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Quantifying Hard Breaking Events Occurring Prior to Secondary Crashes on Indiana Interstates

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Abstract

Secondary crashes on the interstate frequently occur when traffic is queued because of a primary crash and can be quite severe when high-speed vehicles crash into the back of the queue (BOQ). Transportation agencies are aware of this challenge, but there has been limited quantitative data to assess the risk of secondary crashes. This paper examines 47 primary crashes and associated secondary crashes, to quantify the relation between hard braking (HB) events and secondary crashes. These crashes occurred across a diverse cross section of Indiana Interstate locations. Connected Vehicle (CV) trajectories were used to estimate deceleration rates. Trajectories waypoints with deceleration rates greater than or equal to 0.25 g were classified as HB. In total, 762 HB events occurred between the primary and secondary crashes. Only 15 HB events were identified for the control group. An odds ratio statistical measure was used to compare occurrence of HB events and the secondary crash occurrence. The analysis showed it was approximately 62 times more likely that a motorist would experience an HB event when approaching queued traffic associated with a primary crash, in comparison to the control group with free flow conditions. The data and methodologies presented will help agencies incorporate HB into their highway monitoring program and evaluate the impact of incident management and queue protection programs.

Keywords

Secondary Crashes, Hard Braking, Connected Vehicle, Interstates, Safety, Surrogate Measure

1. Introduction

Secondary crashes are a nationally recognized problem and are defined as crashes that occur as a result of traffic disruptions caused by a primary crash. One study estimated that more than 15% of all crashes were caused by an earlier incident [1]. Secondary crashes on interstates are often severe when vehicles, travelling at interstate speeds, impact stopped or slow-moving traffic. Secondary crashes are particularly severe when they involve trucks or large vehicles impacting the back of the queue (BOQ). Although secondary crashes are a well-known phenomenon [2]-[4], there has been very little literature reporting quantitative methods to assess factors that influence BOQ crash rate. Hard braking (HB) events, on the order of 0.25 g (8.05 ft/s^2) have been reported to be a reasonable point of data for crash risk and are attractive for a variety of safety programs because they occur much more frequently than crashes and therefore are a useful tool for identifying emerging safety issues [5]. Agencies that understand the risk and the rate at which HB events occur when a secondary crash happens will be able to properly work to develop protocols to reduce HB risk and secondary crash risk in crash scene response and have a performance measure to compare against.

Objective

The objective of this study is to assemble a curated data set of primary and secondary crashes and a corresponding control data set to develop a model quantifying the relationship between HB events and secondary crashes. The control set of data used in this study was a week before or a week after each crash when traffic was considered to be operating in free flow conditions.

2. Background

There are limited statistics on the relationship between secondary and primary crashes on freeways, but it is widely accepted that there is a relationship between a primary and secondary crash [1] [6] [7] and, as such, this relationship is of critical interest to governmental agencies. A recent Colorado State Patrol press release on the topic details what a secondary crash is, highlights collected secondary crash data, and highlights the Colorado Move Over law [8]. In 2020, the Indiana Department of Transportation (DOT) launched a campaign to better protect queues to help prevent secondary crashes [9], and the FHWA commissioned a ten state study on secondary crashes completed in June 2023 [10].

The literature on secondary crashes generally covers three areas: identifying secondary crashes [11]-[13], identifying characteristics of secondary crashes [12] [14], and modelling [4] [15]. More recent papers focus on prevention methods [16] [17] and integrating AI elements into prediction modelling [11] [18] [19]. All the studies listed above rely on crash report data, which will take time and require relatively long analysis periods to obtain a statistically significant sample size.

Hard braking has been proposed as a crash surrogate. A hard braking event is a sudden deceleration event when a driver aggressively applies the brakes. Historically, agencies would see these as skid marks on the road. More recently, vehicles can measure vehicle kinematics and quantify the braking events in terms of acceleration or g-forces. Other studies using HB data have reported thresholds at approximately 0.27 g [5] [20] and one study examined a range of deceleration rates from 0.1 g through 0.5 g [21]. For the purposes of this study, the threshold for an HB event is defined as 0.25 g (8.05 ft/s^2). However, it is important to recognize that there is some subjectivity in the exact threshold to use. For example, in urban areas where there tends to be more congestion, thresholds closer to 0.3 g might be more appropriate. More details evaluating the correlation of different HB thresholds and crashes can be found in [21].

As connected vehicle (CV) data has become more widely available, HB data has attracted considerable attention because many HB events occur before a crash. Several recent papers have suggested that HB data can be used as a robust crash surrogate measure for crash risk, particularly on Interstates where few hard braking events are expected in uncongested operation [5]. Another study found that there is a strong correlation between HB events and rear-end collisions occurring more than 400 feet upstream of an intersection. It was also found in the same study that approximately 1 month of hard braking data is sufficient to provide a reliable correlation with approximately 4.5 years of crash data at the same intersection [20]. Additional reports in the literature identify opportunity for using HB data for intersection safety assessment [20] and exit and entry ramp monitoring [21].

