Assessing the Safety Implication of Alternative Speed Limits in California

A Research Report from the University of California Institute of Transportation Studies

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16. Abstract

This project combined the statewide crash data (SWIRTS) and traffic data (PeMS) to develop statistical models to determine the safety impacts of alternative speed limits on California highways. The models examined whether various factors about crashes, including average traffic speed and truck-involvement, correlated with outcomes such as crash severity. The models were then used to test the impact of four alternative speed limit policies (B-E) on the predicted number of fatal crashes and unsafe-speed related crashes in urban and rural areas. The policies were: (A) Existing differential speed policy for cars (65 mph) and trucks (55 mph); (B) Raising the speed limit on interstates for trucks from 55 to 65 mph; (C) Raising the speed limit on interstates from 55 to 75 mph for trucks and 65 to 75 mph for cars; (D) Lowering the existing differential speed on interstates from 55 to 50 mph for trucks and 65 to 60 mph for cars; (E) Raising the existing differential speed on interstates from 55 to 70 mph for trucks and 65 to 80 mph for cars. The policy analysis shows a difference in the predicted number of crashes (fatal, unsafe speed) in and between urban and rural areas. The percentage increase/decrease in predicted fatal crashes in rural areas is lower than urban areas across all policy alternatives.

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Speed limits, trucks, highway safety, policy analysis, crash risk forecasting, traffic speeds, logits

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UNIVERSITY OF CALIFORNIA INSTITUTE OF TRANSPORTATION STUDIES

August 2020

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Executive Summary

Background

Speed limits reflect a trade-off between highway safety and mobility. On one hand, higher vehicle speeds require longer stopping distances and generate more energy during a collision, affecting the likelihood and severity of a crash. On the other hand, higher speed limits permit shorter travel time (which increases mobility) and that has a positive impact on economic well-being (especially for the trucking industry) and quality of life. Thus, setting an optimum speed limit on freeways for all types of vehicles, including trucks, is a critical task for highway management agencies.

Acknowledging these conflicting demands on speed limit policies, there are two schools of thought for setting speed limits. One is the uniform speed limit (USL), which mandates the same speed for all types of vehicular traffic. The other is the differential speed limit (DSL), which specifies distinct speed limits for cars and trucks. Notably, there is no conclusive evidence on the impact of these two different speed policies on safety. The State of California, along with six other states, follows the DSL policy for setting the speed limit for cars (65 miles per hour) and trucks (55 mph).

Using a data-driven modeling approach, this study aims to inform current policy discussions on the optimal truck speed limits on California freeways by determining the potential safety impacts of the following alternative policies:

(A) Existing differential speed policy for cars (65 mph) and trucks (55 mph).

(B) Raising the speed limit on interstates (urban and rural) for trucks from 55 to 65 mph.

(C) Raising the speed limit on interstates (urban and rural) from 55 to 75 mph for trucks and from 65 to 75 mph for cars.

(D) Lowering the existing differential speed on interstates (urban and rural) from 55 to 50 mph for trucks and from 65 to 60 mph for cars.

(E) Raising the existing differential speed on interstates (urban and rural) from 55 to 70 mph for trucks and from 65 to 80 mph for cars.

Policy A is the base case for comparison with other alternatives. Policy B and Policy C reflect changing the speed limit to uniform speed or USL scenarios, whereas Policy D and Policy E are scenarios for differential speed or DSL alternatives.

