



## Quit playing games with our lives: Layoffs predict road traffic fatalities

Dritjon Gruda<sup>a,b,\*</sup> , Ricardo Gonçalves<sup>a</sup> , Milad Sharafi Zadehan<sup>b</sup>

<sup>a</sup> Universidade Catolica Portuguesa, Catolica Porto Business School, Research Centre in Management and Economics, Porto, Portugal

<sup>b</sup> Maynooth University, School of Business, Maynooth, Ireland

### ARTICLE INFO

**Keywords:**  
Layoffs  
Traffic  
Accidents  
Psychological state

### ABSTRACT

Economic downturns are typically associated with fewer traffic accidents due to reduced driving. However, the psychological and social shocks of sudden job loss may counterintuitively increase risk on the road. In this paper, we examine whether mass layoffs announcements are associated with short-term increases in traffic fatalities in the United States using spatial autoregressive models. Merging monthly U.S. county-level data on mass layoffs with motor vehicle fatality counts, we find a significant uptick in monthly traffic fatalities following major layoff events. This pattern persists after accounting for seasonal trends and regional factors, including unemployment rates and weather conditions. These findings suggest that the stress and disruption caused by mass layoffs can have deadly consequences beyond the workplace. We discuss psychological mechanisms (e.g., distress-related driving impairment) and implications linked to short-term rises in traffic fatalities and public health implications for fatal crash risk.

### 1. Introduction

Traffic safety represents one of the most pressing public health challenges globally, with road traffic injuries ranking as the 12th leading cause of death worldwide and the leading cause of death for children and young adults aged 5–29 years (WHO, 2023). In the United States alone, motor vehicle crashes claim over 38,000 lives annually and result in millions of injuries, generating economic costs exceeding \$340 billion per year when accounting for medical expenses, lost productivity, legal fees, and decreased quality of life (NHTSA, N. H. T. S. A., 2023). Understanding the multifaceted determinants of traffic safety, ranging from infrastructure design and vehicle technology to human factors and socioeconomic conditions, remains critical for developing effective prevention strategies.

While traditional traffic safety research has primarily focused on engineering solutions, enforcement strategies, and driver demographics (Noland, 2003), a growing body of literature acknowledges that broader socioeconomic factors significantly influence road safety outcomes. Economic conditions, in particular, demonstrate complex relationships with traffic fatalities. For example, during economic downturns, reduced vehicle miles traveled and decreased alcohol consumption at bars and restaurants can lead to improved road safety (Ruhm, 2000). However, economic stressors can simultaneously generate psychological distress that may impair driving performance through multiple

pathways, creating competing effects that require careful examination. One major economic stressor, both on the macro and micro level, is job loss.

Job loss is widely recognized as a significant life stressor, with “dismissal from work” appearing among the most stressful life events on the Holmes and Rahe stress scale (Holmes & Rahe, 1967). Beyond economic consequences, these events generate psychological distress in workers who lose their positions as well as in “survivor” who remain but often face heavier workloads and persistent job insecurity (Ahhammer et al., 2023; Elser et al., 2019). Such distress can degrade mental and physical health (Kim et al., 2025; Sullivan & Von Wachter, 2009; but see Salm, 2009), and even manifest in harmful behaviors that extend beyond the workplace. The traffic psychology literature provides robust evidence that psychological stress impairs multiple cognitive functions essential for safe driving, including attention allocation, hazard perception, decision-making speed, and executive control (Clinton et al., 2022; Turgeman-Lupo & Biron, 2017). Stressed drivers demonstrate narrowed attention fields, delayed reaction times, and increased risk-taking behaviors; this constellation of impairments parallels those observed in fatigued or intoxicated drivers (Wickens et al., 2013).

In this study, we argue that large-scale layoffs (i.e., the termination of many employees at once) act as acute socioeconomic shocks that ripple through entire communities (Quinlan & Bohle, 2009), and as a result, are associated with an increase in subsequent traffic fatalities.

\* Corresponding author.

E-mail addresses: [jgruda@ucpt.pt](mailto:jgruda@ucpt.pt) (D. Gruda), [rgoncalves@ucp.pt](mailto:rgoncalves@ucp.pt) (R. Gonçalves), [milad.sharafizadehan.2025@mumail.ie](mailto:milad.sharafizadehan.2025@mumail.ie) (M.S. Zadehan).

<https://doi.org/10.1016/j.aap.2025.108302>

Received 15 August 2025; Received in revised form 10 October 2025; Accepted 31 October 2025

Available online 4 November 2025

0001-4575/© 2025 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY-NC license (<http://creativecommons.org/licenses/by-nc/4.0/>).

This relationship likely operates through multiple behavioral pathways beyond simple distraction. The Job Demands-Resources model (Bakker & Demerouti, 2017) suggests that workers facing job loss experience resource depletion that affects all life domains, including driving. Moreover, stressed individuals may engage in compensatory behaviors, such as increasing speed to reduce commute time, aggressive driving as an emotional outlet, or substance use for coping, which further elevate crash risk (Kontogiannis, 2006). Similarly, cognitive load theory (Patten et al., 2006) predicts that the mental burden of processing job loss likely reduces available cognitive resources for the complex task of driving, particularly in demanding traffic situations.

### 1.1. Economic factors in traffic safety

Prior research examining the relationship between economic factors and traffic safety has yielded mixed findings, largely due to the use of different analytical approaches and time horizons. Macroeconomic studies often find procyclical relationships, with fatalities decreasing during recessions due to reduced exposure (Ruhm, 2000). Studies examining specific economic shocks paint a different picture: stock market crashes increase accident risk (Giulietti et al., 2020) and bankruptcy filings predict higher crash rates (Browning & Heinesen, 2012). The discrepancy between macro and micro findings suggests that while reduced economic activity may lower overall exposure, acute economic stressors generate behavioral responses that increase the risk of traffic fatalities.