While there has been previous research into correlating HB events with crashes [5] [20]-[23] and studies have examined using CV data and surrogates to reduce secondary crashes [24] [25], there have been no studies examining the relationship between a primary crash and a secondary crash using hard braking data. The following sections describe the data and analysis of HB events that occur between the occurrence of a primary crash and a secondary crash.

3. Data Description

To evaluate the relationship between primary and secondary crashes, the study assembled a curated set of crash data, CV trajectories, and HB data. The following section describes the curation process for that data and provides visualizations to illustrate the typical pattern of HB events that occur between a primary and secondary crash. Additionally, some corresponding illustrations from a control period are used to illustrate the pattern of HB events a week before or week after the primary and secondary crash.

3.1. Crash Data

Interstate crash data is collected weekly from the Automated Reporting Information Exchange System (ARIES) Portal. ARIES Portal is a central database run by Indiana State Police (ISP), which hosts all submitted crash reports in the state of Indiana [26]. The research team has developed a database that is referenced by route, direction, mile marker (MM), date, and time for all Interstate crashes that have occurred over the past 6 years in Indiana. That database currently has approximately 115,000 records. Figure 1 quantifies the number of primary and secondary crashes that have been recorded since 2019. As with any human data entry, there are some discrepancies. Some secondary crash reports refer to a prior crash that has no known crash report associated with it. For example, in 2024 there were 227 primary crashes that were recorded, however there were only 212 primary crashes that had a crash report associated with them and reflected in Figure 1. Additionally, some primary crashes have more than one secondary crash associated with them and are referred to as tertiary crashes in this study. A tertiary crash is defined as a secondary crash that occurs as a result of the queue created by a prior secondary crash. For this study, the research team focused on primary, secondary, and tertiary crashes in 2024. Subsequent sections will discuss the curation of the 2024 data set for the study.

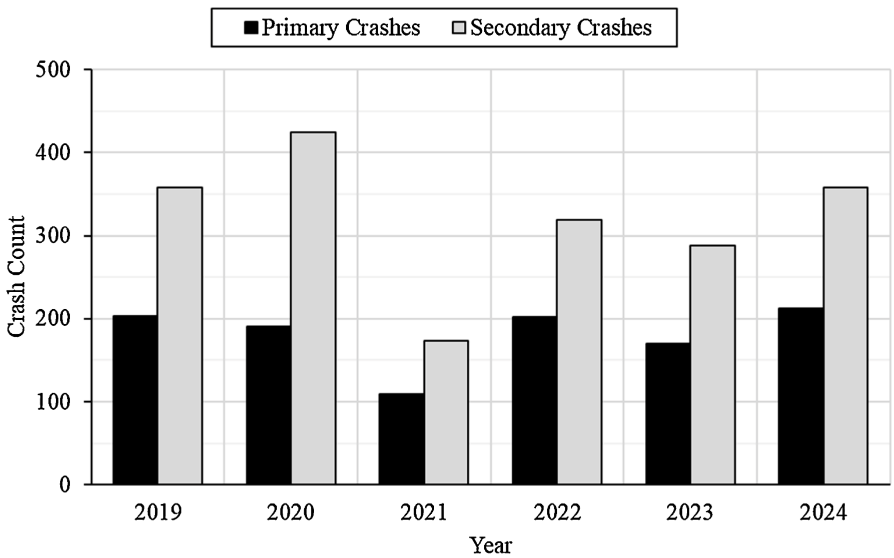


Figure 1. Primary and secondary crashes on Indiana interstates from 2019 to 2024.

3.2. Connected Vehicle Trajectory Data

CV data is a particularly valuable resource for agencies and practitioners looking to obtain near real-time views of prevailing traffic conditions on their roadways. Additionally, this data can also be used for validating and corroborating reported crash locations, times as well as impacts to traffic. The CV data utilized for this study comprises trajectory waypoints available at 3-second frequency and is composed of a fleet of passenger vehicles. Assuming a hard braking threshold of -0.25g, this accounts for a decrease in speed of 16.46 mph over three seconds. It was also previously found that the CV data used in this study has a penetration rate of 4.6% on interstate routes in Indiana [27]. Each such waypoint has an associated timestamp, geolocation, speed, heading, and an anonymized unique trajectory identifier [28]. CV waypoints with the same trajectory identifier can be linked together as a CV trajectory and visualized through distance-time graphs such as the one shown in Figure 2. The resulting shockwaves from crashes can be easily identified and associated with a primary and secondary crash.

