# The association between crashes and safety-critical events: synthesized evidence from crash reports and naturalistic driving data among commercial truck drivers

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**Abstract**

The past decade has witnessed continuous growth of naturalistic driving studies (NDSs). In NDSs, safety-critical events (SCEs) are commonly used to measure safety since crashes are very rare. However, the association between SCEs and crashes is not consistent in previous studies and has not been verified among commercial truck drivers. Based on routinely collected kinematic data from 31,828 truck drivers in a large commercial trucking company, this paper examines the association between four types of SCEs (headway, hard brake, collision mitigation, and rolling stability) and crashes, as well as injuries and fatalities. While previous NDSs have involved about 2 million miles driven, our study involves an estimated number of over 2.3 billion miles driven. Bayesian negative binomial models were applied to examine the association between three outcomes (crashes, injuries, and fatalities) and the four SCEs. It was found that a unit increase in the number of any type of SCEs per 10,000 miles was associated with 8.4% (95% credible interval CI: 8.0-8.8%) increase in crashes per mile and 8.7% (95% CI: 4.8-13.6%) increase in the number of injuries per mile. The increase was different in different types of SCEs: 3.3% (95% CI: 2.6-4%) for headways, 8.1% (95% CI: 7.5-8.7%) for hard brakes, 50.4% (95% CI: 41.4-60%) for rolling stability, and 22.2% (95% CI: 19.8-24.5%) for collision mitigation. The results are consistent when stratified by different business units and driver types. This study provides statistically strong and robust evidence that SCEs are positively associated with crashes and injuries among commercial truck drivers. NDS and kinematic data routinely collected by trucking companies provide a promising opportunity for future data analytic research.

*Keywords:* truck, naturalistic driving studies, safety-critical events, crashes, injuries, fatalities

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## 1. Introduction

Truck drivers "form the lifeblood of [the U.S.] economy" (The White House, 2020), moving more than 70% of goods, transporting approximately 10.8 billion tons of freight, and generating annual revenues of over $700 billion (John, 2019). Because of the sheer size of trucks, it is imperative that we reduce the prevalence and severity of crashes involving commercial trucks. Tsai et al. (2018) pointed out three aspects related to this concern: (a) in 2017, 5,005 lives were claimed in 4,455 fatal crashes involving large trucks or buses, and 170,000 persons were injured in 116,000 injury crashes involving trucks and buses (FMCSA, 2019); (b) larger property damage occurred, which can increase the likelihood of injuries and human loss, as well as increase travel-time for other commuters; and (c) indirect losses in efficiency arose from the slowing and damage of essential goods during transit. Despite the significant advances in trucking safety technologies (e.g., deployment of forward-collision mitigation and lane departure warning systems), large truck crash rates have increased over the past decade. In the U.S., the involvement rate per 100 million large-truck miles traveled increased from 1.32 in 2008 to 1.48 in 2016 for fatal crashes, and from 21 in 2008 to 31 in 2015 (most recent data at the time of writing) for injury crashes (NHTSA's National Center for Statistics and Analysis, 2019).

Traditionally, the literature focusing on analyzing trucking crashes relied on police reports data. Due to the retrospective nature of these reports, they are subject to four major limitations. First, the post-hoc nature of the reports results in recall and information bias (Stern et al., 2019). The second limitation stems from the fact that crashes constitute rare events when compared to non-crashes, which makes it difficult to make statistically valid conclusions on the risk factors of crashes (Guo et al., 2010; Theofilatos et al., 2019). Third, critical behavioral factors, such as fatigue, distraction and cell-phone use, are under-reported by those involved in crashes in an attempt to avoid penalties, fines and legal actions (Dingus et al., 2011; Stern et al., 2019). Finally, minor crashes, resulting in no injuries and no/minor physical damages, tend to be under-reported (Blower, 2017), which impacts the total reported crashes and hence, the understanding of crash risk.

The emergence of sensor-based monitoring technologies, which generate microscopic data about both the truck and truck driver's performance, can enhance our understanding of road safety especially when integrated with data analytic techniques (Shi and Abdel-Aty, 2015; Katrakazas et al., 2015; Imprialou and Quddus, 2019; He et al., 2019; Wali and Khattak, 2020; Mehdizadeh et al., 2020; Hu et al., 2020). The coupling of these sensors with computational advances, which can harness the resulting big datasets, have allowed for conducting several naturalistic driving studies (NDSs) that can overcome the aforementioned limitations in the retrospective crash analysis literature. For example, the 100-car study (Neale et al., 2005), UDRIVE (Eenink et al., 2014) and SHRP2 (Hankey et al., 2016) NDSs collected acceleration, video and location data for crashes and non-crashes, thus, providing superior ability to estimate the risk or rate of crashes due to the inclusion of non-crashes, and also to investigate the short period prior to crashes or safety events without being subjected to information/recall bias (Guo et al., 2010).

Despite the massive amounts of data captured in NDSs, the recorded number of crashes, in any given study, remains small. For example, the 100-car study captured around two million vehicle miles, 40,000+ hours of driving, and yet included only 69 crashes (Neale et al., 2005). This is an expected result since crashes are rare events; hence their rates are reported per 100 million miles driven. In view of these limitations, naturalistic driving studies often use surrogate events in place of actual crashes. Such surrogates are usually referred to as safety-critical events (SCEs) and are selected to intuitively represent (more numerous) "near misses", i.e., special types of accident precursors that have all features of accidents, except that potentially catastrophic outcomes were avoided by last-second evasive maneuvers (Dingus et al., 2011; Saleh et al., 2013). A fundamental question then is whether some specific classes of SCEs (e.g., hard brakes, initiation of collision mitigation systems, rolling stability alerts, etc.) can be used as a surrogate for crashes. Since this less severe events are more frequent than crashes, a strong positive correlation between the two would allow for statistically valid modeling crash risk event when the number of crashes is limited.

### *1.1. Research gaps*

The study of the association between surrogate measures and more rare accident events can be first attributed to Heinrich (1931) who attempted to apply the scientific method to the field of industrial accident prevention. In the context of motor vehicle crash analysis, the earlier works focused on estimating the conversion factor between the two types of events (Evans and Wasielewski, 1982, 1983; Cooper, 1984; Risser, 1985; Hydén, 1987). With the advancements in sensor-based technologies and the transition to NDS, we found several research studies (Dingus et al., 2006; Guo et al., 2010; Gordon et al., 2011; Simons-Morton et al., 2012; Wu and Jovanis, 2012; Guo and Fang, 2013; Wu et al., 2014; Pande et al., 2017; Gitelman et al., 2018) that examined the relationship between kinematic-based SCEs and crashes. Table 1 provides an overview of these studies on the relationship between SCEs and crashes, highlighting the sample size, driver types, driving locations, number of observed crash and surrogate events for the participating vehicles/drivers, statistical approach used, and statistically significant effects. While the largest of these studies involved about 43,000 hours driven and 2 million miles driven, our study involves 66 million hours driven and 2.3 billion miles driven.

Table 1: Differences between existing literature and our study regarding sample size, crash surrogates, statistical models, and conclusion.

| **Ref.** | **Data set** | **Study size** | **Region** | **Statistical model** | **Crash surrogates (effect direction)** |
|---|---|---|---|---|---|
| Dingus et al. (2006) | 100-car | Drivers: 241 commuters<br>Hours driven: 43,000<br>Miles driven: ∼2M<br>Time frame: 1 year<br>Crashes: 69<br>Surrogates: 761 | Northern Virginia & Washington D.C., USA | 95% confidence limits modeled using a Poisson distribution | Braking (↑)<br>Steering (↑)<br>Accelerating (↑) |
| Guo et al. (2010) | 100-car | Drivers: 241 commuters<br>Hours driven: 43,000<br>Miles driven: ∼2M<br>Time frame: 1 year<br>Crashes: 69<br>Surrogates: 761 | Northern Virginia & Washington D.C., USA | Sequential factor analysis,<br>Poisson regression | Near crashes (↑) |
| Gordon et al. (2011) | - | Drivers: 78 commuters<br>Hours driven: NR<br>Miles driven: ∼0.08M<br>Time frame: 10 months<br>Crashes: NR<br>Surrogates: NR | Michigan, USA | Seemingly unrelated regression,<br>Poisson regression | Lateral deviation (-)<br>Lane-departure warning (↑)<br>Time to edge crossing (↑) |
| Simons-Morton et al. (2012) | - | Drivers: 42 newly licensed teenagers<br>Hours driven: NR<br>Miles driven: NR<br>Time frame: 18 months<br>Crashes: 37<br>Surrogates: NR | Virginia, USA | Logistic regression using generalized estimating equations | Elevated gravitational-force (↑) |
| Wu and Jovanis (2012) | 100-car | Drivers: 241 commuters<br>Hours driven: 43,000<br>Miles driven: ∼2M<br>Time frame: 1 year<br>Crashes: 13<br>Surrogates: 38 | Northern Virginia & Washington D.C., USA | Logistic regression | Yaw rate (-)<br>Lateral acceleration (-) |
| Guo and Fang (2013) | 100-car | Drivers: 102 young and high mileage<br>Hours driven: 43,000<br>Miles driven: ∼2M<br>Time frame: 1 year<br>Crashes: 60<br>Surrogates: 7,394 | Northern Virginia & Washington D.C., USA | Negative binomial regression | Critical-incident events (↑) |
| Wu et al. (2014) | 100-car | Drivers: 90 commuters<br>Hours driven: NR<br>Miles driven: ∼1.1M<br>Time frame: 1 year<br>Crashes: 14<br>Surrogates: 182 | Northern Virginia & Washington D.C., USA | Poisson regression | Run-off-road events (↑) |

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**Table 1 – continued from previous page**

| Ref. | Data set | Study size | Region | Statistical model | Crash surrogates (effect direction) |
|---|---|---|---|---|---|
| Pande et al. (2017) | - | Drivers: 33 commuters<br>Hours driven: NR<br>Miles driven: NR<br>Time frame: 10 days<br>Crashes: NA<br>Surrogates: NA | California, USA | Negative binomial regression | High magnitude jerks while decelerating (↑) |
| Gitelman et al. (2018) | - | Drivers: 64 commuters<br>Hours driven: NR<br>Miles driven: NR<br>Time frame: 1 year<br>Crashes: NA<br>Surrogates: NA | Israel | Negative binomial regression | Braking (↑)<br>Speed alerts (↓) |
| **This paper** | - | Drivers: 31,828 commercial truck drivers<br>Hours driven: ∼66M<br>Miles driven: ∼2.3B<br>Time frame: 1 year<br>Crashes: 34,884<br>Surrogates: 450,758 | National data, USA | Bayesian negative binomial regression | Headway (↑)<br>Hard brakes (↑)<br>Collision mitigation (↑)<br>Rolling stability (↑) |

Abbreviations: NR indicates that the parameter was not reported (or reported in combination with another parameter and hence cannot be inferred). M and B denote that the reported numbers are in millions and billions, respectively.