Data and Modeling

To address these multiple scenarios, a model was developed to estimate the probability of various types of crashes at different highway speeds based on available state crash data collected between 2014 to 2018. Data collection and pre-processing involved multiple efforts to augment the publicly available Statewide Integrated Traffic Records System (SWITRS) dataset with more robust and operational traffic attributes. First, the SWITRS data was combined with California Highway Incident Reporting System (CHIPS) data to add more accurate data on crash locations and other relevant factors. This procedure proved less than successful and produced few useful data points, due to mismatches between the time, location, and other attributes of the crashes documented in the two data sets, and the lack of common data fields to use to link individual crash data (information on this effort is contained in the Appendix). Second, the SWITRS data was merged with Performance Measurement System (PeMS) data to match specific crashes with critical traffic attributes (average speed, flow, occupancy) collected at a Vehicle Detecting Station (VDS) adjacent to the crash location in SWITRS for the specific date, time, and direction of travel (North, South, East, West) of the incident. The merging and matching resulted in a large set of data points: approximately 150,000 for the study period. The modeling part of the study was carried out based on the results from this second approach.

The combined dataset was divided into four different subsets based on the type of roadway segment (urban, rural, special 70 mph speed zone, and truck network) to assess the impact of speed and other traffic factors in crashes for each of the four road types. Three binary logit models (described fully in the modeling section of this report) were developed to quantify how much certain factors or input variables (e.g., traffic speed, weather, use of alcohol, etc.) contributed to different types of accidents. The three binary logit models have as their outcome measures (performance variables), respectively, the probability that a crash was truck-related, that the crash was speeding-related, or that the crash resulted in a fatality.

Policy Discussion

The models were developed using a sample of 70 percent of the crash records in the database and validated by using them to estimate the actual number and type of accidents in the entire database. Then the fatal crash and speeding (unsafe speed) related crash models were used to predict the probability of an increase or decrease in the number of those type crashes in the crash dataset based on presumed changes in the average speed of the traffic from the proposed changes in speed limits.

For USL policy alternatives, Policy B involves raising the truck speed limit (55 mph) to the level of passenger cars (65 mph) to attain a uniform speed. This policy is accomplished in two stages: B1(60/65 mph), and B2(65/65 mph). USL Policy C is also introduced in two stages: C1 (70/70 mph), and C2 (75/75 mph).

For DSL policy alternatives, Policy D lowers the current speed limit (55/65 mph) to 50 mph for trucks and 60 mph for cars. Policy E raises the current speed limit from 55 to 70 mph for trucks and from 65 to 80 mph for cars. Policy E is introduced in three stages: E1(60/70 mph), E2(65/75 mph), and E3(70/80 mph). For the special speed zone, the DSL policy alternatives (Policy D and Policy E) have a speed variance of 15 mph between cars and trucks (50/65 mph or 65/80 mph).

The predictive modeling for USL Policy B2(65/65 mph) reflects a lower potential increase in fatal crashes in rural areas than that of urban areas (0.1 vs. 1.6 percent). On the other hand, the changes (increase/decrease) in the predicted number of unsafe speed-related crashes vary for different roadway types. For instance, rural areas show a maximum increase of 0.3 percent and urban areas exhibit a maximum decrease of 0.2 percent depending on the chosen probability level. The special speed zone roads exhibit potential increases as high as 3 percent for fatal crashes and 2 percent for predicted unsafe speed crashes, again depending on the chosen probability level.

For the DSL policy alternatives (D and E), the predicted number of fatal crashes increased significantly for urban areas compared to rural areas when the speed limit is raised (Policy E). Similar increases are also predicted for the special speed zone. Lowering the posted speed limits (Policy D) results in fewer fatal crashes for both urban and rural areas, but a small increase (< 2 percent) in the predicted number of speeding related crashes. For DSL Policy E1, the increase in the predicted number of fatal and unsafe speed crashes in rural areas is at most only 0.6 percent across probability levels.

In testing the various scenarios, modelling data was only available for average highway speeds for all vehicles on the roadway at the time the accidents in the database occurred, not for trucks and cars separately. Therefore, in the differential speed scenarios it was not feasible to simulate directly what would occur if only average truck speeds are increased while automobile speeds remain the same. Therefore, in carrying out the analysis it was necessary to make some simplifying assumptions regarding changes in average truck speeds from increasing/decreasing truck speed limits. Although these assumptions produce plausible results, without explicit average speed data according to vehicle type a direct comparison whether DSL scenarios are safer than USL scenarios or vice-versa is not feasible. Therefore, the results of the USL scenarios should be considered less reliable than those of the DSL scenarios.