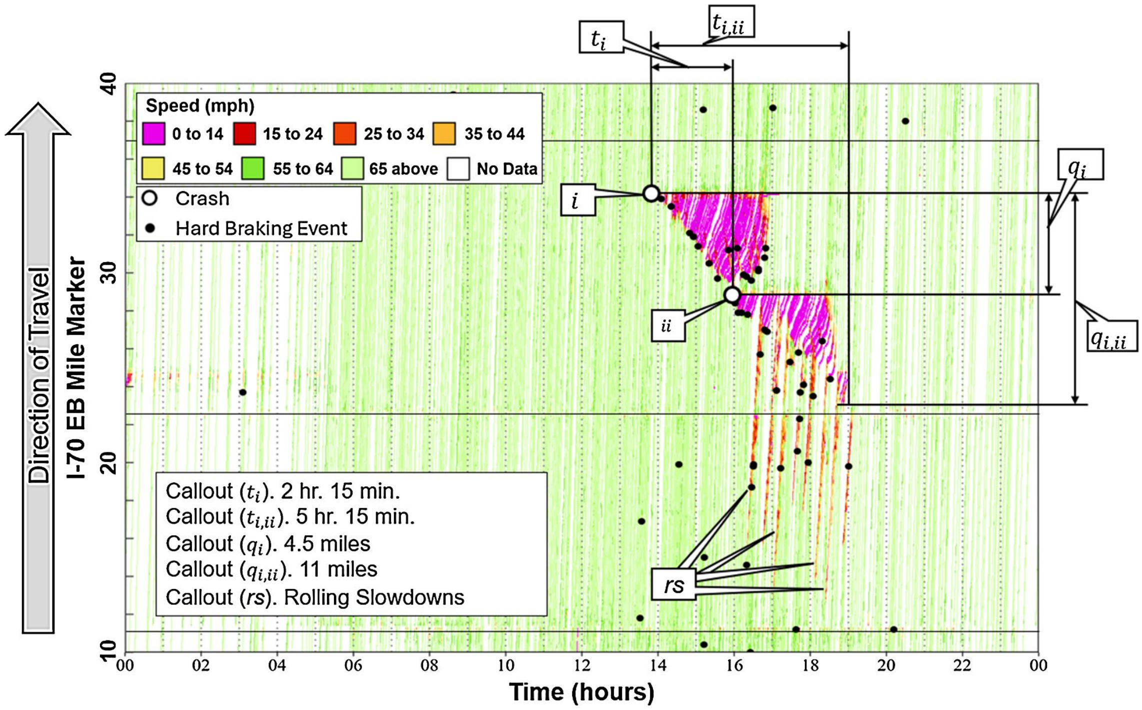


Figure 2. Traffic Speed Heatmap along I-70 EB from MM 10 to 40 on June 3, 2024 showcasing primary and secondary crash with HB events.

There are certain challenges and limitations associated with the use of CV data especially in a constantly evolving landscape where providers try to balance the usability of the data while ensuring privacy protections. Some OEMs have adopted data fuzzification techniques around 0.5 miles of frequently visited locations. In the case of this study, as existing literature has pointed out, data fuzzification does not lead to a significant drop in data representativeness for interstate routes [27].

Figure 2 shows an example of a primary crash and a secondary crash eastbound (EB) on I-70. Callouts (i) and (ii) show the location and time of the primary and secondary crash respectively. Callout (t_i) represents the difference in time between the primary and secondary crash, Callout ($t_{i,ii}$) represents the difference in time between the primary crash and the end of all traffic impacts from the entire event. Callout (q_i) represents the distance between where the primary and secondary crash occurred and callout ($q_{i,ii}$) represents the miles of interstate impacted by both the primary and secondary crash. Callout (rs) is a callout to the rolling slowdowns that ISP performed in an attempt to reduce secondary crash risk. The primary crash occurred at 1:50 PM on June 03, 2024, near MM 34 and the secondary crash occurring at 4 PM near MM 28. The details for each crash were initially extracted from crash reports and were further verified using CV data plots similar to those shown in **Figure 2**. When CV data is displayed visually with the crash location and time, the corresponding slowdown in traffic can be identified just before 1400 hours on the x-axis and a little after MM 32 on the y-axis. The secondary crash can be confirmed in the same way by visually confirming where the start of the secondary queue begins. CV data can also be used to identify crash times and locations when a crash report is missing. Additionally, the CV data also confirms the date and direction with the date verified with the time stamp and the direction being verified using the heading. Beyond verifying crash details, CV data can be used to identify external factors impacting traffic, such as when adverse weather conditions are impacting speeds [29], where re-occurring congestion occurs, and where construction is occurring [30].

3.3. Secondary Crash Inventory

The secondary crash inventory was developed using the interstate crash data collected weekly. At the end of the calendar year, a search through traffic heatmaps displaying the collected crash data, similar to **Figure 2**, covering all Indiana interstate miles for the full calendar year is performed. Any crash pairing that is connected through congestion is saved for further investigation. A potential secondary crash that appears to be missing a primary crash report is also saved for further investigation. Additionally, a potential primary and secondary crash pair is excluded if the time impact is less than 2 hours. The 2-hour duration was used to ensure a sufficient sampling window for hard braking data. After the search is completed, all crash reports associated with the found potential primary and secondary crash are read to verify the primary-secondary relationship.