Although the studies we collected in Table 1 use different surrogate measures of SCEs, they reached similar conclusions that their crash surrogates had positive or zero association with crashes, except for speed alert events in Gitelman et al. (2018). Based on Table 1, there are four main gaps in the literature:

- Although two separate NDS datasets, the *Drowsy Driver Warning System Field Operation Test* and the *Naturalistic Truck Driving Study*, have been sponsored by the Federal Motor Carrier Safety Administration (Hickman et al., 2018), no studies have examined the association between crashes and surrogates using NDS data sets that specifically target commercial truck drivers. It is unclear whether the associations identified for a general driving population can hold for commercial drivers.
- The sample sizes reported in those studies are limited, with the largest studies (Dingus et al., 2006; Guo et al., 2010) examining 241 drivers. Thus, the number of reported crashes $< 100$. Note this observation only pertains to the literature examining the association between crash and SCEs since the number of reported crashes in the overarching NDS study can be larger.
- The studies investigating the association between surrogates and crashes were confined to small geographic areas, which may limit the generalizability of the conclusions to regions having different weather conditions, regulations, and commuting behavior (Tsai et al., 2015).
- The individual sample sizes in these studies were small and the surrogate measures were very different,

which made it difficult to synthesize the evidence and to reach strong conclusions.

### *1.2. Study focus, goals and contributions*

Owing to the four identified gaps in the literature, the primary objective of this paper is to investigate the association between crashes and SCEs among commercial truck drivers. This study is performed in collaboration with a leading shipping freight company in the U.S. The collaboration with an industry partner provides the following unique settings:

- At the time of data collection, the company's entire fleet utilized the Bendix® Wingman® Advanced™ monitoring system. Both the data management and system maintenance operations were performed by the company. Note that this system is also widely used by other U.S. based trucking operators.
- The truck drivers included in this study were all employed by the company at the time of data collection. The data were collected routinely as a part of their job.
- Unlike previous studies, the routes chosen by the drivers are subject to company policies, delivery windows and government regulations, i.e., naturally follow realistic commercial driving patterns.

Consequently, we can capitalize on data generated by 30,000+ trucks, which accumulate over 2 billion total miles per year. The implication of the large sample size is two-fold. First, we can overcome the sample size and driving location restrictions that can affect the inference from the previous studies. Second, the large sample size provide an opportunity for not only studying the relationship between the surrogates and crashes, but to also study the relationship between the surrogates and both injuries and fatalities.

This study investigates whether kinematic events captured from a popular, commercial sensor-based system can be used as surrogates for crash events. If such a relationship can be established, then our insights can be incorporated by other trucking companies employing (similar) systems. The sensor-based monitoring system used by the company captures four different kinematic events:

- Headway, which signals an instance of tailgating for at least 118 seconds at an unsafe gap time (a measure of distance between leading and trailing vehicles of 2.8 seconds or less (Grove et al., 2015).
- Hard brakes, which are defined as instances of deceleration rate 9.5 miles per hour per second or more.
- Activation of the rolling stability system, which intervenes by applying brake pressure (in addition to potentially applying trailer pressure) assisting the driver in aligning the vehicle when the system's critical thresholds are approached (Bendix®, 2007).
- Activation of the forward collision mitigation system.

Our goal is to explain the association between these four SCEs and trucking crashes, injuries and fatalities. To achieve this goal, we examine the following research questions:

(A) To what extent are the SCEs associated with crashes, injuries, and fatalities among commercial truck drivers?

(B) Is the association between crashes and SCEs consistent for all four different SCEs (headway alerts, hard brakes detected, collision mitigation activation, and rolling stability activation)?

(C) Does the association between crashes and SCEs hold for the different business units of our industrial partner (dedicated, intermodal, and final-mile) and driver types (local, regional, and over-the-road)?

Note that the question of what factors affect the likelihood of a crash, or predict crashes is a separate topic, (Shmueli et al., 2010) which we do not address here.

By addressing the research questions above, this paper provides three main contributions to the literature. First, the large sample size (66 million driving hours and 2.3 billion driving miles) provides the statistical power to estimate the correlation between SCEs and crashes. Second, four types of SCEs (headways, hard brakes, collision mitigation, and rolling stability) are examined in this study, and we show that the magnitude of associations between crashes and the four types of SCEs are different. Third, since most of the crashes have no human injuries or fatalities, sample sizes in previous studies are usually too small to infer an association between SCEs and severe crashes. In this data set, we are able to examine the association between injuries, fatalities, and SCEs.

## 2. Data description

The data used in this study were collected by a U.S.-based trucking company, which provides transportation, delivery, and logistics services to customers and consumers in North America. The data captures three of the logistical services provided by the company: (a) dedicated contract carriage, where trucks and drivers are assigned to a singular customer with familiar routes, task and work duties; (b) intermodal freight services, where the freight is transported in intermodal containers between shipping ports, rail terminals and inland shipping docks; and (c) final mile delivery services, where non-conveyable products are delivered to customers. It is important to note that the purposes of data collection, which covers the company's entire fleet, were routine performance monitoring, drivers' assistance and regulatory compliance. All the data were anonymized prior to the research team's access. The study protocol and data usage for research purposes were approved by the Institutional Review Board of Saint Louis University.

### *2.1. Drivers' characteristics*

The company provided a driver's characteristics table that linked age, gender, business unit and driver type to the anonymized driver ID. Driver types include (a) local drivers who transport freight within a 200-mile radius and return home on the same day, (b) regional drivers moving freights in regional routes that may include several surrounding states, and (c) over-the-road drivers who specialize in hauling freight long distances, requiring them on the road for days/weeks.

The original dataset provided by the company included 34,348 drivers. We have excluded 2,520 drivers (i.e., 7.4% of the original dataset) from our analysis based on the following criteria: (a) driver inactivity, where we required the driver to have at least 100 GPS pings in the data to be included; (b) the unique identification code for the driver is not found in the provided demographics table; and/or (c) the number of SCEs reported were identified as obvious outliers (we only removed drivers who had an unrealistically large number of SCEs). Hereafter, all reported data will correspond to only those generated by the remaining 31,828 drivers, whose characteristics are summarized in Table 2.

Table 2: A summary of driver characteristics including their average age ± SD, number of drivers per gender, business unit and driver types (with their % in parentheses).

| Variable | Statistics |
|---|---|
| Age: | |
| Range | 20 to 82 years |
| Mean age ± SD | 44.48 ± 11.72 |
| Gender: (%) | |
| Male | 29,248 (91.9%) |
| Female | 1,583 ( 5.0%) |
| Unknown | 997 ( 3.1%) |
| Business unit: (%) | |
| Dedicated | 16,152 (50.7%) |
| Final-mile | 5,908 (18.6%) |
| Intermodal | 9,768 (30.7%) |
| Driver type: (%) | |
| Local | 13,381 (42.0%) |
| Regional | 15,707 (49.3%) |
| Over-the-road | 2,740 ( 8.6%) |

### *2.2. Data acquired from the sensor-based monitoring system*

#### *2.2.1. Ping data*

Our study is based on data captured from April 1, 2015 to March 31, 2016 by the company's sensor-based monitoring system on their entire fleet. Our dataset includes intermittently collected real-time driving *ping* records, which ranges between every couple of seconds to approximately 15 minutes. Over 50% of the time intervals between two pings were less than 5 minutes and over 95% of them were less than 15 minutes. The time intervals varied among drivers, places, and trips, and there were no clear patterns explaining the variations in interval lengths. Each ping is a data point that includes the exact date and time of the record (year, month, day, hour, minute, and second), GPS (latitudes and longitudes with five decimal place recordings), GPS quality, speed, and drivers' anonymized unique identification code.

We must emphasize that these data were collected as part of the company's ongoing monitoring and surveillance plan. The data were not collected specifically as part of a planned NDS. Only afterward was thought given to using the data to assess road safety. That said, the data are still measurements on factors that could affect safety and are therefore still valid for the purpose of answering the questions we pose in

Section 1.2. Since we were not involved in the design stage, we had to accept the decisions made regarding the data collection plan.

The included 31,828 commercial truck drivers had a total of $1,494,678,173$ pings. Based on the GPS quality indicator, 98.7% of these pings were "good quality". An overview of the pings' locations is shown in Figure 1, where the active (speed $> 0$ MPH) and inactive (speed $= 0$ MPH) pings are depicted in Figures 1a and 1b, respectively. Note that the plot was created by aggregating the GPS locations to two decimal places in order to ensure the anonymity of the data, and only displaying locations with at least fifty pings. Both Figures 1a and 1b utilize a sequential color scheme, where a darker color indicates a higher number of pings. The background grey lines are the major roads in the United States (United States Geological Survey, 2014) and the solid black lines are state boundaries. The geographical point patterns suggest that most of the trucking transportation closely matches the U.S. population density distribution (i.e., it is more concentrated along the coasts). The active and inactive pings are generally consistent, but active pings are more concentrated in major midwest roads.