With over 1200 workers affected annually, motor vehicle incidents are the number one killer of work-related fatalities in the United States (French & Gumus, 2021). When economic uncertainty increases, so does the number of monthly traffic fatalities (Kanavos & Vandoros, 2023). Relatedly, when the economy contracts and unemployment rises (i.e., workers are laid off), fewer commuters typically reduce roadway congestion, often leading to a decrease in crash frequencies (Ruhm, 2000). Yet, these aggregate statistics may overlook the substantial time lag between when employees learn of impending layoffs and when their official unemployment status begins. In the United States, the Worker Adjustment and Retraining Notification (WARN) Act requires most employers to provide 60 days' notice before laying off a large number of employees. During this window, when workers are legally still employed but know job separation is imminent, intense worry and emotional upheaval can peak (Chadi, 2023). The mismatch between actual driving-related risks during this high-stress notice period and official unemployment data collected after the layoff is final may help explain why some large-scale analyses suggest that job loss correlates with reduced traffic deaths (He, 2016; Kanavos & Vandoros, 2023). We argue that the psychological toll of a layoff can be most acute before the laid-off employees are formally counted among the unemployed.

In various cultural contexts (Clainche & Lengagne, 2023), these psychosocial strains are associated with compromised cognitive functioning and emotional regulation (Frone and Blais, 2020). Additionally, the stress response triggers physiological changes, including elevated cortisol, increased blood pressure, and muscle tension (Starcke & Brand, 2012), all of which can affect motor control and reaction times critical for vehicle operation. During this time, individuals may experience stress, distraction, or depression, each of which can impair safe driving practices (Probst, 2002; Turgeman-Lupo & Biron, 2017). Meanwhile, surviving employees must often adapt quickly to heavier workloads, atypical schedules, or "role overload" further depleting the attentional resources necessary to drive safely (Frone & Blais, 2020). Simultaneously, broader spillover effects mean that a relatively small group of newly stressed or impaired drivers can increase accident risk for the entire community, especially in more densely populated counties, where even modest lapses in driving performance can produce significant dangers (Ahammer et al., 2023). A single moment of inattention at the wheel (e.g., failing to notice a stop sign or swerving due to anxiety) can cause multi-vehicle collisions that threaten bystanders and uninvolved

motorists alike.

To address these complexities, the present study examines whether and to what extent organizational layoffs on the community level significantly affect subsequent fatal accident rates. To do so, we leverage granular data on monthly county-level layoff notifications alongside subsequent monthly county-level traffic fatalities. Doing so allows us to examine the "hidden costs" of layoffs, which extends beyond standard economic metrics.

## Methods.

### 1.2. Data sources and Construction

We developed a monthly, county-level panel dataset spanning 2018–2019 and 2021–2022. The selected time period reflects the most recent years for which complete and finalized county-level data from all sources (WARN, FARS, and BLS) were publicly available at the time of analysis. We explicitly excluded 2020 due to the COVID-19 pandemic's unprecedented disruption to both employment and mobility patterns. During 2020, traffic fatalities increased by 10.5 % (NHTSA, 2021). These anomalous patterns, driven by factors including reduced congestion enabling higher speeds, changed enforcement priorities, and altered driver demographics, would confound any analysis of typical layoff-crash relationships (Cajner et al., 2020).

This dataset incorporated multiple information streams to capture both economic and traffic outcomes. We collected mass layoff data from Worker Adjustment and Retraining Notification (WARN) Act notices, which require employers above a certain size to file public announcements of large-scale layoffs. Each monthly report provided the corresponding total number of affected workers, which we then scaled by the employer's county population (per 1,000,000). This normalization allowed us to compare layoff intensities across counties of different sizes. We subsequently merged these layoff data with fatal accident counts derived from the National Highway Traffic Safety Administration's Fatality Analysis Reporting System (FARS). For each county in each month, we recorded the number of fatal crashes (involving at least one fatality). We converted that count into a rate per 1,000,000 residents, consistent with standard public health metrics.

Accident data and layoff data were merged using a manually calculated layoff announcement date, rather than the provided layoff reporting date. The official layoff reporting date in the WARN dataset indicates only when a company notifies the government, which may not coincide with the day employees learn about impending layoffs, creating discrepancies between recorded and actual events. To correct this mismatch, we calculated a layoff announcement date set 60 days before the implementation date, aligning with the WARN Act's minimum notice requirement and capturing a more realistic timeframe in which workers would be informed. This approach also addresses issues such as missing or incorrect reporting dates and improves overall reliability by minimizing errors and delays in how layoff information is documented and communicated. Moreover, we then decided to aggregate the data on a monthly basis to provide a more stable basis for analysis (and less prone to possible errors when inferring the actual announcement day from the WARN official layoff date).

We also considered the county population density (i.e., the number of residents per square mile) in our analysis to capture differences in traffic patterns between densely populated and sparsely populated areas. Additionally, population density serves as a proxy for the complexity of the driving environment and the presence of vulnerable road users, as higher-density areas typically have more pedestrians, cyclists, and complex intersections where stress-impaired driving poses greater risks. When setting a minimum population density threshold for our analyses, it is essential to consider how both low and high population densities may influence the observed relationships. Counties with very low population densities typically have fewer drivers and minimal total vehicle miles traveled, leading to infrequent and highly irregular fatal crashes. Additionally, low-density counties often differ

substantially from more densely populated areas in terms of road infrastructure, commuting behaviors, and emergency medical services, potentially introducing substantial variability and weakening (possible) systematic associations. Conversely, selecting an excessively high population density threshold restricts the analysis primarily to urban centers, limiting the generalizability of the findings. In such densely populated counties, baseline levels of commuting stress, congestion, and accident frequency may already be so elevated that the incremental impact of layoffs becomes difficult to detect, potentially obscured by ceiling effects and confounded by other urban-specific factors, such as reliance on public transportation and alternative commuting modes.

To balance these considerations and ensure both meaningful and generalizable results, we selected a moderate minimum population density threshold of 1000 residents per square mile for our primary analyses. Out of a total of 154 U.S. counties meeting this minimum population density threshold, our sample comprises 111 counties (72.08 % of all applicable counties), with a total of 5,328 observations (48 months of data for each county). This could be due to either a lack of accidents or layoffs in the remaining 43 counties during the considered time period (i.e., 2018–2022). Nonetheless, our sample covers a population of approximately 101.6 million (101,606,238) residents, including the top 243 cities in the United States. This threshold helps avoid the variability and infrequency problems associated with very low-density counties while ensuring that our results remain broadly applicable and not overly limited to highly urbanized areas.