Study Limitations

Accurate modeling requires a dataset incorporating geometric information, elevation, and traffic attributes. However, for this study, the dataset was limited to crash and traffic attributes. The natural extension of this study would be to incorporate segment-based analysis with geometric information such as roadway length, number of ramps, lane width, median width, shoulder width, road profile, curvature, and alignment for individual crashes. Models based on such data elements would be comprehensive and enable more detailed inferences about the safety and operational impact of changing the speed limit.

Glossary

BL	binary logit
CATC	California Assembly Transportation Committee
CHIPS	California Highway Incident Reporting System
DSL	differential speed limit
OL	ordered logit
OR	odds ratio
PCF	primary collision factor
PeMS	Performance Measurement System
SWITRS	Statewide Integrated Traffic Records System
TIMS	Traffic Injury Mapping System
USL	uniform speed limit
VDS	Vehicle Detecting Station

Introduction

Speed limits represent a trade-off between safety and mobility. On one hand, higher vehicle speeds require longer stopping distances and generate more energy during a collision, increasing the likelihood and severity of a crash. On the other hand, higher speed limits permit shorter travel time (which increases mobility) and that has a positive impact on economic well-being (especially for the trucking industry) and quality of life. Thus, setting an optimum speed limit on freeways for all types of vehicles, including trucks, is a critical task for highway management agencies [1].

There have been three major Congressional actions setting speed limits across the United States. The first was the *National Maximum Speed Limit (NMSL)*, which established a national maximum speed limit of *55 mph* as part of the Emergency Highway Conservation Act of 1974. The second was the relaxation of NMSL in 1987, allowing states to selectively increase speed limits up to *65 mph* on rural interstate highways. The third decision came in 1995 when the NMSL was repealed, providing states full authority to determine appropriate speed limits for their roadways. As part of these policy changes, the truck speed limit received major attention as a critical component of commercial development.

In response to these policy changes, several research studies examined the impact of speed limits on traffic crashes and fatalities. Considering the objective and the available data, some study results implied that higher speed limits have a negative impact on traffic safety by increasing the number and/or rate of traffic fatalities [1], [2]. In contrast, others suggested that an increase in the speed limit is not necessarily associated with fatal crashes or safety, and some reported a positive impact from speed limit increases on safety in terms of reduced traffic fatalities [3].

These studies prompted a discussion about whether truck operating speed has a significant influence on the frequency and severity of crashes. Two different schools of thought are followed on setting truck speed limits: (i) uniform speed limit (USL); and (ii) differential speed limit (DSL). USL is a uniform maximum speed limit policy for all classes of vehicles (passenger cars, trucks). DSL consists of different speed limit policies for different classes of vehicles, setting a lower speed limit for trucks than passenger cars [4]. DSL policy recommends lowering the truck speed limit on the assumption that it reduces the potential crash risks for all other surrounding traffic, given the greater size, weight, and limited braking power of trucks during a crash. Moreover, higher speed means more fuel consumption that in turn increases environmental pollution and monetary cost. In contrast, the philosophical argument for a USL policy is that lower truck speeds compared to cars contribute to the formation of randomly moving bottlenecks, causing breakdowns and a greater likelihood of crashes, particularly as cars attempt to overtake slower trucks [3]. Thus, there are trade-offs between safety and mobility in setting speed limits. Furthermore, considerable debate exists on the true impacts of speed limit policies on traffic crashes and fatalities. Analysis over a broad range of traffic safety and operational data is a first step to ascertaining these impacts and trade-offs.

