury severity than drivers (the baseline) across all facility types, reflecting their lower level of physical protection. Age effects are also consistent, with younger groups (< 45) exhibiting lower injury severity relative to the 65+ group, indicating increased vulnerability among older road users.

Temporal effects vary by facility type. Most facilities show higher injury severity in 2021 compared to 2024 and lower severity in 2019, suggesting pandemic-era shifts in severity patterns, though many estimates are not statistically significant. Monthly effects indicate seasonal variability, with higher severity during warmer months (March-October) on freeways and multilane roads, while two-lane roads show more context-specific patterns.

Gender and restraint use show consistent relationships. Male parties are associated with slightly lower injury severity than females, while restraint use is consistently associated with significantly lower injury severity across all facility types. Conversely, alcohol and drug involvement are strongly associated with increased injury severity in all models.

Dark conditions are associated with higher injury severity relative to daylight on freeways and multilane facilities, while effects are smaller or not significant on two-lane facilities. Roadway geometry and access characteristics show facility-specific patterns. Higher curvature is associated with increased injury severity on freeways and undivided multilane facilities, while wider shoulders and graded ditches on freeways are associated with lower severity. Intersection crashes are associated with higher injury severity on two-lane and multilane facilities, whereas the presence of traffic control is associated with lower severity. Access density effects are small and generally inconsistent across facility types.

Crash type is one of the strongest predictors. Relative to rear-end crashes, sideswipe crashes are less severe, while head-on, angle, and single-vehicle crashes show substantially higher injury severity across facility types.

Finally, operating speed relative to the posted speed limit is consistently associated with injury severity. Across all facility types, higher operating speeds and conditions where vehicles approach or exceed posted speed limits are associated with greater injury severity, although the magnitude varies by facility type and posted speed regime. These results highlight the importance of roadway context, user vulnerability, and operating speed in explaining injury severity outcomes.

7 CONCLUSION AND RECOMMENDATIONS

This study examined changes in traffic fatality trends following the COVID-19 pandemic using a multi-scale analytical framework that progressed from national comparisons to increasingly detailed analyses within the state of Michigan. The purpose of this approach was to first determine how Michigan's fatality patterns compared with those observed across the United States and then identify the factors contributing to these patterns through progressively more detailed analyses at finer spatial and analytical levels.

The analysis began with a state-level comparison across the United States, where fatality trends in Michigan were evaluated relative to those observed in other states. This comparison provided a national benchmark and helped determine whether Michigan's trends reflected broader national patterns or differed from those experienced elsewhere. The analysis then expanded to a national county-level study to evaluate how fatality outcomes varied across counties throughout the United States.

Following the national analyses, the focus shifted to Michigan. County-level fatality trends were examined to identify regional differences and evaluate patterns across several crash categories, including total fatalities, pedestrian and bicyclist fatalities, impaired-driving-related crashes, and non-animal crashes. These analyses also allowed comparisons across MDOT regions, providing insight into geographic variation in safety outcomes within the state. The study then examined crash occurrence at the roadway segment-level across five facility types, including freeways, multilane divided highways, multilane undivided highways, rural two-lane, and urban two-lane roads, to evaluate how roadway characteristics, traffic exposure, and operational conditions influence crash frequency. Finally, party-involved crash data was analyzed to examine injury severity outcomes among individuals involved in crashes, focusing on driver characteristics, behavioral factors, crash circumstances, and roadway conditions.

7.1 Comparisons Across States

At the state level, the analysis revealed substantial variation in the degree to which fatal crash risks varied across states during and after the pandemic. Several states exhibited noticeably higher fatality rates than Michigan, including Texas, Florida, and California. A few other states also experienced higher fatality levels but to a lesser degree, such as Louisiana, North Carolina, and

South Carolina. Differences were even more pronounced for pedestrian and bicyclist fatalities and involved many of these same states.

Clear temporal patterns were also observed following the onset of the pandemic. Relative to 2019, fatalities increased in all subsequent years, with the largest increase occurring in 2021. Although moderate reductions were observed in 2022 and 2023, fatalities remained elevated relative to pre-pandemic levels. Pedestrian and bicyclist fatalities increased beginning in 2020 and remained elevated through 2023 with little evidence of decline. Seasonal patterns were also evident. Total fatalities increased during the late spring and summer months, with peak levels occurring in August and September. In contrast, pedestrian and bicyclist fatalities were highest in the fall, particularly from October through December.