### 1.3. Measures

#### 1.3.1. Fatal accidents

The primary dependent variable is the monthly number of fatal accidents per county, expressed as fatal crashes per 1,000,000 residents to standardize for differences in population size. Data on fatal accidents were obtained from the Fatality Analysis Reporting System (FARS), a publicly accessible database managed by the National Highway Traffic Safety Administration (NHTSA, N. H. T. S. A., 2023). Because the FARS dataset only includes dates and locations where fatal accidents occurred, we supplemented the dataset by adding zero counts for all days without any recorded fatal crashes per county. Subsequently, daily accident data (incl. zero counts) were aggregated at the monthly county level.

#### 1.3.2. Layoffs

The primary independent variable is the number of layoffs per county, expressed as layoffs per 1,000,000 residents. Layoff data were obtained from Worker Adjustment and Retraining Notification (WARN) notices and aggregated to the monthly county level.

$$FatalAccidents_{i,t} = \beta_1.Layoffs_{i,t-1} + \beta_2.X_{i,t} + \theta_1.WLayoffs_{j,t-1} + \theta_2.WFatalAccidents_{j,t} + \theta_3.WX_{j,t} + \alpha_i + t + \epsilon_{i,t}$$

#### 1.3.3. Population density

Population density refers to the number of individuals per unit area. It is essential to consider population density because variations in density can impact traffic volume, commuting behaviors, and road infrastructure, all of which influence the likelihood of fatal accidents. Only counties with a minimum population density threshold of 1000 were included in the primary analysis. County-level population data were obtained from the U.S. Census Bureau (U.S. Census Bureau, 2019, 2023), and county area size (in square miles) was sourced from World Population Review. Population density was calculated by dividing the county's population by its land area (in square miles).

#### 1.3.4. Weather

We controlled for monthly county-level weather conditions using data provided by the National Centers for Environmental Information (NCEI) to capture weather-specific changes in road conditions that could elevate crash risk (e.g., snow or heavy rainfall). Specifically, we included mean precipitation (measured as the total depth of fallen water in inches, including rain, snow, sleet, and other forms of precipitation), and average monthly temperature, recorded in degrees Fahrenheit.

#### 1.3.5. Macro-economic indicators

We controlled for county-level unemployment rate, defined as the percentage of the labor force currently without employment but actively available to work. Monthly unemployment data at the county level were obtained from the Bureau of Labor Statistics (BLS). In a robustness check, we also controlled for several additional macro-economic indicators, including annual county-level GDP growth data and annual state-level gasoline prices. We obtained annual county-level GDP data from the U.S. Bureau of Economic Analysis, based on which we calculated GDP growth (GDP Growth Rate = [(GDP in Current Year – GDP in Previous Year) / GDP in Previous Year] × 100 (Cameron et al., 2010). Gasoline price data were gathered from GasBuddy, a crowdsourced website that offers real-time fuel prices over the past 10 years at the state level, verified through payment transactions.

### 1.4. Data analysis

Recognizing potential spatial spillovers in crash patterns (e.g., highways spanning multiple counties, commuters traveling between counties), we estimated a spatial panel model (Gruda et al., 2024) with random effects. Specifically, we employed a spatial Durbin model (SDM), which incorporates spatially lagged predictors defined by a first-order contiguity matrix  $W$ . Conceptually, this means that the fatal accident rate in county  $i$  at time  $t$  may partly depend on layoffs occurring in neighboring counties  $j$  at the prior month. It may also depend on traffic patterns and/or county-specificities that occurred in neighboring counties. To account for this, we include in our regression the possibility that the fatal accident rate, as well as the unemployment rate and weather patterns in neighboring counties, could affect the fatal accident rate in any given county. This is intuitive: individuals often travel across counties, and traffic fatalities in one county (or particular weather conditions in a given county) could have ripple-through effects in other neighboring counties due to increased traffic, for example. The SDM specification thus enables us to determine whether the effect of layoffs on fatal crashes holds after accounting for cross-county spillover effects. The spatial Durbin model is specified as follows:

$$FatalAccidents_{i,t} = \beta_1 Layoffs_{i,t} - 1 + \theta W Layoffs_{i,t} - 1 + \beta_2 X_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}$$

where  $FatalAccidents_{i,t}$  denotes fatal crashes per 1,000,000 population in county  $i$  at month  $t$ ,  $Layoffs_{i,t-1}$  is the WARN-based layoff date lagged by one month,  $X_{i,t}$  is the vector of control variables for county  $i$  in month  $t$ ,  $WLayoffs_{j,t-1}$  represents the spatial lag of layoffs (capturing layoffs occurring in neighboring counties in the previous month),  $WFatalAccidents_{j,t}$  are the fatal crashes per 1,000,000 population in neighboring counties,  $WX_{j,t}$  represents control variables for neighboring counties,  $\alpha_i$  represents the county random-effects, and  $t$  represents a (monthly) time trend, respectively.

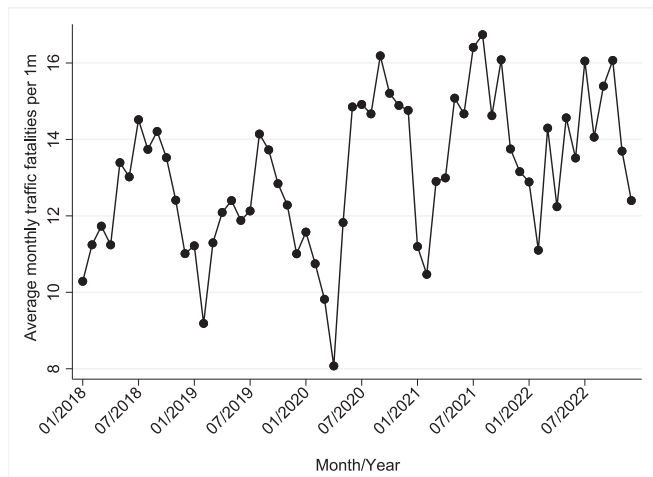


Fig. 1. Timelines of fatal traffic accidents per 1 million for the period 2018–2022.

2. Results

An overview of fatal accidents per county per month is provided in Fig. 1. A clear seasonal pattern is visible in the data. Additionally, a slight upward trend is also evident. Both are accounted for in our regression approach: precipitation and temperature capture seasonality, while a trend term captures the increase, over time, in the fatal accident rate.

The main results are provided in Table 1.

Direct effects of our regression show a significant positive relationship between monthly county-level layoffs per 1,000,000 population and next-month traffic fatalities per 1,000,000 population (unstandardized coefficients:  $b = 0.00044$ ,  $SE = 0.0002$ ,  $z = 2.86$ ,  $p = 0.004$ ). While the regression coefficient appears modest numerically, its practical implications are substantial.