### *2.2.2. Safety critical events*

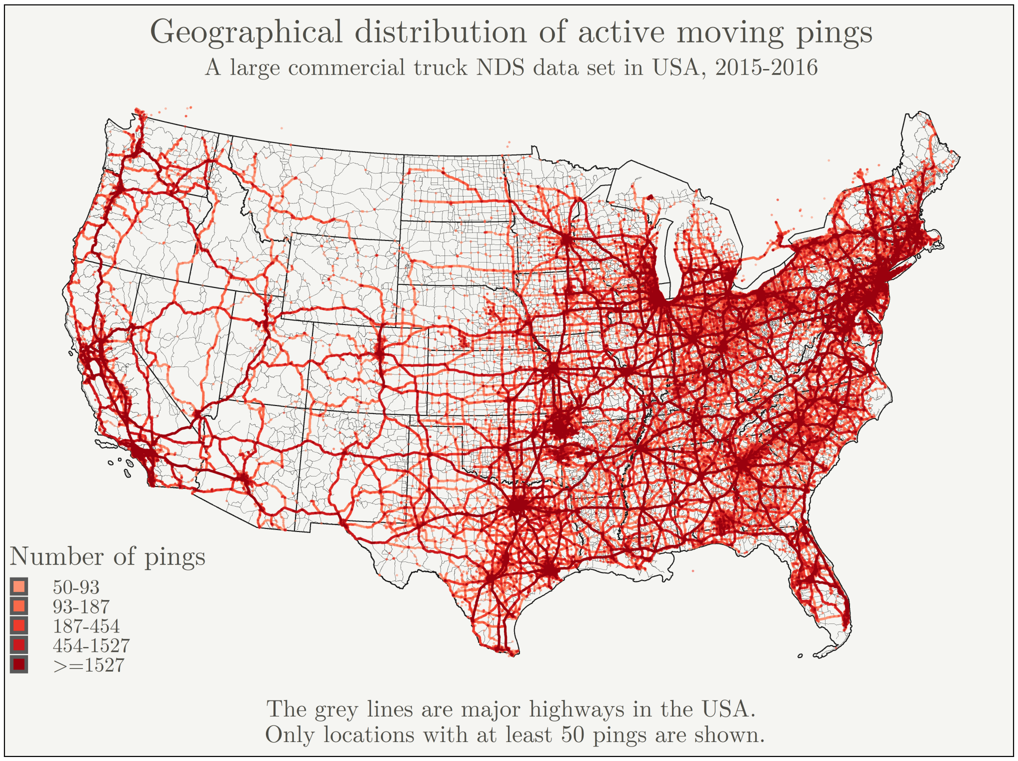
The SCEs were collected independently from the ping data. A SCE is recorded whenever a pre-specified kinematic threshold, defined in Section 1.2, of the Bendix® Wingman® Advanced™ monitoring system was triggered while driving. The collected SCE data include the exact date and time, latitude and longitude (specific to five decimal places), driver, and the type of SCEs. A total of $450,758$ SCEs were collected, which were divided into (a) $170,421$ headway events, (b) $218,419$ hard brakes, (c) $55,243$ initiations of the forward-collision mitigation system, and (d) $6,675$ initiations of the rolling stability system.

## *2.3. Crashes*

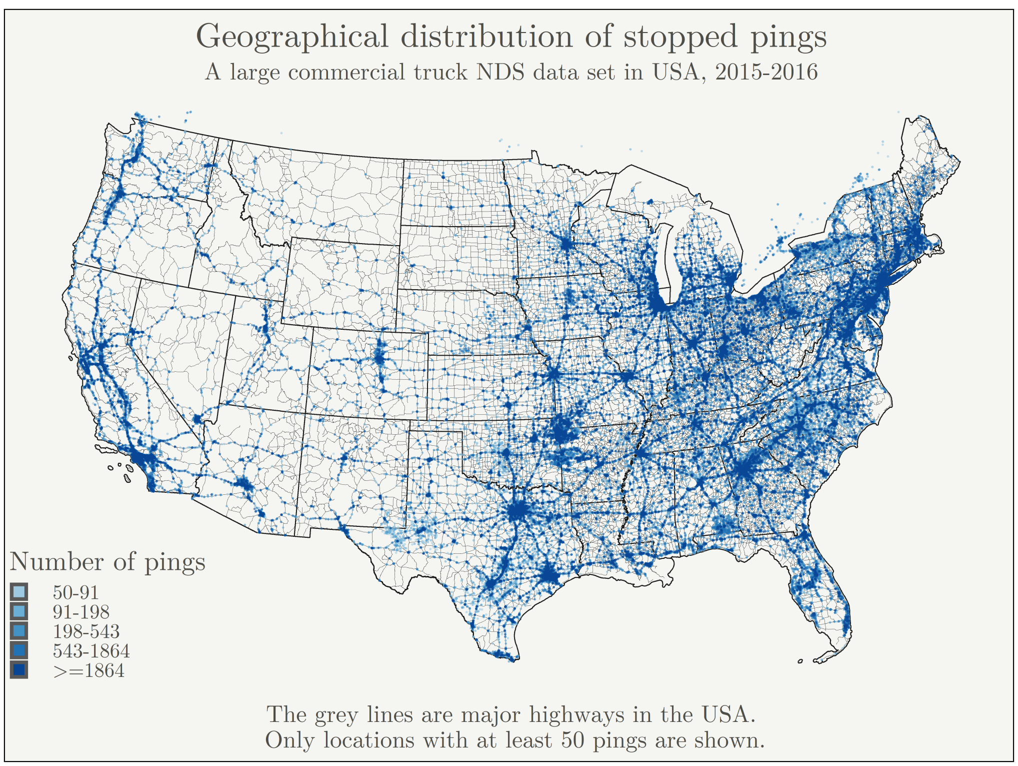
In addition to the sensor-based data, the trucking company provided a crash dataset, which included the anonymized driver ID, state, city, report time, the number fatalities, and the number of injuries. Every row in this dataset corresponded to a unique crash. In total, the 31,828 drivers included in this study were involved in 34,884 crashes, 239 injuries, and 22 fatalities.

## *2.4. Data aggregation*

To draw inferences from the ping data, it should be aggregated to provide insights about trips, routes, and/or any other unit of analysis of interest. In this study, we aggregated the ping data into trips based on the approach of Pande et al. (2017). Specifically, we define a trip as a continuous period of driving, which can contain sub-periods of stopping as long the length of any period is under 30 minutes. In our analysis, we sorted the original ping by driver using the observed timestamp for each driver. Then, if the ping speed




(a) Active pings captured from the 31,828 truck drivers from April 1, 2015 to March 31, 2016.




(b) Inactive pings captured from the 31,828 truck drivers from April 1, 2015 to March 31, 2016.

Figure 1: Geographical point patterns of active and inactive pings in a large commercial NDS data set.

data showed that the truck was not moving (the speed of the ping equals zero) for more than 30 minutes, the ping data were separated into two different trips.

The aggregation of pings into trips is demonstrated in Figure 2, where the $x$-axis shows the date and time of pings, and the $y$-axis captures the speed (in miles per hour, MPH). Each point represented a ping at that date and time, with different colors indicating the real-time speed category. Whenever the truck stopped (the grey points) for at least 30 minutes, the pings were separated into different trips, indicated by the purple arrows in the bottom (Trip 1, Trip 2, ..., Trip 6). The trip time was then calculated by taking the difference between the trip end time and start time.

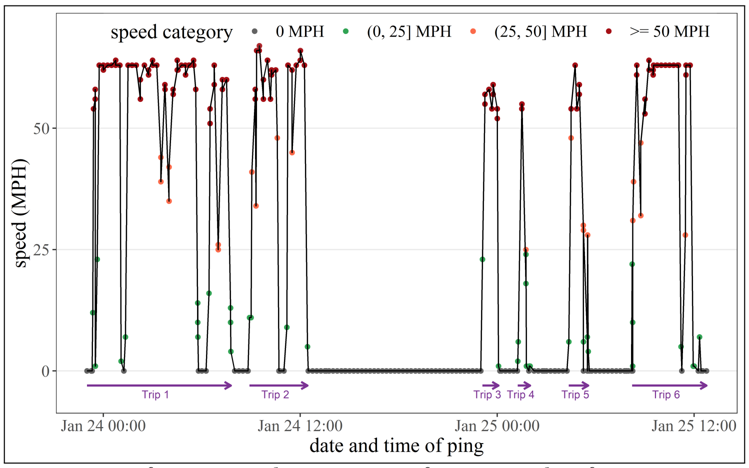



Figure 2: Data aggregation from ping data to trips for a sample of a commercial NDS data set.

The traveled distance within a trip was computed using a three sequential-step procedure. First, we sorted the ping data by driver, date, and time. Then, in step 2, we computed the distance between each two nearest ping locations for each driver using the haversine method (Sinnott, 1984), which assumes a spherical earth and ignores all ellipsoidal effects. Although this haversine method does not reflect the true distance since it calculates the shortest distance between two points, it is the most feasible algorithm we could use for this huge data set. The third step involved summing up all the distances traveled within a trip for each driver. This procedure aggregated the original ping data into $18,740,142$ trips, with a total of $2,320,967,467$ miles traveled in $65,646,731$ hours. The total number of miles recorded is consistent with the estimates provided by the company pertaining to their total annual incurred miles. Furthermore, the median trip time was 2.61 hours and the median number of miles per trip was 77.06 miles. A summary of the total number of events described in Sections 2.1-2.4 is provided in Table 3.