3.4. Hard Braking Data

Prior to June 2023, HB data was initially provided by original equipment manufacturer (OEM) sensors [5] [20]. There was limited visibility on the algorithms employed to derive HB events and during the period 2020 to 2023 there were a number of changes to those algorithms. Subsequently in 2024, the commercial distribution of directly measured OEM HB data was discontinued. To address variations in the underlying HB data and produce an alternative reliable and transparent source of hard braking data, the research team developed techniques to calculate HB directly from the CV speeds reported at 3s intervals. HB events were identified by first estimating deceleration rates between two successive waypoints by examining the change in velocity between successive waypoints divided by the time interval between each waypoint. In cases where the deceleration is greater than or equal to the threshold set for HB, then the first waypoint is classified as an HB event. For this study, deceleration at or greater than 0.25g (8.05 ft/s^2) was considered an HB event. To ensure consistency, filter outliers and account for data reporting inaccuracies, only waypoints 3-second apart were utilized for this computation. Past research has indicated this threshold for HB correlates reasonably well with crashes [5] [20] [21] [23].

3.5. Integrating Crash, Trajectory and Hard Braking into One Graphic

Figure 2 displays an example of a heatmap composed of approximately 1755 vehicle trajectories, color coded by speed. The x-axis represents the time of day, meanwhile the y-axis represents the linear referenced MM location along I-70 EB. Each trajectory corresponds to an individual CV travelling EB on I-70 through this 30-mile section of road between MM 10 and 40.

The small black points on the heatmap are the derived HB points and can be seen concentrated along the back of the queue between callouts (i) and (ii) and the back of the queue created from the secondary crash. The black horizontal lines across the heatmap indicate exit ramp locations on the interstate. Additionally, the red lines, as called out by (rs), are indicative of rolling slowdowns performed by ISP attempting to reducing the chance for a tertiary crash. In Figure 2, one can identify 8 different rolling slowdowns that were used in this specific event as can be seen by the 8 different red lines at the back of the queue. These rolling slowdowns are occasionally used in Indiana. As can be seen by the HB events at the back of the rolling slow down queues, it is unclear if the rolling slowdowns have any substantial impact once a queue forms and it is worth further study.

4. Methodology

Connected vehicle data was only available for the last 7 months of 2024. As such, 91 out of 227 recorded primary crashes were removed due to the lack of connected vehicle data from January to May. Additionally, a number of the secondary crashes left were difficult to attribute solely as a secondary crash as a result of confounding factors such as re-occurring congestion, complex interchanges, and inclement weather such as snow, ice, heavy rain, or fog. As such, secondary crashes with confounding factors were excluded from this study. Secondary crashes were also filtered based on whether they occurred in the queue or at the back of the queue. The back of the queue can be seen in Figure 2, between the crashes at (i) and (ii) where the higher speeds, the green, meet the lower speeds, the yellows and reds. A secondary crash that occurred within the queue, after the vehicle has already slowed down, typically has much smaller speed differentials and lower severity. However, a crash that occurs in the back of a queue, where the speed differential is high, typically has a much high severity. As a result, the focus of this study was crashes that occurred at the back of the queue. From the collection of 227 primary crashes that were recorded in 2024 in Figure 1, 47 primary crashes with 47 secondary crashes and 7 tertiary crashes were selected for detailed analysis. The tertiary crashes used the secondary crash as their primary crash for the purposes of this analysis. The secondary and tertiary crash pairs were treated as if they were an individual primary and secondary crash not impacted by the primary crash. The secondary and tertiary crashes were both analyzed as 54 secondary crashes. The location of the 47 primary crashes is displayed in Figure 3.