To illustrate, consider a mid-sized county (population 500,000) that experiences the closure of a primary manufacturing plant, affecting 2,500 workers; this layoff represents 5,000 layoffs per million residents. Based on our model, this would predict an increase of 2.2 fatal crashes in the following month ( $0.00044 \times 5,000 = 2.2$ ). Given that this county typically experiences 6–8 fatal crashes monthly, this represents a 27–37 % increase in fatal crash risk. Another example is a three-county

metropolitan region where a major employer announces 15,000 layoffs, distributed across its various facilities. If distributed as 6,000 (County A, population 1.5 million), 5,000 (County B, population 1 million), and 4,000 (County C, population 800,000) layoffs, the predicted regional impact would be: County A: 1.76 additional fatal crashes; County B: 2.2 additional fatal crashes; County C: 2.2 additional fatal crashes. Total regional impact: 6.16 additional fatal crashes per month, not accounting for spatial spillover effects, which could amplify this impact.

Overall, our analysis indicates that approximately 0.48 % (219 deaths) can be directly attributed to economic layoffs in the examined period. These findings identify potentially preventable deaths associated with economic downturns and highlight a crucial public health consequence of labor market disruptions, particularly in densely populated areas.

2.1. Robustness Checks

2.1.1. Multiverse analysis of population density thresholds

To verify that our findings were not dependent on our choice of population density threshold, we conducted a multiverse analysis. Multiverse analysis is an analytical strategy that involves systematically exploring how sensitive empirical findings are to different analytical decisions, model specifications, or exclusion criteria (Gruda et al., 2022; Steegen et al., 2016). This approach helps ensure transparency and reduces the risk of reporting findings contingent on arbitrary or idiosyncratic decisions. Specifically, we repeated our spatial panel regression analyses across a broad range of minimum population density thresholds, incrementally increasing the cutoff from 100 to 2500 residents per square mile. This robustness approach allowed us to confirm the stability and generalizability of our results across different minimum population density thresholds. These results are presented in Table 2 and visually displayed in Fig. 2.

Results indicate that the association between layoffs and traffic fatalities remains consistent and robust across a wide range of population density thresholds, namely from 600 to 2000 residents per square mile. This consistency strengthens confidence that the observed relationship is not a statistical artifact tied to an arbitrary choice of population density cutoff. At very high population densities (above 2250 residents per square mile), layoffs no longer significantly predict traffic fatalities. At these high-density levels, commuting patterns and transportation modes shift significantly, with more residents relying on public transit or active transportation methods (e.g., cycling or walking). In addition,

Table 1

Spatial regression results for the relationship between layoffs and next-month traffic fatalities (min. county population density threshold of 1000 residents/sqm).

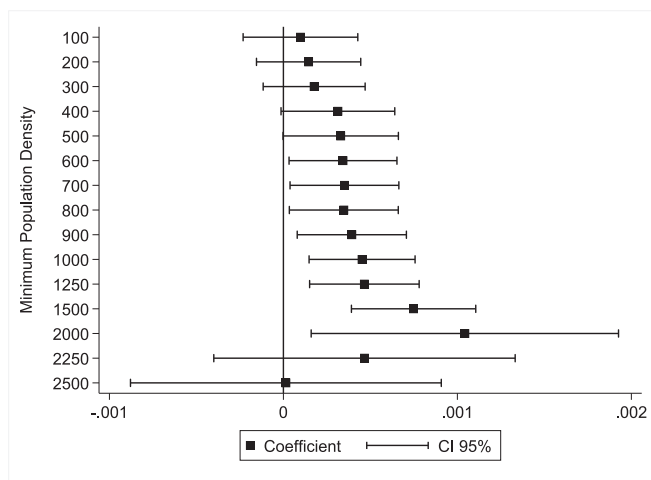
	b	SE	z	p	[95 % CI]	
<i>Direct Effects</i>						
Layoffs (per 1 m)	0.000445	0.000152	2.89	0.004	0.00014	0.00075
Unemployment	0.198605	0.088246	2.25	0.024	0.02564	0.37156
Precipitation	-0.036610	0.048264	-0.76	0.448	-0.13121	0.05798
Temperature	0.030754	0.006986	4.40	0.000	0.01706	0.04445
Time Trend	0.045303	0.005614	8.07	0.000	0.03430	0.05631
<i>Indirect Effects</i>						
Layoffs (per 1 m)	0.000335	0.000447	0.75	0.454	-0.00054	0.00121
Unemployment	-0.111162	0.051890	-2.14	0.032	-0.21287	-0.00946
Precipitation	-0.00340	0.039815	-0.09	0.932	-0.08143	0.07464
Temperature	-0.00533	0.004457	-1.17	0.243	-0.01428	0.00362
Time Trend	0.00103	0.00721	1.44	0.151	-0.00038	0.00245
<i>Total Effects</i>						
Layoffs per (per 1 m)	0.00078	0.000525	1.66	0.098	-0.00014	0.00170
Unemployment	0.08744	0.070587	1.32	0.188	-0.04272	0.21760
Precipitation	-0.04000	0.033717	-1.11	0.269	-0.11096	0.03095
Temperature	0.02542	0.005028	4.78	0.000	0.01501	0.03584
Time Trend	0.04634	0.00572	8.10	0.000	0.03512	0.05755

Note: unstandardized coefficients.

**Table 2**  
Direct effects results of multiverse analysis with varying minimum population density thresholds (per square mile).