## 3. Methodology

### *3.1. Data preparation for statistical modeling*

With the modeling objectives in mind, we can categorize the data from Section 2 into three statistical categories. First, our outcome/response variables capture the number of (a) crashes, (b) injuries, and (c)

Table 3: A summary of the trucking data that is analyzed in this study.

| Pings | | Trips | | SCEs | | Crashes | |
|---|---|---|---|---|---|---|---|
| Total pings | 1,494,678,173 | Total trips | 18,740,142 | Total SCEs | 450,758 | Crashes | 34,884 |
| Drivers | 31,828 | Total miles | 2,320,967,467 | Headway | 170,421 | Injuries | 239 |
| | | Total hours | 65,646,731 | Hard brakes | 218,419 | Fatalities | 22 |
| | | Median miles | 77.06 | Collision mitigation | 55,243 | | |
| | | Median hours | 2.61 | Rolling stability | 6,675 | | |

fatalities reported for a given driver. Thus, the outcome variables capture data that is aggregated/added over the 1-year period of data collection. Note that we hypothesize that these three outcome variables should be positively correlated with the total miles driven, and hence we also record the total miles driven by each driver. The second category includes our primary predictor variables of interest, where the rate of SCE per 10,000 miles is computed for each SCE, i.e., four rates are computed for each driver capturing headway, hard brakes, rolling stability and forward collision mitigation events. We also compute a pooled SCE rate per 10,000 miles for each driver, representing the aggregation of the four SCEs (i.e. the rate if any of the four SCEs were observed). Note that all five SCE predictor variables are also based on the driver's total driving activity over the course of the data collection period. The third, and final category, captures the following driver-specific covariates: (a) age, (b) gender, (c) mean ping speed, (d) business unit, and (e) driver type. With the exception of the computed mean ping speed, the other four covariates are obtained using the company provided demographics table. A summary of the computed variables is provided in Table 4. Note that the distribution of the other covariates was provided in Table 2.

Table 4: A summary of the computed response, predictor variables and covariate.

| Variable | Mean ± SD |
|---|---|
| Number of crashes per driver | 1.10 ± 1.69 |
| Headways per driver per 10,000 miles | 5.35 ± 27.01 |
| Hard brakes per driver per 10,000 miles | 6.86 ± 22.75 |
| Rolling stability initiations per driver per 10,000 miles | 0.21 ± 1.20 |
| Collision mitigation initiations per driver per 10,000 miles | 1.74 ± 4.66 |
| Ping speed per driver | 29.85 ± 7.23 |

The final step in preparing the data for modeling was to examine whether the number of predictors and/or covariates can be reduced based on a correlation analysis. Note that the variables included both continuous (primary predictors, age and mean ping speed) and polytomous (gender, business unit, and driver type) variables. To account for the mixed variable types, we adopted the approach of Revelle et al. (2010, 2016) to compute the Pearson, polychoric and polyserial correlation coefficients for the pairwise evaluation of continuous, polytomous and mixed variables, respectively. We present the results in Figure 3.

Based on Figure 3, there are two observations to be highlighted. First, the Pearson correlation coefficient values between any two rates of SCEs were small ($< 0.2$). Second, none of the correlation coefficients exceeded 0.6 in magnitude. Accordingly, we concluded that the resulting statistical models will not have

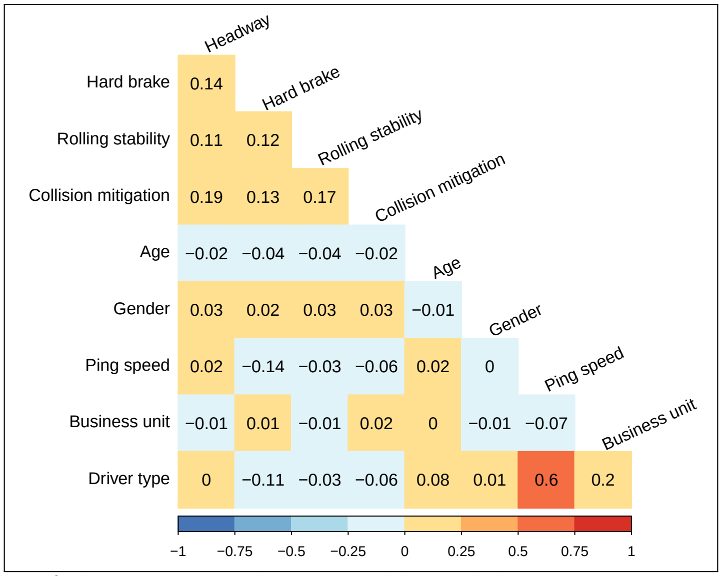



Figure 3: A correlation plot of the primary predictor variables and the covariates. Note that multiple correlation coefficients were used to account for the mixed (i.e., categorical and numeric) nature of the variables. The top four variables are the SCEs and the others are the predictor variables.

any serious multicollinearity issues (which will be examined in greater detail during the model assessment stage).

*3.2. Modeling strategy and its relation to the examined research questions*

When making our modeling strategy, we considered two factors choosing an appropriate distribution for the outcome variable, and Bayesian vs. frequentist estimation. Our outcome (number of crashes, injuries, or fatalities) is a strictly non-negative integer. In the literature, Poisson regression or negative binomial models have been commonly applied for this type of outcome variable (e.g., see Table 1). Compared to Poisson regression models that by nature assumes the outcome distribution has equal mean and variance, negative binomial models can adjust for the variance independently from its mean, which allows for handling potential overdispersion or underdispersion issues in the data (Lord and Mannering, 2010). For the second factor, we adopted the Bayesian estimation approach since it provides more flexibility in specifying statistical models when compared to traditional maximum likelihood estimation methods (Dunson, 2001). Furthermore, in the case of rare-events, even relatively flat priors can increase the precision of parameter estimation.

Using the Bayesian negative binomial models, we can investigate the three research questions introduced in Section 1.2. It is important to note that such an investigation requires analyses based on different samples, outcome variables, and primary predictors. Table 5 shows the different combinations of samples and models.

Table 5: An overview of how the data is sampled and modeled to examine the three research questions.

| **Research question** | **Samples** | **Model** |
|---|---|---|
| **Question 1**: Are SCEs associated with crashes, injuries, and fatalities? | All data | # Crashes = $f$(Pooled SCE rate and all covariates)<br># Crashes = $f$(Individual rate for each of the 4 SCEs and all covariates)<br># Injuries = $f$(Pooled SCE rate and all covariates)<br># Injuries = $f$(Individual rate for each of the 4 SCEs and all covariates)<br># Fatalities = $f$(Pooled SCE rate and all covariates)<br># Fatalities = $f$(Individual rate for each of the 4 SCEs and all covariates) |
| **Question 2**: Is the association between crashes and SCEs consistent for all four different SCEs? | All data | # Crashes = $f$(Headway rate and all covariates)<br># Crashes = $f$(Hard brake rate and all covariates)<br># Crashes = $f$(Rolling stability initiation rate and all covariates)<br># Crashes = $f$(Collision mitigation rate and all covariates) |
| **Question 3**: Does the association between crashes and SCEs hold for the different business units and driver types? | Stratified sampling by:<br>Dedicated ∩ Local<br>Dedicated ∩ Regional<br>Dedicated ∩ Over-the-Road<br>Intermodal ∩ Local<br>Intermodal ∩ Regional<br>Final Mile ∩ Regional<br>Final Mile ∩ Over-the-Road | # Crashes = $f$(Individual rate for each of the 4 SCEs, mean speed, age and gender).<br>Note that the model above is applied to each individual stratified sample. |

### *3.3. Statistical models*

#### *3.3.1. Model specification*

Let $Y_i$ denote an outcome variable (i.e., the number of crashes, injuries or fatalities) over a distance of $T_i$ miles for the $i$th driver. Each of the three outcomes were modeled in different Bayesian negative binomial models. We assume that $Y_i$ has a negative binomial distribution with the mean parameter $\mu_i$ and a common auxiliary parameter $\phi$. The corresponding probability mass function of $Y_i$ is parameterized as

$$P(y_i|\mu, \phi) = \binom{y_i + \phi - 1}{y_i} \left(\frac{\mu}{\mu + \phi}\right)^{y_i} \left(\frac{\phi}{\mu + \phi}\right)^{\phi}, \qquad y_i = 0, 1, 2, \ldots. \tag{1}$$

The mean and variance of $Y_i$ are $E[Y_i] = \mu$ and $V(Y_i) = \mu + \frac{\mu^2}{\phi}$. The inverse of $\phi$ controls the overdispersion, which is scaled by $\mu^2$. By assuming that the number of SCEs per 10,000 miles has a multiplicative effect on the logarithm of rate of crashes $\mu_i$, we have the following log-linear Bayesian negative binomial regression:

$$\begin{aligned} Y_i &\sim \text{Negative Binomial}(T_i \times \mu_i,\ \phi) \\ \log \mu_i &= \alpha_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_J x_{iJ} + \theta_1 z_{i1} + \cdots + \theta_K z_{iK}, \end{aligned} \tag{2}$$

where the total miles driven $T_i$ is considered as an offset variable to account for the mileage difference among drivers. $\alpha_0$ is the intercept. $\beta_j,\ j = 1, 2, \ldots, J$ is the coefficient of the $j$-th primary predictor $x_{ij}$. $J = 1$ for pooled SCE rate models ($x_{i1}$ represents the rate of any SCE) and one SCE rate at a time models ($x_{i1}$ represents the rate of headway, hard brakes, rolling stability, or collision mitigation, with only one of them used at a time). Note that the values of $J$ and $K$ depend on the application of the models as shown in Table 5. Specifically, $J = 4$ for four SCEs models ($x_{i1}, x_{i2}, x_{i3}, x_{i4}$ represent the rate of headway, hard brakes, rolling stability, and collision mitigation, respectively, with all four variables used in the same model at a time). $\theta_k$, $k = 1, 2, \ldots, K$ is the coefficient of the $k$-th covariate $z_{ik}$. $K = 4$ (age, mean speed, gender) for models stratified by business units and driver types, while $K = 8$ (age, mean speed, gender, business unit, and driver types) for non-stratified models. Gender, business units, and driver types were coded using one-hot encoding: (a) gender included female (reference group), male, and unknown; (b) business units included dedicated (reference group), intermodal, and final-mile; and (c) driver types included local (reference group), regional, and over-the-road. We took relatively noninformative priors for $\beta_k$ and $\phi$. Specifically, we assumed $\alpha_0,\ \beta_1, \ldots, \beta_J,\ \theta_1, \ldots, \theta_K \sim \text{Normal}(0, 10^2)$ and $\phi \sim \text{Exponential}(1)$.