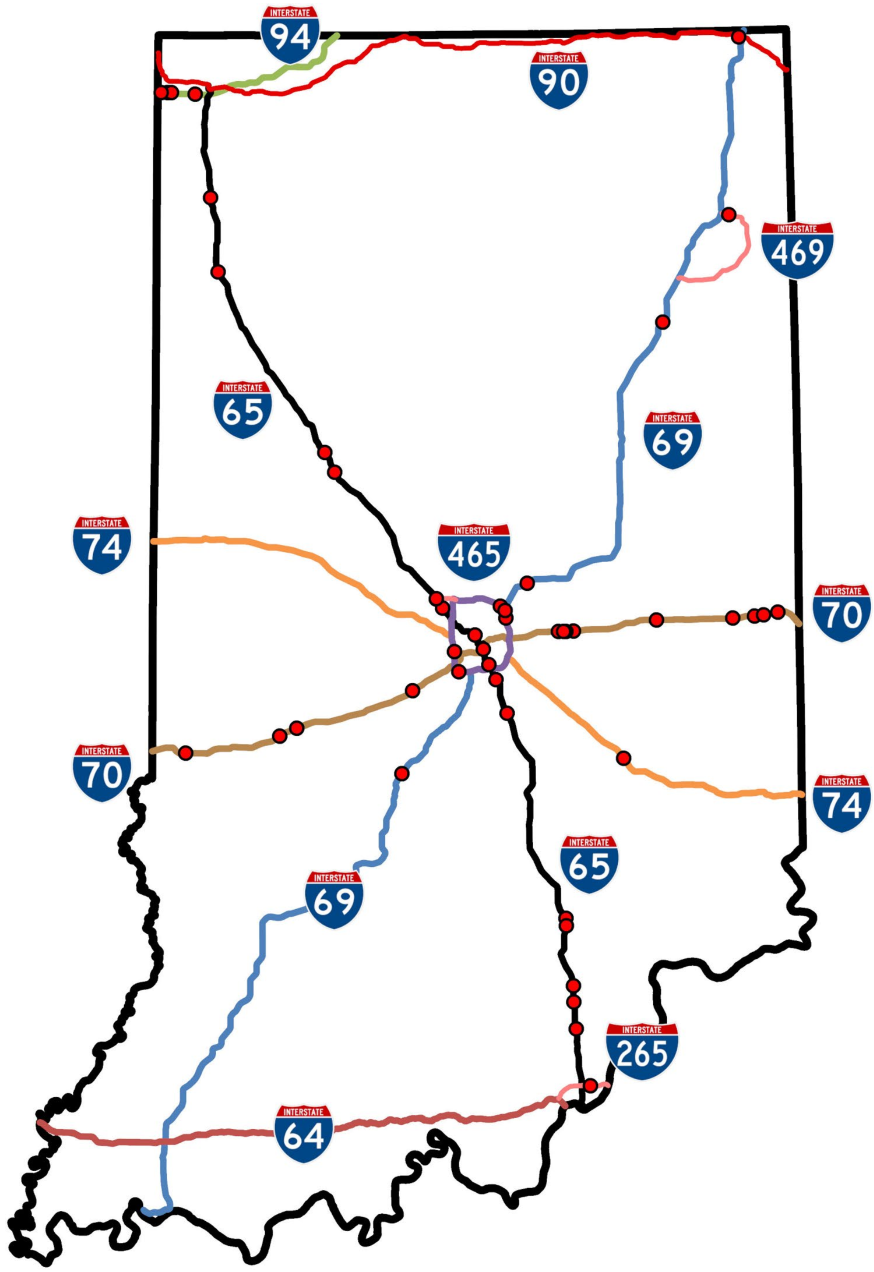
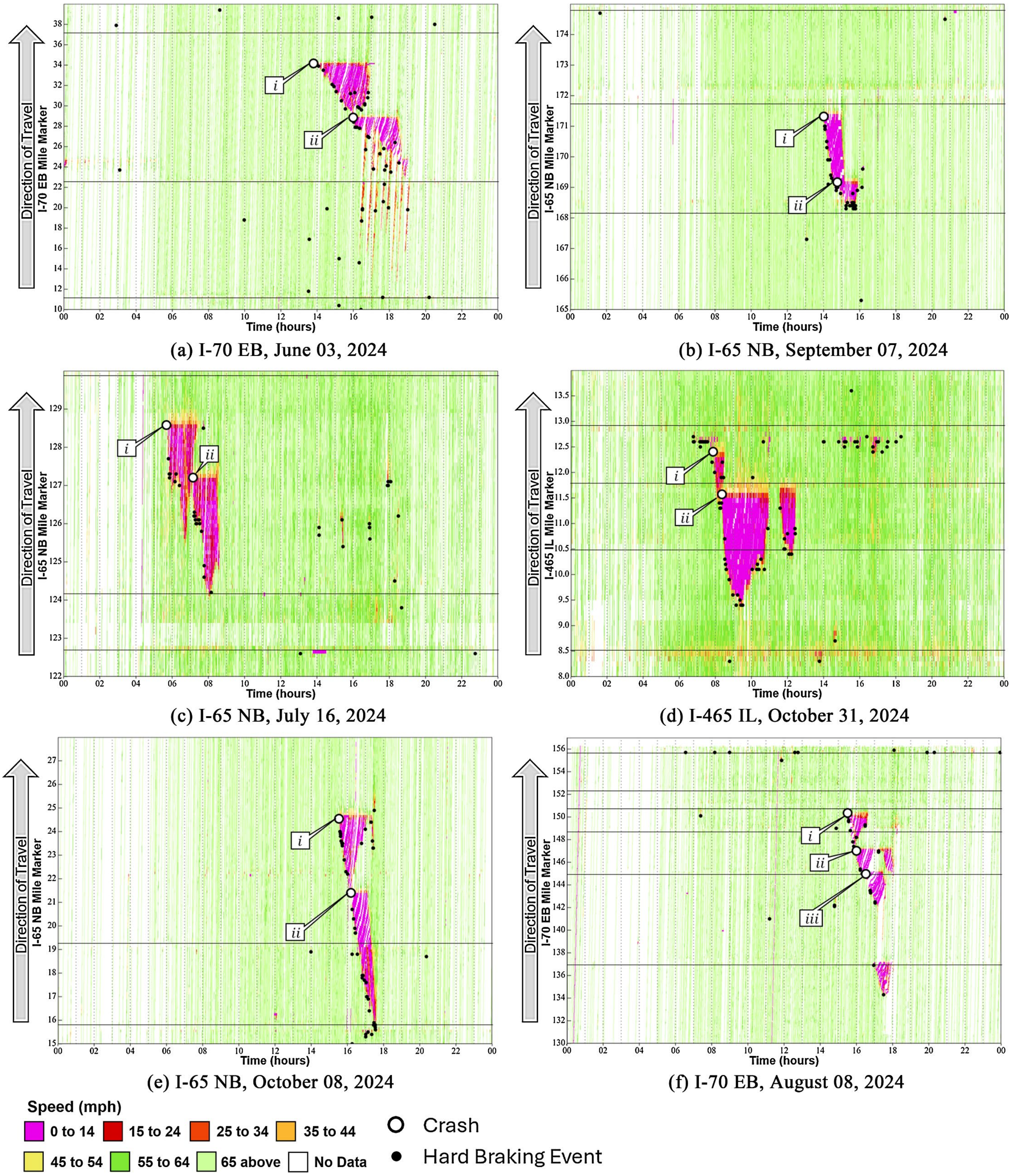