The State of California follows the DSL policy for setting different speed limits for cars (65 mph) and trucks (55 mph). Since few states (only seven) follow the DSL policy and increasing the speed limit provides an opportunity to improve mobility and increase economic growth, it would be useful to investigate the impact of DSL and USL policies in the California context. Using a data-driven modeling approach, this study aims to assist the California Assembly Transportation Committee (CATC) in setting the optimal truck speed limits on California freeways by determining the potential safety impacts of the following alternative policies:

(A) Existing differential speed policy for cars (65 mph) and trucks (55 mph).

(B) Raising the speed limit on interstates (urban and rural) for trucks from 55 to 65 mph.

(C) Raising the speed limit on interstates (urban and rural) from 55 to 75 mph for trucks and from 65 to 75 mph for cars.

(D) Lowering the existing differential speed on interstates (urban and rural) from 55 to 50 mph for trucks and from 65 to 60 mph for cars.

(E) Raising the existing differential speed on interstates (urban and rural) from 55 to 70 mph for trucks and from 65 to 80 mph for cars.

Policy A is the base case for comparison with other alternatives. Policy B and Policy C represent uniform speed or USL scenarios, whereas Policy D and Policy E reflect differential speed or DSL alternatives.

Speed Limit: Policy Direction

Since the repeal of the National Maximum Speed Law, each state has had complete control over its speed limits. A total of 41 States have set speed limits of 70 mph or higher on some portion of their freeways (Figure 1) [1]. Over the years, the popularity of DSL policy has diminished [5] as there are only seven states (California, Idaho, Indiana, Michigan, Montana, Oregon, and Washington) still employing the DSL policy on their freeways (Table 1). Since 2011, 28 states have raised their posted speed limits, and three states—Montana, Texas, and Oregon—have raised speeds limits for trucks as well [6]. For instance, the State of Utah passed legislation in 2013, which allowed the state Department of Transportation to increase the speed limit to 80 mph on certain sections of the state highway; Maine passed legislation in 2013 allowing speeds up to 75 mph on interstates and other divided access-controlled highways.

In 2015, several states (Montana, Nevada, South Dakota, Wyoming, Maryland, Oregon, Wisconsin, and Washington) increased their speed limits. Montana, Nevada, South Dakota, and Wyoming increased the speed limit to 80 mph. Montana also increased the truck speed limit to 65 mph. Similarly, Wisconsin increased its overall speed limit to 70 mph, whereas Maryland and Oregon increased the speed limit to 70 mph on some freeway sections. Following the policy direction of these other states and in light of the potential benefits, Washington increased its speed limit to 75 mph.