*3.3.2. Bayesian estimation and parameter interpretation*

We applied the Hamiltonian Monte Carlo procedure to estimate the posterior distributions of all parameters. Compared to its two predecessor Markov chain Monte Carlo samplers, the Metropolis-Hastings algorithm and Gibbs sampling, Hamiltonian Monte Carlo is much more efficient in making valid proposal samples, and there is a well-developed statistical package to achieve this algorithm (McElreath, 2020). To make sure the Hamiltonian Monte Carlo converged to the true posterior distributions, we set 4,000 iterations for each of the four chains, with the first 2,000 being warm-up iterations. The Markov chains were considered as converged when the Gelman-Rubin diagnostic $\hat{R}$ was less than 1.1 for each variable (Gelman et al., 1992).

In the Bayesian setting, parameters are considered as random variables that have probabilistic distributions instead of unknown fixed values, so no p-values are reported here. The posterior mean and 95% credible intervals (CIs) of the incidence rate ratios ($\exp(\beta)$) were reported. The interpretation of the incidence rate ratios in this Bayesian negative binomial model is this: as the number of SCEs per 10,000 miles increases by one unit, the number of crashes per mile will be multiplied by $\exp(\beta)$. A 95% credible interval is the posterior probability that the parameter of interest falls into that range given the data is 95% (McElreath, 2020). If the 95% CI of the incidence rate ratio includes one, then one is a plausible value for the true incidence rate ratio and such the parameter of the variable will be deemed statistically insignificant; otherwise, the parameter will be considered as statistically significant.

*3.3.3. Model validation and assessment*

Since four different SCEs and/or multiple covariates were included in the models at the same time, it is important to check for the presence of multicollinearity. Recall that in Section 3.1, we examined the correlations among pairs of predictors and found that the pairwise correlations are small. Here, we attempt to investigate whether a linear dependence exist among three or more of our variables through computing the variance inflation factors (VIFs). If the regressors are uncorrelated, VIF obtains its minimum value of 1. In statistical practice, a VIF less than 4 requires no additional investigation of linear dependence among the regressors and values greater than 10 indicate serious multicolinearity requiring model corrections.

We used Pareto smoothed importance-sampling leave-one-out (PSIS-LOO) cross-validation to check the goodness-of-fit of and compare different models (Vehtari et al., 2015, 2017). Instead of exact cross-validation that refits the model with different subsamples, the PSIS-LOO uses fast, efficient, and stable importance sampling weights to approximate leave-one-out cross-validation (Gelfand et al., 1992; Gilks et al., 1996). It estimates the expected log predicted density (ELPD), estimate number of parameters, and the LOO Information Criterion (LOOIC) for a new data set. Compared with other statistics such as Widely Applicable Information Criterion, Deviance information criterion, and other variants (Spiegelhalter et al., 2002; Watanabe, 2010), PSIS-LOO is both fast and stable in computing. Apart from PSIS-LOO, we also used posterior predictive checks to examine the prediction accuracy (Gelman et al., 2013, Chapter 6). The interpretation of these goodness-of-fit and model comparison statistics will be explained in Section 4.

### *3.4. Statistical software used*

All data cleaning, statistical modeling, and visualization were performed in the statistical computing environment **R** 3.6.0 (R Core Team, 2019). The haversine method distance was computed using the `distHaversine()` function in `geosphere` package (Hijmans, 2019). The Bayesian negative binomial model was conducted using the `stan_glm()` function in `rstanarm` package (Goodrich et al., 2018). The PSIS-LOO statistics were computed using the `loo()` function in `loo` package (Vehtari et al., 2019). To facilitate the adoption of our methodology, we provide a link of a compiled **R** Markdown file, containing the code for data aggregation and model building, and their associated results, in the supplementary materials section.

## 4. Results

### *4.1. The association of SCEs with crashes, injuries, and fatalities among commercial truck drivers*

Table 6 presents the Bayesian negative binomial models' results explaining the variation in number of crashes, injuries, and fatalities separately using either a pooled SCE predictor (i.e., four SCEs as one variable), or four SCE predictors (i.e., the four SCEs represented using four variables). In column 2, we present the results for explaining the differences in the number of crashes accumulated by each driver as a function of pooling the counts of SCEs, while accounting for differences in the observed covariates and differences in total miles driven. The coefficient of the "all SCEs" predictor in the second column suggests that a unit increase in the number of any type of SCEs per 10,000 miles was associated with an 8.4% (95% CI: 8.0-8.8%) increase in the rate of crashes. When broken down by the four different SCEs in the third column, one can note the following: (a) the coefficients of all four predictors and their 95% CI are larger than 1, indicating (similar to the pooled model) that an increase in any of the four SCEs is associated with an increase in the number of crashes; (b) a unit increase in the number of instances of rolling stability system initiation was associated with the largest, 50.4% (95% CI: 41.4-60.0%), in the number of crashes per mile; and (c) when holding other SCEs constant, a unit increase in either the initiation of the rolling stability or collision mitigation systems has larger effects when compared to increases in hard brakes or headyway alerts. An implication from observation (c) is that the effect of driver-less maneuvers are larger than alerts and actions where the driver may be involved. Conceptually, this is an intuitive result since these maneuvers can be categorized as more "aggressive last-minute" interventions that attempt to mitigate a crash by overriding the driver's control. The coefficients of the covariates suggested that older drivers, higher average speed, male, as well as final-mile and intermodal (compared to dedicated) drivers, were associated with lower rate of crashes.

Compared with the models for crashes, the results for injuries and fatalities (columns 4-7) tend to be less conclusive since the number of recorded injuries and fatalities are much smaller. In the injuries-pooled model (column 4), a unit increase in the number of any type of SCEs per 10,000 miles was associated with 8.7% (95% CI: 4.8%-13.6%) increase in the number of injuries per mile. When stratified into four different types of SCEs, all 95% CIs of incidence rate ratios included one, which indicated weak (statistically insignificant) evidence for modeling injuries or fatalities, although the posterior means were positive. In the two models using the number of fatalities as the outcome variable (columns 6 and 7), all 95% CIs of incidence rate ratios included one and the CIs were very wide, which suggested that the observed sample size was not sufficient to yield statistically significant results.

*4.2. The consistency of the association between crashes and the four different SCEs*

Table 7 shows the estimates of posterior incidence rate ratios and their CIs in the Bayesian negative binomial models for all the included drivers. Note that we include both the pooled and four SCE models from Table 6 to facilitate the comparison with the four different models corresponding to when each of the headways, hard brakes, rolling stability or collision mitigation predictors were included. From the presented results, similar conclusions can be made to the insights gained from examining the pooled and four SCE models. Specifically, the coefficients of each of the main predictors were larger than one (with the associated 95% credible interval excluding one), providing statistically strong evidence that the rates of the individual SCEs were positively associated with the rates of crashes. Furthermore, the rolling stability coefficient is the largest, followed by the crash mitigation coefficient, confirming that an increase in more aggressive interventions results in more crashes.

Table 6: Bayesian negative binomial regressions with the rate of SCEs predicting crashes, injuries, and fatalities