Figure 3. Location of all 47 primary crashes on Indiana interstates analyzed in this study.

Data Collection

For the 54 secondary crashes, a corresponding control data set for the same location and day of week was identified. In general, the week after was used for the control data. However, if abnormal conditions were occurring during that week (such as weather or adjacent incident), a control data set for the location and day of week was selected from the week prior.

Following the curation process, the HB and trajectory counts need to be determined. Each primary crash had a heatmap generated for it, similar to **Figure 2**, in which HB events are displayed. All the HB events that are located along the back of the queue between the primary and secondary crash were counted visually using the generated heatmaps. For example, in **Figure 4(a)**, the HB points between callouts (i) and (ii), the primary crash and the secondary crash respectively, were manually counted if located at the back of the queue. Each queue is different and



(a) I-70 EB, June 03, 2024

(b) I-65 NB, September 07, 2024

(c) I-65 NB, July 16, 2024

(d) I-465 IL, October 31, 2024

(e) I-65 NB, October 08, 2024

(f) I-70 EB, August 08, 2024

Figure 4. Selected 6 case examples with primary and secondary crash.

is not necessarily a linear growth between the primary and secondary crash making it difficult to create a script that can count HB events along the back of the queue that accounts for all the different potential queuing patterns. As such, it was decided that HB events would be counted by hand. There are two HB points that occurred in the queue created by the primary crash at callout (i) that were excluded in the HB event count because this study focused on crashes at the back of the queue instead of anything that occurred within the queue.

The trajectory count was tabulated using a database query where all used CV data is stored. The database query takes the time and locations of the primary and secondary crash on the heatmap and counts each unique trajectory that travelled in the region bounded by the primary and secondary crash. This was repeated for the control week using the same time and location as well. **Figure 4** illustrates 6 representative examples of secondary crashes. Additionally, **Figure 4(f)** and **Figure 5(f)** include a tertiary crash, which is notated by callout (iii). **Figure 5** shows the corresponding control week data for those 6 examples. **Table 1** details the collected results for each example in **Figure 4** and **Figure 5**. The serial number provides a quick way to reference from the table to figures. The HB and trajectory count for the week of the crash are in relation to what can be seen in **Figure 4**. The HB events can be directly counted from the figure and can be self-verified.

5. Results

The HB counts for the curated dataset of 54 secondary crashes were plotted against the trajectory counts for both the week of crash and the corresponding control week in **Figure 6**. The slope of the trendline, with the intercept forced through zero, is 0.0686. In general terms, this indicates approximately 7% of all trajectories experiencing an HB event when approaching the queue associated with a primary crash. The R-squared value for this was 0.74. It was also found that the t-stat was 12.32 and had a p-value of 3.43E−17. In comparison, the control week had approximately 0.1% of all trajectories with an HB event. These HB events during the control week are effectively a random event as they occur in what should be free flow conditions making them difficult to model for. The R-squared

Table 1. Summary statistics for case examples.

Serial Number	Interstate	Primary MM	HB Count, Week of Crash	Trajectory Count, Week of Crash	HB Count, Control Week	Trajectory Count, Control Week
a	I-70 EB	34.2	8	196	0	78
b	I-65 NB	171.0	9	48	0	87
c	I-65 NB	128.6	7	89	0	108
d	I-465 NB	12.4	3	113	0	143
e	I-65 NB	24.5	10	49	0	52
f.i	I-70 EB	150.3	6	30	0	49
f.ii	I-70 EB	147.0	9	41	0	37