Min. pop. density threshold	n <sub>counties</sub>	n <sub>observations</sub>	b	SE	z	p	l95	h95
>100	492	23,616	0.000098	0.0001682	0.58	0.56	-0.000232	0.000428
>200	361	17,328	0.0001449	0.0001529	0.95	0.343	-0.000155	0.000445
>300	279	13,392	0.0001767	0.0001495	1.18	0.237	-0.000116	0.000470
>400	232	11,136	0.0003133	0.0001668	1.88	0.06	-0.000014	0.000640
>500	196	9408	0.0003294	0.0001692	1.95	0.052	-0.000002	0.000661
>600	167	8016	0.0003426	0.0001582	2.17	0.03	0.000033	0.000653
>700	148	7104	0.0003509	0.0001595	2.2	0.028	0.000038	0.000664
>800	136	6528	0.0003472	0.0001597	2.17	0.03	0.000034	0.000660
>900	119	5712	0.0003889	0.0001585	2.45	0.014	0.000078	0.000700
>1000	111	5328	0.0004459	0.0001542	2.89	0.004	0.000144	0.000748
>1250	91	4368	0.0004576	0.0001591	2.88	0.004	0.000146	0.000769
>1500	76	3648	0.0007337	0.0001808	4.06	0.00	0.000379	0.001088
>2000	50	2400	0.0009742	0.0004533	2.15	0.032	0.000086	0.001863
>2250	43	2064	0.0004552	0.0004142	1.1	0.272	-0.000357	0.001267
>2500	35	1680	0.0004803	0.0004465	1.08	0.282	-0.000395	0.001355

Note: unstandardized coefficients.



**Fig. 2.** Results of multiverse analysis with varying minimum population density thresholds (per square mile). Note: unstandardized coefficients.

under these population density conditions, the role of layoffs in influencing driving behavior and associated stress responses may diminish substantially, potentially obscured by other urban-specific stressors or by already high baseline congestion and accident rates.

**2.1.2. Multiple-month lags**

To assess the stability and timing of the layoff-accident link, we tested two additional lag structures, including zero- and two-month lags from the calculated layoff announcement month, applying the same threshold as in the primary analysis (i.e., 1000 residents/square mile). If accidents spike immediately in the same month as a layoff or only after a delay, varying the lag specification would detect those differences.

Layoff announcements were not significantly associated with traffic fatalities occurring within the same month ( $b = 0.00028$ ,  $SE = 0.00015$ ,  $z = 1.84$ ,  $p = 0.066$ ). This finding suggests that stress-related behavioral changes stemming from layoff announcements do not manifest immediately. Instead, there appears to be a lagged effect, emerging approximately one month after layoffs are announced. In contrast, we observed a significant negative association between monthly layoffs and traffic fatalities two months later ( $b = -0.00034$ ,  $SE = 0.00016$ ,  $z = -2.23$ ,  $p = 0.025$ ). This pattern is consistent with the structure of WARN notices, which require employers to announce layoffs at least 60 days in advance. Consequently, by the second month following layoff announcements, many of these layoffs have taken effect, resulting in a reduction of the overall number of commuters and vehicles on the road. The resulting decrease in traffic volume at that point logically translates

into fewer traffic fatalities.

**2.1.3. Additional macroeconomic controls**

Adding macroeconomic controls (i.e., annual county-level GDP growth, and monthly state-level retail gasoline prices) did not alter the core finding. The association between layoffs and next-month traffic fatalities remained robust and significant (direct effects:  $b = 0.00075$ ,  $SE = 0.00032$ ,  $z = 2.35$ ,  $p = 0.019$ ), albeit the sample size was reduced to 4,656 observations and 97 counties, due to some missing GDP growth data.

**3. Discussion**

Driving is a complex task requiring attention, quick decision-making, and emotional regulation. Our findings support the psychological argument that the acute stress following a layoff announcement impairs these critical cognitive functions. We propose a the following psychological pathway: the news of impending job loss creates significant psychological distress, which elevates cognitive load and degrades attentional control (e.g., [Turgeman-Lupo & Biron, 2017](#)). This impairment manifests in riskier driving behaviors and a reduced ability to perceive and react to hazards, leading to an increase in fatal crashes approximately one month after the layoff announcement (i.e., 30 days), a period where the stress may peak as the reality of securing another job within the provided timeframe (i.e., 60 days) becomes imminent. We add to the existing knowledge base, since traditionally, traffic fatalities have been analyzed in relation to road engineering, enforcement, and driver demographics ([Noland, 2003](#)). Our results indicate that mass layoffs constitute a possible additional factor to consider in relation to road traffic fatalities.

**3.1. Community-Wide impact**

Layoffs not only impact those directly losing employment but also indirectly affect other individuals within the community. For instance, laid-off workers might drive while anxious or upset, whereas “survivors” could experience heavier workloads and emotional strain, thus reducing attentiveness on the road. And since all drivers share the same public roads, this increased risk for recently laid-off individuals consequently elevates accident risks for other, unrelated drivers. Thus, even drivers who are not personally experiencing job loss can face greater danger, as their likelihood of encountering impaired drivers on the road increases, making layoffs a broader concern for traffic safety within the community. Particularly concerning is the increased risk to vulnerable road users, including pedestrians and cyclists, who have no protective vehicle structure and are therefore more susceptible to severe injury or death when encountering stress-impaired drivers. In higher-density areas

where our effects are most potent, these vulnerable road users represent a significant proportion of traffic participants, thereby amplifying the public health impact of driving impairments related to layoffs. This study takes this into account, examining how layoffs affect fatal accident rates at the county level.

### 3.2. Cumulative effects and regional considerations

Moreover, the impact of repeated layoffs over consecutive months can compound over time. For instance, a county might face thousands of layoffs in Month 1 and an additional round in Month 2, amplifying the predicted upturn in crash fatalities. This cumulative phenomenon echoes the observation by French and Gumus (2021) that persistent economic disruptions create compounding effects on road safety outcomes. Consequently, communities experiencing multiple back-to-back layoff events may endure a sustained rise in fatal accidents, underscoring the need for timely policy interventions and preventative measures.

And while our findings indicate a meaningful 0.4 % increase in traffic fatalities associated with layoffs, this likely understates the full impact on public safety. To contextualize the public health burden, we calculated the economic costs related to layoff-related traffic fatalities. Using NHTSA’s comprehensive cost estimates, each traffic fatality generates approximately \$11.3 million in economic and quality-of-life costs (NHTSA, 2021). Based on our finding that 219 deaths during the study period are attributable to layoffs, the total economic burden equals \$2.74 billion. This figure encompasses both direct costs (medical care, emergency services, property damage, and legal proceedings) and indirect costs (lost productivity and reduced quality of life for victims and

their families).