| Variables | Crashes: pooled | Crashes: four SCEs | Injuries: pooled | Injuries: four SCEs | Fatalities: pooled | Fatalities: four SCEs |
|---|---|---|---|---|---|---|
| Intercept | 0.054<br>(0.047, 0.062) | 0.048<br>(0.042, 0.054) | 0.013<br>(0.002, 0.070) | 0.012<br>(0.002, 0.064) | 0.008<br>(0.000, 1.855) | 0.011<br>(0.000, 5.179) |
| All SCEs | 1.084<br>(1.080, 1.088) | | 1.087<br>(1.048, 1.136) | | 0.973<br>(0.791, 1.149) | |
| Headways | | 1.033<br>(1.026, 1.040) | | 1.061<br>(0.961, 1.181) | | 0.955<br>(0.592, 1.478) |
| Hard brakes | | 1.081<br>(1.075, 1.087) | | 1.080<br>(0.995, 1.177) | | 0.957<br>(0.652, 1.387) |
| Rolling stability | | 1.504<br>(1.414, 1.600) | | 1.773<br>(0.684, 5.439) | | 1.631<br>(0.043, 102.8) |
| Collision mitigation | | 1.222<br>(1.198, 1.245) | | 1.174<br>(0.987, 1.535) | | 0.866<br>(0.200, 3.632) |
| Age | 0.992<br>(0.990, 0.993) | 0.992<br>(0.991, 0.993) | 0.987<br>(0.970, 1.004) | 0.986<br>(0.969, 1.004) | 0.966<br>(0.912, 1.020) | 0.965<br>(0.906, 1.030) |
| Mean speed | 0.979<br>(0.976, 0.982) | 0.982<br>(0.979, 0.985) | 0.967<br>(0.929, 1.007) | 0.970<br>(0.931, 1.009) | 0.915<br>(0.797, 1.049) | 0.910<br>(0.778, 1.050) |
| Gender: male | 0.817<br>(0.756, 0.886) | 0.808<br>(0.754, 0.867) | 0.825<br>(0.301, 2.149) | 0.800<br>(0.298, 2.176) | 1.770<br>(0.074, 54.444) | 1.953<br>(0.062, 80.045) |
| Gender: unknown | 0.975<br>(0.785, 1.199) | 0.954<br>(0.777, 1.149) | 1.022<br>(0.094, 8.499) | 0.993<br>(0.092, 9.338) | 0.093<br>(0, 76.2) | 0.093<br>(0, 115.6) |
| Business unit: Inter-modal | 0.698<br>(0.670, 0.727) | 0.717<br>(0.690, 0.745) | 0.459<br>(0.265, 0.788) | 0.467<br>(0.280, 0.789) | 0.354<br>(0.068, 1.573) | 0.341<br>(0.044, 2.057) |
| Business unit: Final-mile | 0.907<br>(0.861, 0.954) | 0.897<br>(0.852, 0.943) | 0.710<br>(0.352, 1.420) | 0.675<br>(0.330, 1.321) | 1.576<br>(0.209, 10.438) | 1.536<br>(0.140, 13.475) |
| Type: Over-the-road | 1.071<br>(0.994, 1.151) | 1.094<br>(1.022, 1.174) | 0.785<br>(0.321, 1.942) | 0.801<br>(0.306, 1.955) | 0.410<br>(0.022, 5.402) | 0.388<br>(0.014, 6.205) |
| Type: Regional | 1.003<br>(0.957, 1.045) | 1.012<br>(0.969, 1.057) | 0.472<br>(0.265, 0.821) | 0.463<br>(0.263, 0.820) | 0.389<br>(0.064, 1.970) | 0.379<br>(0.050, 2.214) |
| **Fit statistics:** | | | | | | |
| sample size | 31828 | 31828 | 31828 | 31828 | 31828 | 31828 |
| elpd_loo | -39985.2<br>(236.5) | -39770.2<br>(233.5) | -1134.5<br>(80.8) | -1137.3<br>(81.1) | -182.4<br>(37.9) | -182.4<br>(37.9) |
| p_loo | 18.1<br>(1.1) | 30<br>(2.4) | 13.9<br>(3.6) | 16.4<br>(4) | 11.3<br>(3.2) | 11.3<br>(3.2) |
| looic | 79970.4<br>(472.9) | 79540.5<br>(467.1) | 2269.1<br>(161.5) | 2274.6<br>(162.1) | 364.7<br>(75.7) | 364.7<br>(75.7) |

**Notes:**
The SCEs were measured as the number of events per 10,000 miles driven.
Incidence rate ratios and their associated 95% credible intervals are reported for all variables (predictors and covariates).
For the fit statistics, (.) indicates the standard error of the computed statistic.

Table 7: Bayesian negative binomial regressions predicting crashes with different combination of SCEs

| Variables | Pooled model | Four SCEs | Headways | Hard brakes | Rolling stability | Collision mitigation |
|---|---|---|---|---|---|---|
| Intercept | 0.054 (0.047, 0.062) | 0.048 (0.042, 0.054) | 0.090 (0.079, 0.103) | 0.057 (0.050, 0.066) | 0.082 (0.072, 0.093) | 0.073 (0.064, 0.083) |
| All SCEs | 1.084 (1.080, 1.088) | | | | | |
| Headways | | 1.033 (1.026, 1.040) | 1.077 (1.069, 1.085) | | | |
| Hard brakes | | 1.081 (1.075, 1.087) | | 1.109 (1.102, 1.116) | | |
| Rolling stability | | 1.504 (1.414, 1.600) | | | 2.147 (2.015, 2.295) | |
| Collision mitigation | | 1.222 (1.198, 1.245) | | | | 1.343 (1.316, 1.369) |
| Age | 0.992 (0.990, 0.993) | 0.992 (0.991, 0.993) | 0.989 (0.988, 0.990) | 0.991 (0.989, 0.992) | 0.989 (0.988, 0.991) | 0.990 (0.988, 0.991) |
| Mean speed | 0.979 (0.976, 0.982) | 0.982 (0.979, 0.985) | 0.971 (0.968, 0.973) | 0.980 (0.977, 0.983) | 0.973 (0.970, 0.976) | 0.975 (0.973, 0.978) |
| Gender: male | 0.817 (0.756, 0.886) | 0.808 (0.754, 0.867) | 0.848 (0.785, 0.919) | 0.823 (0.762, 0.887) | 0.845 (0.787, 0.909) | 0.826 (0.770, 0.891) |
| Gender: unknown | 0.975 (0.785, 1.199) | 0.954 (0.777, 1.149) | 1.097 (0.896, 1.347) | 1.096 (0.884, 1.349) | 1.018 (0.842, 1.239) | 1.058 (0.870, 1.299) |
| Business unit: Inter-modal | 0.698 (0.670, 0.727) | 0.717 (0.690, 0.745) | 0.706 (0.679, 0.735) | 0.701 (0.672, 0.730) | 0.735 (0.706, 0.765) | 0.729 (0.700, 0.758) |
| Business unit: Final-mile | 0.907 (0.861, 0.954) | 0.897 (0.852, 0.943) | 0.925 (0.882, 0.971) | 0.904 (0.865, 0.948) | 0.922 (0.880, 0.967) | 0.901 (0.859, 0.942) |
| Type: Over-the-road | 1.071 (0.994, 1.151) | 1.094 (1.022, 1.174) | 1.053 (0.981, 1.131) | 1.064 (0.994, 1.140) | 1.067 (0.990, 1.144) | 1.106 (1.030, 1.182) |
| Type: Regional | 1.003 (0.957, 1.045) | 1.012 (0.969, 1.057) | 0.971 (0.928, 1.015) | 0.994 (0.950, 1.037) | 0.973 (0.932, 1.016) | 0.984 (0.943, 1.028) |
| **Fit statistics:** | | | | | | |
| sample size | 31828 | 31828 | 31828 | 31828 | 31828 | 31828 |
| elpd_loo | -39985.2 (236.5) | -39770.2 (233.5) | -40792.7 (238.9) | -40315.5 (237.2) | -40710.1 (237.8) | -40503.2 (239.4) |
| p_loo | 18.1 (1.1) | 30 (2.4) | 19.8 (1.9) | 18.2 (1.2) | 15.9 (0.8) | 16.1 (1) |
| looic | 79970.4 (472.9) | 79540.5 (467.1) | 81585.4 (477.8) | 80631 (474.5) | 81420.1 (475.7) | 81006.5 (478.7) |

**Notes:**
The SCEs were measured as the number of events per 10,000 miles driven.
Incidence rate ratios and their associated 95% credible intervals are reported for all variables (predictors and covariates).
For the fit statistics, (.) indicates the standard error of the computed statistic.

### 4.3. The influence of business units and driver types on the association between crashes and SCEs

Since the driving behaviors and routing patterns vary significantly among different business units and driver types, we also conducted Bayesian negative binomial models (four SCEs) for drivers in different business units and types, and the results are shown below in Table 8. The posterior incidence rate ratios and CIs of four SCEs are consistent with those in Table 6. All four type of SCEs were positively associated with the number of crashes per mile. None of the CIs included one except for headways in the dedicated and over-the-road unit. These stratified results indicate strong evidence that SCEs were positively associated with crashes in different business units and driver types. Among the four types of SCEs, rolling stability had the highest incidence rate ratios, followed by collision mitigation, hard brake, and headway.

### 4.4. Diagnostic statistics and model selection

We computed the variance inflation factors described in Section 3.3.3 to test for multicollinearity. Table 9 captures the results for all the negative binomial models where individual predictors are used for each of the SCEs. The results capture all three investigated outcomes (crashes, fatalities and injuries) as well as the stratification of the drivers' data set by business unit and driver type. From the table, all $VIFs \leq 1.3$. Hence, we can conclude that the variation of each of the regression coefficients are not inflated and that there is no evidence of any multicollinearity issues.

All the models and truck drivers have Pareto $k$ diagnostic statistics of less than 0.7 (not shown in the tables), which suggests no signal for model misspecification (Vehtari et al., 2015, 2017). The estimated effective number of parameters (`p_loo` in Tables 6, 7, 8), were similar to the total number of parameters in the models. These two results suggest that the negative binomial models were reasonably specified models given the large number of observations in this study (Vehtari et al., 2017, 2015). The LOOIC in the tables can be used to compare different models, with lower values indicating better models. For example, in Table 7, the "Four SCEs" model has the lowest LOOIC (79,540.5) among the six models. However, the standard errors of the LOOIC statistic (in the bracket) suggest that the model with all four SCEs was not significantly better than the pooled model.

To investigate the models' predictive accuracy, we adopt the approach of Gelman et al. (2013, Section 6.3) who suggested simulating some function of the data and parameter, and comparing it with the observed value of a particular quantity. For our trucking safety application, we examined the proportion of zero crashes since it corresponds to a crash-free trip, which is of interest to truck drivers and operators alike. The probability of having zero crashes is, of course, an unknown quantity, but its posterior distribution can be estimated by simulating samples using Hamiltonian Monte Carlo. In this section, we limit our analysis to the models whose outcomes were crashes since the accident and fatality models indicated that