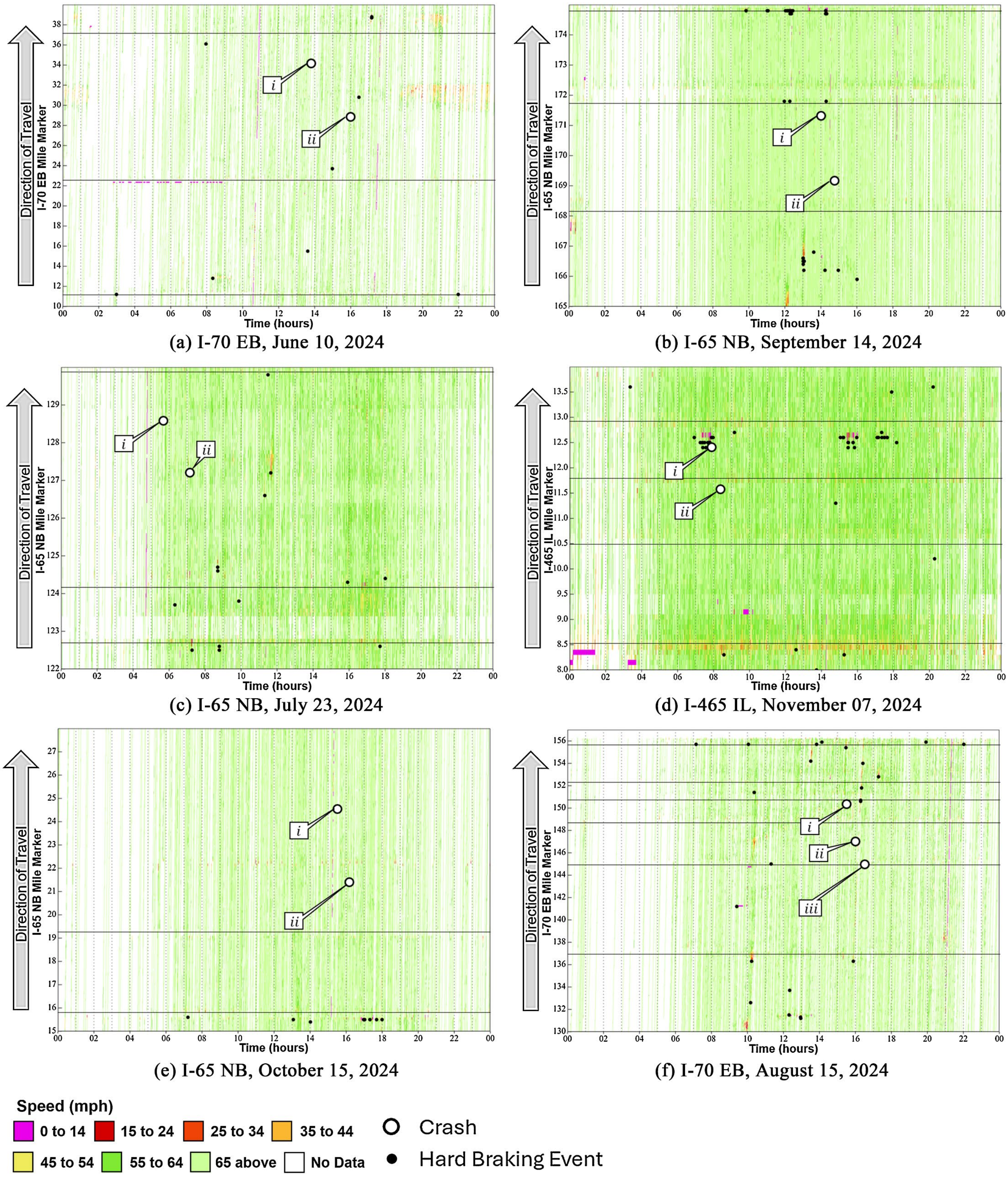


Figure 5. Selected 6 case examples during the control week.

value for the control week was 0.23 and the t-stat and p-value were 3.92 and 2.53E−4 respectively. The trendlines clearly indicate a relationship between HB and trajectory counts compared to the control week. In general, the proportion of connected vehicles in the traffic stream is approximately 4.6%, which can be