Additional insights were gained from the national county-level analysis. As in the broader analysis, fatalities increased sharply during the summer of 2020, particularly between May and September, and remained elevated through 2021 and portions of 2022. Although early 2023 showed some return toward pre-pandemic levels, fatalities increased again later in the year. Changes in travel demand patterns explain some of these trends. Vehicle miles traveled declined sharply in spring 2020, with the largest reduction occurring in April, when travel decreased by approximately 25–32 percent relative to April 2019. Travel demand then gradually recovered and exceeded pre-pandemic levels in many months beginning in 2021. Demographic and socioeconomic factors were also significantly associated with fatalities. Fatality risks tended to be lower in urban areas, apart from pedestrian and bicyclist fatalities. Fewer fatalities also tended to occur in counties with higher median income and lower levels of unemployment. During the course of the pandemic, stay-at-home orders and select business closures tended to reduce travel demand. Fatalities also declined initially, but then increased sharply over time, especially as these travel restrictions were relaxed.

7.1.1 Michigan County-Level Findings

The Michigan county-level analysis revealed similar pandemic-related patterns but also highlighted important regional differences. The Metro region exhibited the highest crash levels across multiple outcomes, with substantially higher totals for total crashes, as well as fatal and serious injury crashes. In contrast, northern areas of the state consistently experienced lower crash levels. The early pandemic period saw substantial reductions in crashes and mobility, particularly in spring 2020, when total crashes declined sharply. However, crash frequencies returned to baseline levels in summer 2020 and remained elevated in subsequent years for several severe crash categories. Mobility trends closely mirrored these patterns, with travel declining sharply in early 2020 before gradually recovering and exceeding pre-pandemic levels by 2021 and 2022.

Segment-level analyses showed that total crashes tended to track very closely with changes in traffic volume, with rural two-lane highways exhibiting greater sensitivity to changes in traffic demand than freeways. Crashes tended to increase significantly as travel speeds became more variable. Roadway geometry also influenced safety as crashes increased with horizontal curvature and decreased on segments with wider shoulders and medians.

The person-level analyses showed that pedestrians and bicyclists consistently experienced higher injury severity than drivers. Older individuals were also associated with higher injury severity outcomes. Risky driving behaviors, including alcohol and drug involvement, were strongly associated with higher injury severity, while restraint use was associated with lower severity. These issues were exacerbated during the pandemic, and some, but not all, of these risks have remained elevated over time.

7.2 Recommendations and Countermeasures

The findings in this study suggest that an effective safety strategy countermeasure should address both roadway system characteristics and driver behavior. The analysis indicates that traffic exposure, operating speeds, driver behavior, and roadway design characteristics all contributed to variations in crash outcomes during and after the COVID-19 pandemic.

Roadway safety management typically relies on a combination of engineering, enforcement, education, and policy interventions designed to reduce crash frequency and crash severity (AASHTO, n.d.). Many effective strategies are documented through the Federal Highway Administration's Proven Safety Countermeasures program and related crash modification factor research, which identify treatments with demonstrated safety benefits across a range of roadway environments (FHWA, 2013). The recommendations below are organized around the primary risk mechanisms identified in the Michigan analyses.

7.2.1 Speed and Operating-Condition Management

The segment-level analysis indicates that crash occurrence is strongly associated with traffic exposure and operating conditions. The party-involved analysis further shows that injury severity increases when operating speeds exceed posted speed limits, particularly in higher-speed environments. These findings are consistent with prior research showing that higher operating speeds increase both crash likelihood and crash severity (Elvik, 2005; Gargoum & El-Basyouny, 2016).

Speed management should therefore be a central component of countermeasure programs aimed at reducing fatal and serious injury crashes. Recommended strategies for Michigan include targeted speed enforcement in corridors and time periods with elevated operating speeds. High-visibility enforcement programs have been shown to improve compliance with traffic laws and reduce high-risk driving behaviors (Erke et al., 2009). Enforcement and policy strategies targeting speeding behavior can also improve compliance with posted speed limits and reduce excessive speed variability. For example, there has been continuing discussion as to the use of automated enforcement in select settings, such as work zones. Available evidence suggests that broader use of such enforcement may also help to reduce the prevalence of these speeding-related crashes.