Table 8: Bayesian negative binomial regressions with SCEs predicting crashes, stratified by business units and driver types

| variables | Dedicated Local | Dedicated Over-the-road | Dedicated Regional | Inter-modal Local | Inter-modal Regional | Final-mile Over-the-road | Final-mile Regional |
|---|---|---|---|---|---|---|---|
| Intercept | 0.055 (0.040, 0.076) | 0.015 (0.008, 0.027) | 0.062 (0.046, 0.084) | 0.026 (0.020, 0.033) | 0.021 (0.013, 0.033) | 0.047 (0.021, 0.102) | 0.033 (0.022, 0.049) |
| Headways | 1.026 (1.011, 1.042) | 1.001 (0.993, 1.010) | 1.048 (1.032, 1.067) | 1.026 (1.012, 1.042) | 1.060 (1.038, 1.082) | 1.082 (1.020, 1.149) | 1.050 (1.031, 1.068) |
| Hard brakes | 1.069 (1.057, 1.080) | 1.241 (1.194, 1.293) | 1.163 (1.140, 1.188) | 1.047 (1.040, 1.054) | 1.114 (1.093, 1.138) | 1.086 (1.049, 1.131) | 1.183 (1.154, 1.211) |
| Rolling stability | 1.528 (1.367, 1.733) | 1.648 (1.269, 2.229) | 1.676 (1.467, 1.951) | 1.419 (1.284, 1.578) | 2.477 (1.590, 3.717) | 4.320 (2.210, 9.522) | 1.175 (1.039, 1.369) |
| Collision mitigation | 1.163 (1.127, 1.203) | 1.318 (1.132, 1.540) | 1.362 (1.292, 1.440) | 1.212 (1.174, 1.252) | 1.577 (1.422, 1.766) | 1.134 (0.952, 1.353) | 1.170 (1.121, 1.234) |
| Age | 0.992 (0.989, 0.995) | 0.988 (0.982, 0.993) | 0.993 (0.990, 0.996) | 0.995 (0.993, 0.998) | 0.986 (0.982, 0.990) | 0.999 (0.989, 1.010) | 0.997 (0.993, 1.000) |
| Mean speed | 0.976 (0.970, 0.983) | 1.016 (1.005, 1.027) | 0.968 (0.962, 0.974) | 0.994 (0.987, 1.000) | 1.000 (0.988, 1.012) | 0.973 (0.958, 0.988) | 0.983 (0.973, 0.994) |
| Gender: male | 0.883 (0.702, 1.083) | 0.868 (0.631, 1.227) | 0.844 (0.716, 0.997) | 0.749 (0.650, 0.862) | 0.841 (0.691, 1.029) | 0.675 (0.433, 1.027) | 0.751 (0.634, 0.893) |
| Gender: unknown | 1.065 (0.589, 1.908) | 1.378 (0.706, 2.617) | 0.576 (0.325, 0.980) | 1.287 (0.774, 2.079) | 0.194 (0.044, 0.626) | | 0.816 (0.571, 1.158) |
| **Fit statistics:** | | | | | | | |
| sample size | 6950 | 1797 | 7405 | 6429 | 3339 | 943 | 4963 |
| elpd_loo | -9300.8 (125.3) | -2416.9 (52.2) | -9799.1 (112.1) | -7624.2 (90.8) | -3912.6 (70.5) | -1139.8 (40) | -5293.9 (85.4) |
| p_loo | 30.6 (5) | 14.3 (2.5) | 20.4 (2.6) | 17.4 (2.3) | 13.9 (1.7) | 11 (1.6) | 19.4 (2.9) |
| looic | 18601.6 (250.6) | 4833.8 (104.5) | 19598.1 (224.2) | 15248.3 (181.6) | 7825.2 (141) | 2279.5 (79.9) | 10587.7 (170.8) |

**Notes:**
The SCEs were measured as the number of events per 10,000 miles driven.
Incidence rate ratios and their associated 95% credible intervals are reported for all variables (predictors and covariates).
For the fit statistics, (.) indicates the standard error of the computed statistic.

our observed events were insufficient for statistical inference (based on the size of the credible interval in Table 6).

Figure 4 shows the posterior distributions, which are indicated by the histograms in light black, for the posterior probability of zero crashes under each of the six models considered in Table 7. The observed proportion of zero crashes is indicated by the vertical line in each part of Figure 4. For all six models, the observed proportion of zero crashes was considerably less than what would be predicted by the model. Note that the magnitude of this prediction bias is small, usually around 0.015. In other words, while both models

Table 9: Variance inflation factor test for multicollinearity.

| Outcome | Crash | Fatality | Injury | Crash | Crash | Crash | Crash | Crash | Crash | Crash |
|---|---|---|---|---|---|---|---|---|---|---|
| Samples | All drivers | All drivers | All Drivers | Dedicated ∩ Local | Dedicated ∩ Regional | Dedicated ∩ OTR | Intermodal ∩ Local | Intermodal ∩ Regional | Final-mile ∩ Regional | Final-mile ∩ OTR |
| Headways | 1.030 | 1.030 | 1.030 | 1.049 | 1.024 | 1.012 | 1.044 | 1.040 | 1.073 | 1.037 |
| Hard brakes | 1.031 | 1.031 | 1.031 | 1.027 | 1.063 | 1.047 | 1.020 | 1.031 | 1.077 | 1.184 |
| Rolling stability | 1.024 | 1.024 | 1.024 | 1.029 | 1.013 | 1.047 | 1.024 | 1.010 | 1.053 | 1.159 |
| Collision mitigation | 1.038 | 1.038 | 1.038 | 1.024 | 1.048 | 1.056 | 1.056 | 1.046 | 1.118 | 1.236 |
| Age | 1.006 | 1.006 | 1.006 | 1.003 | 1.007 | 1.005 | 1.004 | 1.004 | 1.004 | 1.011 |
| Ping speed | 1.270 | 1.270 | 1.270 | 1.007 | 1.012 | 1.012 | 1.015 | 1.015 | 1.011 | 1.047 |
| Gender | 1.005 | 1.005 | 1.005 | 1.001 | 1.002 | 1.005 | 1.004 | 1.004 | 1.010 | 1.008 |
| Business unit | 1.096 | 1.096 | 1.096 | | | | | | | |
| Driver type | 1.140 | 1.140 | 1.140 | | | | | | | |

(with and without business units and driver types) perform reasonably well in predicting the mean numbers of SCEs, the model with business units and driver types does a better job predicting the proportion of zero crashes. This suggests that different business units and driver types should be accounted for in the model.

Based partly on the result from Figure 4, we ran the model with all four SCEs (model 2) separately for each of the seven business units and driver types. The corresponding posterior predictive check for zero crashes is shown in Figure 5. Here, the vertical lines are much closer to the simulated posterior distribution. This suggests that different business units and driver types should be accounted for in the model.

## 5. Discussion and conclusions

### *5.1. Summary of the main contributions*

In line with previous studies on the association between crashes and SCEs in NDSs (Guo et al., 2010; Gordon et al., 2011; Simons-Morton et al., 2012; Wu and Jovanis, 2012; Guo and Fang, 2013; Pande et al., 2017; Gitelman et al., 2018), this study provides statistically significant and robust evidence that there is positive association between SCEs and crashes based on routinely collected NDS and kinematic data from 31,828 American truck drivers. We found that one unit increase in the number of any type of SCEs per 10,000 miles was associated with 8.4% (95% CI: 8-8.8%) increase in SCEs per mile and 8.7% (95% CI: 4.8%-13.6%) increase in the number of injuries per mile. The increase was different for different types

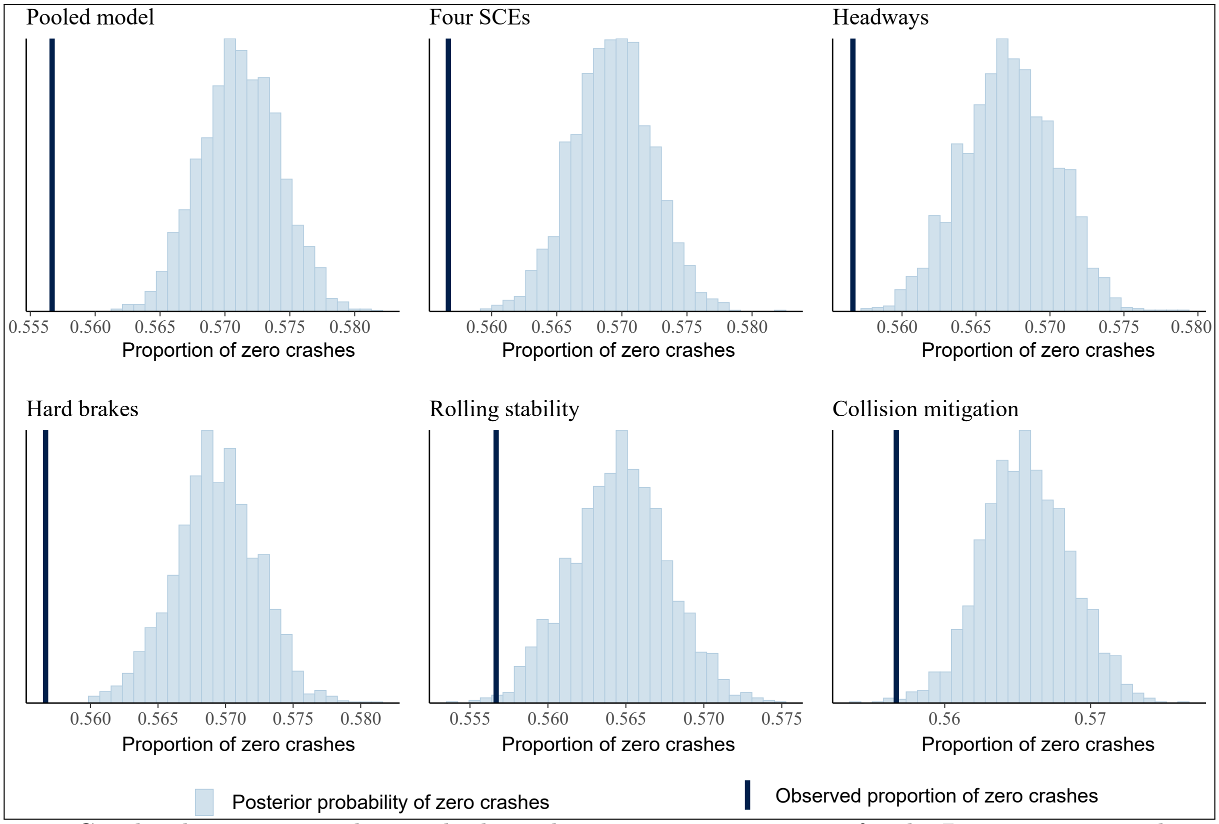



Figure 4: Graphical posterior predictive checks with zero count test statistic for the Bayesian negative binomial models for all drivers. The $x$-axis is the proportion of zero crashes and $y$-axis is probability density. The solid black line is the observed proportion, while the light black histogram is from 100 simulated predictions

of SCEs: 3.3% (95% CI: 2.6-4.0%) for headways, 8.1% (95% CI: 7.5-8.7%) for hard brakes, 50.4% (95% CI: 41.4-60.0%) for rolling stability, and 22.2% (95% CI: 19.8-24.5%) for collision mitigation. The results are consistent when stratified by different business units and driver types. This work provides statistically strong and robust evidence that SCEs are positively associated with crashes and injuries among commercial truck drivers. Furthermore, this study demonstrates that the "severity" of the SCE is associated with the crash rate, where the two automated maneuvers (involving the initiation of the forward-collision mitigation and rolling stability systems) were shown to have a statistically significant larger effects on crash rates when compared to hard brakes and head way (which can be seen as less severe maneuvers/alerts).