Importantly, our analysis focuses on fatal accidents because these data are publicly available at the monthly county level. However, the broader impact becomes apparent when considering non-fatal injuries, which are only reported at the national level. According to NHTSA data, the U.S. recorded an average of approximately 2.54 million people injured in motor vehicle crashes annually during 2018–2022 (excluding 2020). Compared to the roughly 36,000–39,000 annual traffic fatalities during the same period, injury crashes are approximately 70 times more common than fatal ones. This suggests the total impact of layoffs on traffic safety extends well beyond fatalities, potentially affecting tens of thousands of additional injury crashes annually across affected communities. Based on our finding that 219 deaths during the study period are attributable solely to layoffs, mass layoffs may contribute to approximately 15,330 additional injury crashes during our study period. With average injury crash costs of roughly \$40,000 (NHTSA, 2023) per injured person and (since crashes often involve multiple people, the cost per crash would be higher than per person), this represents an additional \$1.92 billion in economic losses, bringing the total estimated economic burden to \$4.66 billion over four years, or approximately \$1.17 billion annually.

Just as we now recognize that mobile phone use, fatigue, and substance impairment compromise driving safety, we must acknowledge that acute economic stressors can create similar vulnerabilities. As communities worldwide grapple with economic volatility and workforce transitions, recognizing layoffs as a traffic safety risk factor and implementing evidence-based countermeasures can help protect both economic and human capital during challenging times.

**Table 3**  
Intervention Framework for Layoff-Related Traffic Safety.

Stakeholder	Intervention	Implementation Timeline	Estimated Cost	Expected Impact
<b>Employers</b>	<ul style="list-style-type: none"> <li>- Provide on-site counseling services</li> <li>- Conduct stress management workshops</li> <li>- Include safe driving reminders in severance materials</li> <li>- Offer flexible transition schedules</li> </ul>	Immediate upon WARN notice filing	\$500–1,000 per affected employee	Reduction in stress-related incidents among affected workers
<b>State Department of Transportation</b>	<ul style="list-style-type: none"> <li>- Deploy variable message signs with safety reminders</li> <li>- Increase enforcement presence on high-risk corridors</li> <li>- Temporary speed limit reductions</li> <li>- Enhanced work zone safety measures</li> </ul>	Within 1 week of public announcement	\$50,000–100,000 per major layoff event	Decreased aggressive driving behaviors
<b>Public Health Department</b>	<ul style="list-style-type: none"> <li>- Launch targeted mental health awareness campaigns</li> <li>- Expand crisis hotline capacity</li> <li>- Mobile counseling units in affected areas</li> <li>- Community support groups</li> </ul>	Within 2 weeks of announcement	\$25,000–50,000 per campaign	Increased mental health help-seeking behavior
<b>Local Government</b>	<ul style="list-style-type: none"> <li>- Coordinate multi-agency response team</li> <li>- Establish real-time monitoring dashboard</li> <li>- Temporary public transit subsidies</li> <li>- Community resource fairs</li> </ul>	Immediate activation and ongoing monitoring	\$100,000 initial setup, \$20,000 monthly operations	Improved response coordination and resource allocation
<b>Insurance Companies</b>	<ul style="list-style-type: none"> <li>- Offer temporary premium relief programs</li> <li>- Promote safe driving app incentives</li> <li>- Defensive driving course discounts</li> <li>- Stress management resources</li> </ul>	Within 30 days of layoff announcement	Revenue neutral through claims reduction	Reduction in claims frequency

Note: Costs are estimated based on typical U.S. metropolitan area implementations. Rural areas may have lower costs but require adapted strategies. Impact estimates derived from analogous public health interventions and should be validated through program evaluation.

### 3.3. Practical implications

For managers and policymakers, these findings suggest that layoffs, while sometimes unavoidable, carry significant hidden human costs. As Pfeffer (2018) argues, layoffs can be “deadly” and our research further emphasizes that this impact can be immediate and extend to innocent bystanders (Eliason & Storrie, 2009; French & Gumus, 2021). We summarize possible intervention strategies in Table 3.

When mass layoffs are announced, local authorities should swiftly mobilize targeted interventions to mitigate driving risks. For instance, safety campaigns can be launched to encourage heightened vigilance among drivers, including those directly impacted by layoffs, and promote safer commuting behaviors while also promoting the use of mental health resources. Recognizing that stress and anxiety resulting from job loss can diminish road attentiveness, proactive measures can likely significantly reduce the likelihood of accidents. Moreover, communities that endure successive rounds of layoffs within a short timeframe may experience a cumulative and prolonged surge in fatal accidents. Policymakers and local stakeholders should, therefore, remain vigilant, dedicating resources to sustained traffic enforcement, mental health support, and infrastructural enhancements to counteract the compounding adverse effects of repeated economic shocks. Community authorities could also increase vigilance (e.g., more traffic patrols) in the aftermath of major layoffs, treating it as a period of elevated risk similar to holidays or significant sporting events that are known to spike accidents (Jakar et al., 2023; Wood et al., 2011).

### 3.4. Geographic concentration effects

The spatial distribution of employment further complicates these safety considerations, as the geographic concentration of certain industries creates particular vulnerabilities in specific regions. The Washington, DC metropolitan area offers an instructive example of this phenomenon. With approximately 15–20 % of all U.S. federal civilian employees (roughly 300,000–400,000 workers) concentrated in this region, any federal workforce reductions, whether through budget cuts, agency reorganizations, or government shutdowns, could have a significant impact on traffic safety. Based on our model, a hypothetical 5 % reduction in federal employment concentrated in the DC metro area could potentially increase traffic fatalities by an estimated 1.2–2.4 % (illustrative example applying a multiplier effect of  $2.5\text{--}5 \times$  to our baseline finding of 0.48 % increase in fatalities ( $0.4\% \times 2.5\text{--}5 = 1\text{--}2\%$ ) based on the geographic concentration of federal workers and shared commuting corridors) in subsequent months across DC, Maryland, and Virginia counties with high federal worker residency. This concentration effect likely extends to other regions dominated by single industries or employers, such as automotive manufacturing in Detroit, technology in Silicon Valley, or energy production in Houston, suggesting that targeted traffic safety interventions should be geographically prioritized when sector-specific economic shocks occur.

### 3.5. Employer Responsibilities

Employers also play a critical role in managing potential spillover effects by proactively supporting employees’ mental and emotional well-being. Programs such as Employee Assistance Programs (EAPs) and counseling services (Waehrer et al., 2016), flexible working hours and time-flexible work policies (Halpern, 2005), and remote work options (Chen et al., 2024; Rafiq et al., 2022) can lessen the immediate stress experienced by both displaced workers and remaining employees, potentially limiting subsequent road fatalities on the community level. Additionally, workforce reduction events should include explicit communication on safe driving practices.