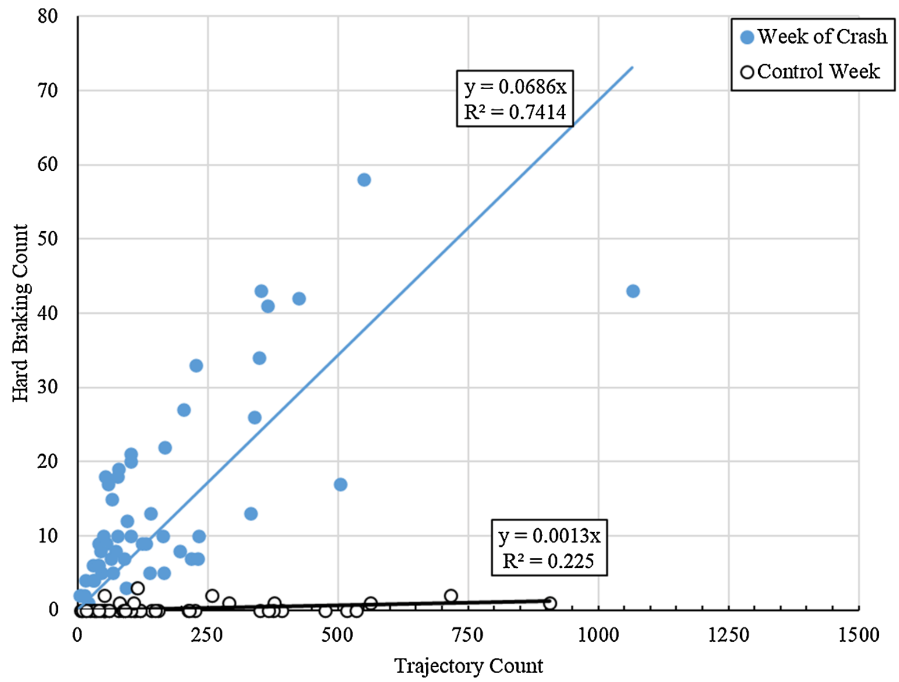


Figure 6. Graph of hard braking count against trajectory count.

interpreted as one in 21.7 vehicles being represented in the data, is sufficient to provide accurate results of overall characteristics in traffic patterns on the roadway.

Overall, there were 762 total HB events and 8449 total trajectories when there was a queue formed from a crash and only 15 total HB events and 9417 trajectories when there was no queue. It was assumed that each trajectory only had one hard braking event. The summary breakdown of trajectories with and without HB events can be seen in Table 2. To compare these two sets of data, an odds ratio statistical test was performed. The results for the odds ratio test can be found in Table 3. The odds ratio was calculated to be 62.13. This indicates that the odds of an HB event happening after a crash increase by approximately a factor of 62, with

Table 2. Summary table of trajectories and HB events

	Trajectories with HB Event	Trajectories without HB Event
Occurrence of a Secondary Crash	762	7687
No Crash	15	9402

Table 3. Odds ratio test for HB events per trajectory.

Measure	Week of Crash	Control Week
HB Odds	0.09	0.002
Odds Ratio	62.13	
Upper 95% CI	103.67	
Lower 95% CI	37.24	

lower and upper confidence intervals of 37.24 and 103.67, respectively.

6. Conclusions

This paper presents a quantitative analysis of the relationship between HB events and secondary crashes from 47 different primary crashes and 54 total secondary and tertiary crashes across the state of Indiana for a 7-month period in 2024. An HB event was defined as an event where deceleration of a vehicle was equal to or exceeded 0.25 g. Trend lines showing the relationship between HB and trajectories are provided for both data sets where there were secondary crashes as well as corresponding control group data in **Figure 6**.

An odds ratio statistic was calculated for this data set. It was found through the odds ratio test that the chance of an HB event occurring increased by a factor of approximately 62 when there is an unexpected queue from a crash in comparison to free flow conditions. When the 95% statistical confidence interval is calculated, this factor can range anywhere from an upper level of approximately 104 and a lower level of approximately 37 as seen in **Table 3**.

This analysis provides quantitative data on the increased crash risk associated with freeway queuing using HB data. The literature is still maturing on the best HB threshold for conducting "near-miss" evaluation and varying values from 0.2 g to 0.5 g have been proposed. In general, the authors believe lower thresholds around 0.25 g are most appropriate for un-interrupted flow conditions, but in urbanized areas higher thresholds may be appropriate. Further research is warranted to provide more rigorous guidance on appropriate HB thresholds for different traffic conditions and use cases [5] [20] [21].

Although all the HB events were counted by hand for this study, primarily to ensure a high-quality curated data set, there are future opportunities to automate that process to improve scalability. Such automation would be desirable so that additional factors such as rural/urban, interchange proximity, weather and frequency of re-occurring congestion can be modelled.

Some agencies are now trying to incorporate highly visible roadside alerting in advance of unexpected queues to reduce crashes and assess that impact using hard braking. For example, Indiana observed that deploying a queue warning trucks and in-vehicle notifications reduced hard braking events by approximately 80% [31]. While a queue truck may be difficult to get onto the interstate quickly, some agencies are now deploying fire trucks or police vehicles approximately 1 mile upstream of queued traffic when major incidents occur that resulted in unexpected queueing on the interstate, particularly in rural areas. Longer term, it would be desirable for consumer and commercial vehicle navigation systems to include real-time alerts when abnormal rates of HB are detected. This could provide significant safety benefits not only in rural interstate areas, but on ramp and secondary roads where horizontal and/or vertical curves may limit long sight lines

There has also been some informal attempt by public safety agencies to implement rolling slowdowns, **Figure 2**, in an attempt to mitigate secondary crashes

[32]. Further investigation into this practice is warranted since once a queue form behind the slow-moving emergency vehicle, there is little visibility of the flashing lights at the front of the queue and there are still a substantial number of hard braking events at the back of the queue.

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Authors' Contributions

The authors confirm contribution to the paper as follows: study conception and design: JM, JD, RS, NS, DB; data collection: JM, JD, RS; analysis and interpretation of results: JM, JD, RS, DB; draft manuscript preparation: JM, JD, DB. All authors reviewed the results and approved the final version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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