From an engineering perspective, context-sensitive engineering treatments, including road diets and access management strategies, can be implemented, particularly along multilane arterial corridors (FHWA, n.d.-d, n.d.-a). Recently, a variety of MDOT studies have shown that the use of active traffic control devices, such as speed feedback signs, has the potential to reduce speeds in various contexts, including horizontal curves, exit ramps, and speed transition zones into communities.

7.2.2 Impaired Driving, and Occupant Protection

The party-involved analysis indicates that alcohol and drug involvement are strongly associated with higher injury severity, while restraint use consistently reduces injury severity across facility types. These findings align with extensive research identifying impaired driving, and non-use of restraints as major contributors to fatal and serious injury crashes (Kirley et al., 2023).

Behavioral countermeasures should therefore include a combination of enforcement, legislation, and public education campaigns designed to reduce risky driving behaviors. The Michigan Office of Highway Safety Planning currently coordinates periodic high-visibility enforcement campaigns for both non-use of safety restraints, as well as impaired driving. Such campaigns have proven effective in reducing alcohol-related crashes (Erke et al., 2009). So have sobriety checkpoints, though these countermeasures are currently prohibited in Michigan. Ignition interlock requirements for convicted impaired-driving offenders have also been associated with reductions in alcohol-involved fatal crashes (McGinty et al., 2017).

7.2.3 Pedestrian and Bicyclist Safety

Pedestrians and bicyclists continue to experience substantially higher injury severity than vehicle occupants across all facility types. These issues were more pronounced during the pandemic and have gotten even worse subsequently. These findings highlight the importance of strategies that reduce exposure to high-speed traffic and improve crossing safety for vulnerable road users.

MDOT and various other road agencies have more aggressively implemented Complete Streets and Safe System Approaches to roadway design. This has included designing for target speeds and introducing engineering countermeasures such as pedestrian refuge islands, pedestrian hybrid beacons (PHBs), and rectangular rapid-flashing beacons (RRFBs), each of which have been shown to improve safety and driver yielding behavior at marked crosswalks (FHWA, n.d.-b, n.d.-c). Systemic pedestrian safety screening approaches can also be used to identify corridors with elevated pedestrian risk based on roadway characteristics, speed environments, and nearby land uses. This includes a recent MDOT project focused on context-sensitive design.

Across all facility types, dark lighting conditions were consistently associated with higher injury severity relative to daylight conditions. Reduced visibility is widely recognized as a contributing factor to severe crashes, particularly those involving pedestrians and bicyclists (Bamney et al., 2025; Dash et al., 2022). Improving roadway lighting and enhancing visual conspicuity can therefore play an important role in reducing nighttime crash severity. Targeted roadway lighting improvements can be implemented at locations with severe nighttime crash patterns, along with enhanced roadway delineation treatments.

7.2.4 Program Delivery and Implementation

Effective implementation of these countermeasures will require coordination across state and local agencies. Many severe crashes occur at dispersed locations, particularly on rural roads and local networks. As a result, systemic safety approaches that deploy low-cost countermeasures across locations with similar risk characteristics can be particularly effective.

The Highway Safety Improvement Program (HSIP) provides a framework for implementing both location-specific and systemic safety improvements using a data-driven approach designed to reduce fatalities and serious injuries on all public roads (FHWA, 2016). In Michigan, the Local

Safety Initiative (LSI) program also supports local agencies in identifying high-risk locations and implementing safety improvements, often emphasizing low-cost systemic countermeasures that can be deployed broadly across the roadway network (MDOT, n.d.).

7.3 Limitations and Future Works

Several limitations should be considered when interpreting results from this study. First, the national analyses rely on aggregated state- and county-level data, which limits the ability to capture detailed crash circumstances and roadway design factors at the national scale. Second, some data (e.g., mental health indicators) used in the national county analysis were only available through 2022, limiting their inclusion in later analyses (e.g., for calendar year 2023). Third, some behavioral risk indicators in crash records (e.g., impairment and distraction) may be subject to underreporting or variability in reporting practices, which can influence estimated relationships. Finally, the COVID-19 period included overlapping changes in travel demand, enforcement practices, economic conditions, and public health policies, making it challenging to isolate individual mechanisms even with extensive controls.

Additional work is also warranted to further connect operating speed patterns to crash outcomes using high-resolution probe speed data, including evaluation of speed variability and speed differential between operating speed and posted speed limits by corridor type. Finally, continued investigation into behavioral factors, including speeding, impairment, distraction, and restraint use, will be critical for designing and targeting high-impact interventions across facility types and regions.

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