### 3.6. Clinical and psychological implications

From a psychological perspective, our findings encourage greater cross-talk between research on economic stress and transportation safety. Concepts like distracted driving could be broadened beyond cell phone use to include cognitive distraction due to life events. Clinicians and counselors who assist unemployed individuals might consider discussing roadway safety, essentially reminding clients that during periods of high stress, extra caution is needed in daily activities like driving.

### 3.7. Limitations

Although our analysis utilizes detailed, monthly county-level data, several limitations should be considered. First, this is an observational study. Despite dynamic-effects and pre-trend diagnostics, the presence of unmeasured confounders remains a possibility. For instance, layoffs may coincide with other disruptive local events such as protests or sudden changes in traffic patterns due to facility closures, which could independently influence accident rates. We sought to address this concern by incorporating fixed effects, but this may not be sufficient to capture all unobserved heterogeneity. Due to the observational nature of this study, the provided results must be interpreted carefully and in a non-causal manner.

Second, we acknowledge the ecological fallacy inherent in our county-level analysis. While we observe aggregate relationships between layoffs and traffic fatalities at the county level, we cannot directly infer individual-level behavioral changes. Not all laid-off workers will experience driving impairments, and not all traffic fatalities in affected counties involve individuals who have been directly or indirectly affected by layoffs. Future research using individual-level data, such as linked employment and crash records, would provide more definitive evidence of causal pathways.

Third, the WARN Act framework limits both the scope and generalizability of our findings. WARN notices only capture mass layoffs from employers with 100 or more employees, missing smaller-scale reductions that nonetheless produce significant local economic stress. Small business closures, which can account for a substantial portion of employment in many communities, are entirely absent from our analysis. Consequently, our results likely underestimate the actual impact on traffic safety. Furthermore, the WARN Act is unique to the United States, limiting its generalizability internationally. Other countries may have different notification requirements or no mandatory notice periods, which could alter the temporal dynamics we observe. Research in various regulatory contexts would help establish whether our findings reflect universal stress responses or are specific to the U.S. framework.

Fourth, our analysis focused exclusively on fatal accidents due to data availability constraints. This represents significant reporting bias, as fatal crashes constitute only a small fraction of total traffic incidents. Non-fatal injuries, property damage, and crashes, as well as “near misses” remain unmeasured. Fatal crashes may also differ qualitatively from non-fatal incidents in terms of contributing factors, crash types, and driver characteristics. Future research should strive to incorporate a more comprehensive set of outcomes, such as the KABCO injury severity scale, to capture non-fatal injuries and property damage crashes, which would provide a more complete understanding of how layoffs influence overall driver safety.

## 4. Conclusion

This study provides robust evidence that large-scale layoffs significantly increase traffic fatalities in affected communities, with each 1,000 layoffs per million residents predicting 0.44 additional traffic deaths the following month. Our findings challenge conventional wisdom about economic downturns and road safety: while recessions may reduce overall traffic exposure, acute localized job losses generate immediate psychological stress that appears to elevate crash risk. The

estimated \$1.17 billion annual economic burden of layoff-related traffic incidents demands urgent policy attention, and we have provided an actionable framework for multi-stakeholder intervention. Ultimately, this research identifies layoffs as a critical, yet overlooked, risk factor in traffic safety, underscoring that the road to economic recovery should not be paved with preventable tragedies.

#### Declaration of Generative AI use

The authors used ChatGPT, Gemini 2.5 Pro, and Claude 4.1 Opus to enhance the language and writing throughout this paper. After using these tools, the authors reviewed and edited the content as needed, taking full responsibility for the content of the publication.

#### CRedit authorship contribution statement

**Dritjon Gruda:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Ricardo Gonçalves:** Writing – review & editing, Methodology, Formal analysis, Conceptualization. **Milad Sharafi Zadeh:** Writing – review & editing, Investigation, Data curation.

#### Funding

This research received no funding. Ethics.

We solely used publicly available data to conduct this work. Therefore, ethics approval was not required.

#### Preregistration

No aspects of the study were preregistered. Materials, Data, and Analysis scripts: All study materials, data, and analysis scripts are publicly available ([https://osf.io/rgtmf/?view\\_only=ec7059f495e341dad56452cb1435aa1](https://osf.io/rgtmf/?view_only=ec7059f495e341dad56452cb1435aa1)).

#### Declaration of competing interest

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

#### Data availability

All data used are public. Link to the respective dataset has been provided in the manuscript.

#### References

- Ahammer, A., Grübl, D., Winter-Ebmer, R., 2023. The health effects of downsizing survival. *Rev. Econ. Stat.* 1–45.
- Bakker, A.B., Demerouti, E., 2017. Job demands–resources theory: taking stock and looking forward. *J. Occup. Health Psychol.* 22 (3), 273.
- Browning, M., Heinesen, E., 2012. Effect of job loss due to plant closure on mortality and hospitalization. *J. Health Econ.* 31 (4), 599–616.
- Bureau, U. S. C. (2019). *County Population Totals: 2010-2019*. Retrieved January 2025 from <https://www.census.gov/data/datasets/time-series/demo/popest/2010s-counties-total.html>.
- Bureau, U. S. C. (2023). *County Population Totals and Components of Change: 2020-2023*. Retrieved January 2025 from <https://www.census.gov/data/datasets/time-series/demo/popest/2020s-counties-total.html>.
- Cajner, T., Crane, L. D., Decker, R. A., Grigsby, J., Hamins-Puertolas, A., Hurst, E., Kurz, C., & Yildirmaz, A. (2020). *The US labor market during the beginning of the pandemic recession* (0898-2937).
- Cameron, A. C., Trivedi, P. K., Cameron, A. C., & Trivedi, P. K. (2010). *Microeconometrics using Stata* (Vol. 2). College Station, TX: Stata press.
- Chadi, C., 2023. Too Stressed to sleep? Downsizing, Job Insecurity and sleep Behavior. *Economics & Human Biology* 51, 101306. <https://doi.org/10.1016/j.ehb.2023.101306>.
- Chen, P., Yang, X., Zhang, Y., 2024. Exploring the interconnection between telecommuting, trip reduction, and transportation equity amidst the coronavirus pandemic. *Transp. Lett.* 1–11.