The current study contributes to the existing literature in three respects. First, this paper overcome the small sample size issues in previous crashes and crash surrogates papers, which typically includes 300 or fewer drivers or vehicles and fewer than 100 crashes (Guo et al., 2010; Gitelman et al., 2018). Our study involves 1,000 times as many driving hours and miles and includes more than $30,000$ commercial truck drivers and $30,000$ crashes; this allows us to investigate the association between four different types of SCEs and crashes, as well as stratified analyses across business units and driver types. Second, the evidence of the association between crashes and crash surrogates among truck drivers has been scarce. Our study gives insights to this less studied field using a nationwide large-scale sample. Third, this paper explores the

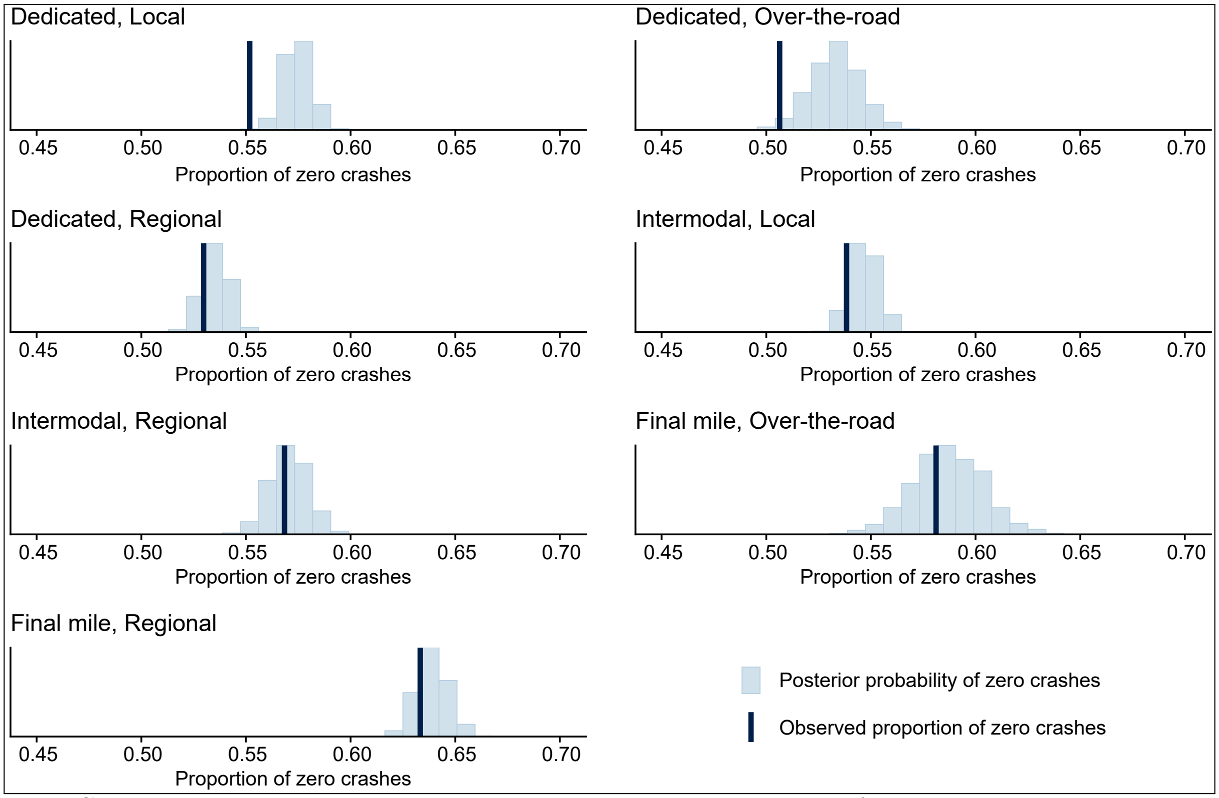



Figure 5: Graphical posterior predictive checks with zero count test statistic for the Bayesian negative binomial models, stratified by business unit and driver types. The $x$-axis is the proportion of zero crashes and $y$-axis is probability density. The solid black line is the observed proportion, while the light black histogram is from 100 simulated predictions.

association between SCEs and human injuries and fatalities, which has not been investigated in previous papers but represents important research questions that require detailed study given that they constitute an important component of truck routing models used in practice (Hu et al., 2020).

*5.2. Practical relevance of our work to trucking operators*

Our findings have given evidence to support the long held belief that critical events are associated with crashes. Much of the literature on truck safety has presumed that such an association exists, but little evidence has been provided. Our study is the only study, to the best of our knowledge, that quantifies this association for commercial truck drivers. Consequently, our results allow for the use of SCEs (specifically the initiation of the rolling stability system, the initiation of the collision mitigation system, hard brakes and/or headway alerts) as proxies for crashes. The ability to use a more frequent outcome will allow for more statistical power when investigating variables that affect (trucking) safety.

From a trucking operator's perspective, the SCE data used in this study are routinely collected with the wide-scale adoption of sensor-based monitoring systems in practice. In many cases, the data have not been used in enhancing/transforming safety operations because: (a) it is unclear whether or how the SCEs and crashes are associated; (b) the trucking operator's may not know how to aggregate the acquired ping data into a more meaningful unit of analysis; (c) the modeling/coding of this data may be difficult especially for smaller operators with limited statistical and engineering resources. In this study, we have demonstrated the positive relationship of the SCEs with the number of crashes recorded for a large number of drivers. Furthermore, our stratified models by driver type and business unit indicate that the incorporation of such information can enhance the predictions obtained from the model. To facilitate the adoption of our work by industry practitioners, we host a compiled **R** Markdown document containing our code, results and analysis on a freely accessible website (see link in the supplementary materials section). The use of the open-source **R** programming language can make the adoption of our work more accessible for trucking operators of different sizes.

The knowledge of the positive association between the four SCEs and crashes can be incorporated by trucking operators using several approaches. First, recent statistics indicate that more than 90% of traffic crashes are influenced by driver behavior (Federal Highway Administration, 2019). While our naturalistic driving data does not include video images, it explicitly captures important behavioral factors such as driving speed, aggressive driving through headway alerts, and potential distraction/drowsiness with an increased rate of the three other SCEs (at least when compared to drivers on similar routes). Thus, trucking operators can use our estimated model coefficients, e.g., 50.4% for the initiation of the rolling stability system, in driver training/education. Second, operators can provide incentives to their drivers to reduce their recorded number of SCEs through behavioral based safety programs (Jun et al., 2007). Third, by examining the operator's historical record of SCE data, operators can develop scheduling and routing policies that attempt to minimize the number of recorded SCEs (Mehdizadeh et al., 2020; Hu et al., 2020).

### *5.3. Limitations and suggestions for future research*

This study has several limitations that can be investigated in future studies. First, since the exact time of the crashes were not recorded, we are not able to find out which and how many SCEs directly cause crashes, which is a crucial question in Heinrich's Triangle (Guo et al., 2010). Second, although we have a relatively large number of drivers and high mileage driven, the number of injuries or fatalities is not sufficiently large for stratified analyses. The statistical evidence on the number of injuries is strong only when we combine four types of SCEs, while the evidence on fatalities in either of the two models is not strong given the small number of fatalities. Third, the data does not include traffic or weather variables, which are important predictors of crashes. Fourth, this study used a cross-sectional observatory design and no experiments were involved, so we should not make any causal statements on this association. Exploring the causal relationship between SCEs and crashes requires well-designed experiments or state-of-start causal inference models for observatory data, which is beyond the scope of this study and could be a direction that future studies can focus on. Fifth, the haversine method to calculate the distance may not reflect the true miles by the sample drivers since it ignores the ellipsoidal effects and calculates the shortest distance between two points. Despite these facts, it is the most feasible and cost-effective algorithm to estimate the distance between two points for this study.

Despite these limitations, we demonstrate in this paper the positive association between safety critical events and crashes/injuries/fatalities. Our study features several orders of magnitude more data volume than previous studies in terms of number of drivers, hours driven, miles driven, number of crashes, and the count of surrogate events, as well as a previously unexamined population: commercial truck drivers. These results indicate that the emerging widespread use of technology for monitoring kinematic events can effectively be used for naturalistic driving studies.

### Supplemental materials

To encourage future research and/or adoption of our work by trucking operators, we provide an **R** Markdown document which provides the code used for aggregating the ping data into trips and statistical modeling. Our code and analysis can be freely accessed at https://caimiao0714.github.io/Github-SCE-crash/. We provide a sample CSV file, where we masked the driver ID as well as the coordinates (by rounding them to one digit) at https://github.com/caimiao0714/Github-SCE-crash/blob/master/data/sample_ping.csv. The purpose of providing the sample file is to provide some insight into the ping data frequency, shape, and speed values. Note that we cannot provide the ping or the aggregated data based on the terms of our nondisclosure agreement.

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