- Clainche, C.L., Lengagne, P., 2023. Economic Layoffs and Mental Health: evidence from French Register-Survey Data. *Revue D Economie Politique*. <https://doi.org/10.3917/redp.333.0367>.
- Clinton, M.E., Hewett, R., Conway, N., Poulter, D., 2022. Lost control driving home: a dual-pathway model of self-control work demands and commuter driving. *J. Manag.* 48 (4), 821–850.
- Eliason, M., Storrie, D., 2009. Job loss is bad for your health—swedish evidence on cause-specific hospitalization following involuntary job loss. *Soc. Sci. Med.* 68 (8), 1396–1406.
- Elser, H., Ben-Michael, E., Rehkopf, D., Modrek, S., Eisen, E.A., Cullen, M.R., 2019. Layoffs and the mental health and safety of remaining workers: a difference-in-differences analysis of the US aluminium industry. *J. Epidemiol. Community Health* 73 (12), 1094–1100.
- French, M.T., Gumus, G., 2021. Death on the job: the Great recession and work-related traffic fatalities. *Soc. Sci. Med.* 280, 113979.
- Frone, M. R., & Blais, A.-R. (2020). Organizational Downsizing, Work Conditions, and Employee Outcomes: Identifying Targets for Workplace Intervention among Survivors. *International Journal of Environmental Research and Public Health*, 17(3), 719. <https://doi.org/10.3390/IJERPH17030719>.
- Giulietti, C., Tonin, M., Vlassopoulos, M., 2020. When the market drives you crazy: Stock market returns and fatal car accidents. *J. Health Econ.* 70, 102245.
- Gruda, D., Hanges, P., McCleskey, J., 2024. Mirror, mirror on the wall, who's the healthiest of them all—the surprising role of narcissism in state-level health outcomes. *J. Res. Pers.* 109, 104465.
- Gruda, D., Karanatsiou, D., Hanges, P., Golbeck, J., Vakali, A., 2022. Don't go Chasing Narcissists: a Relational-based and Multiverse Perspective on Leader Narcissism and Follower Engagement using a Machine Learning Approach. *Pers. Soc. Psychol. Bull.* 01461672221094976.
- Halpern, D.F., 2005. How time-flexible work policies can reduce stress, improve health, and save money. *Stress. Health* 21 (3), 157–168.
- He, M.M., 2016. Driving through the Great recession: why does motor vehicle fatality decrease when the economy slows down? *Soc. Sci. Med.* 155, 1–11.
- Holmes, T. H., & Rahe, R. H. (1967). The social readjustment rating scale. *Journal of psychosomatic research*. Quinlan, M., & Bohle, P. (2009). Overstretched and unreciprocated commitment: reviewing research on the occupational health and safety effects of downsizing and job insecurity. *International Journal of Health Services*, 39(1), 1–44.
- Jakar, G., Gordon, K., He, Q., 2023. The temporal and spatial relationships between professional sport events and reported vehicular crashes: an analysis of Cleveland. *Ohio. Sport Management Review* 26 (4), 628–648.
- Kanavos, P., VANDOROS, S., 2023. Road traffic mortality and economic uncertainty: evidence from the United States. *Soc. Sci. Med.* 326, 115891.
- Kim, M., Beehr, T.A., Brough, P., Troth, A.C., 2025. Job insecurity keeps me awake at night: is my supervisor making me insecure? *Curr. Psychol.* 1–14.
- Kontogiannis, T., 2006. Patterns of driver stress and coping strategies in a Greek sample and their relationship to aberrant behaviors and traffic accidents. *Accid. Anal. Prev.* 38 (5), 913–924.
- NHTSA, N. H. T. S. A. (2023). *Fatality Analysis Reporting System analytical user's manual, 1975-2020*.
- Noland, R.B., 2003. Traffic fatalities and injuries: the effect of changes in infrastructure and other trends. *Accid. Anal. Prev.* 35 (4), 599–611.
- Patten, C.J., Kircher, A., Östlund, J., Nilsson, L., Svenson, O., 2006. Driver experience and cognitive workload in different traffic environments. *Accid. Anal. Prev.* 38 (5), 887–894.
- Pfeffer, J. (2018). *Dying for a paycheck: Why the American way of business is injurious to people and companies*. HarperCollins Publishers.
- Probst, T.M., 2002. Layoffs and tradeoffs: production, quality, and safety demands under the threat of job loss. *J. Occup. Health Psychol.* 7 (3), 211–220. <https://doi.org/10.1037/1076-8998.7.3.211>.
- Rafiq, R., McNally, M.G., Uddin, Y.S., Ahmed, T., 2022. Impact of working from home on activity-travel behavior during the COVID-19 Pandemic: an aggregate structural analysis. *Transp. Res. A Policy Pract.* 159, 35–54.
- Ruhm, C.J., 2000. Are recessions good for your health? *Q. J. Econ.* 115 (2), 617–650.
- Salm, M., 2009. Does job loss cause ill health? *Health Econ.* 18 (9), 1075–1089.
- Starcke, K., Brand, M., 2012. Decision making under stress: a selective review. *Neurosci. Biobehav. Rev.* 36 (4), 1228–1248.
- Steege, S., Tuerlinckx, F., Gelman, A., Vanpaemel, W., 2016. Increasing transparency through a multiverse analysis. *Perspect. Psychol. Sci.* 11 (5), 702–712.
- Sullivan, D., Von Wachter, T., 2009. Job displacement and mortality: an analysis using administrative data. *Q. J. Econ.* 124 (3), 1265–1306.
- Turgeman-Lupo, K., Biron, M., 2017. Make it to work (and back home) safely: the effect of psychological work stressors on employee behaviour while commuting by car. *Eur. J. Work Organ. Psy.* 26 (2), 161–170.
- Waehrer, G.M., Miller, T.R., Hendrie, D., Galvin, D.M., 2016. Employee assistance programs, drug testing, and workplace injury. *J. Saf. Res.* 57, 53–60.
- Wickens, C. M., Mann, R. E., Stoduto, G., Flam Zalcman, R., & Butters, J. (2013). Alcohol control measures in traffic. *Alcohol: Science, policy and public health*, 378-388.
- Wood, S., McInnes, M.M., Norton, D.A., 2011. The bad thing about good games: the relationship between close sporting events and game-day traffic fatalities. *J. Consum. Res.* 38 (4), 611–621.
- World Health Organization, 2023. *Global status report on road safety 2023*. World Health Organization.