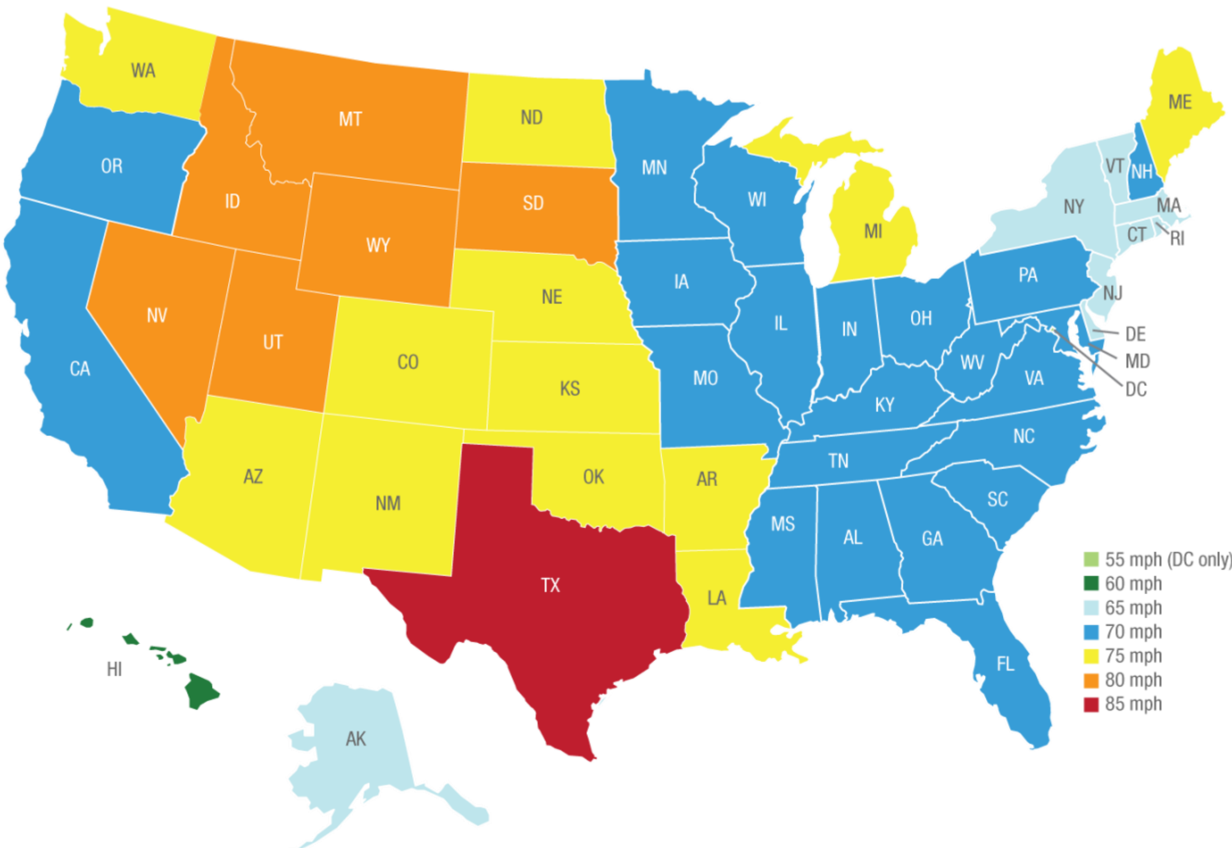

Figure 1. Maximum Interstate Speed Limits Across USA [7]

Table 1. Differential Speed Limit Across USA [7]

State	Rural Interstates (mph)			Urban Interstates (mph)		
	Car	***Truck***	***Difference***	***Car***	***Truck***	***Difference***
California	70	55	15	65	55	10
Idaho	75	70	5	75	65	10
	80	70	10	80	65	15
Indiana	70	65	5	55	55	0
Michigan	70	65	5	70	70	0
	75	65	10			
Montana	80	65	15	65	65	0
Oregon	65	55	10	55	55	0
	70	65	5			
Washington	70	60	10	60	60	0
	75	60	5			

Related Literature

The impacts of speed limits on traffic safety is a critical research topic since a consensus on the optimal relationship between speed and safety has yet to be reached [3]. This section reviews the relevant literature discussing the safety effects of raising or lowering speed limits and other secondary impacts of USL and DSL policies. The review highlights several key points, such as the effect of speed on freeway crashes, factors influencing crash frequency and severity, and the effects of truck safety equipment on crashes.

In general, the studies show that increasing the speed limit typically results in somewhat higher average speeds and increases the probability of fatalities and severe injuries but that lower speeds limits reduce the frequency and severity of crashes. However, highways that are designed for higher speeds showed less likelihood of fatal crashes and severe injuries than where speeds are increased on other roads.

Higher truck speed limits also result in more truck-related fatal crashes but the evidence is mixed on whether differences in car and truck speeds lead to more accidents and some show that even with higher truck speed limits average truck speeds are still lower than automobiles. There is some support for the idea that lower truck speed limits compared to automobiles result in fewer accidents, but the results are not conclusive.

Regarding California specifically, Haselton et al. [8] assessed the crash patterns on California highways in relation to the posted speed limit. Relevant collision, speed, and traffic volume data were collected at locations where the speed limit was increased from 55 to 65 mph, or from 65 to 70 mph, in early 1996. The study implemented three methodologies for comparison including simple regression, analysis of variance (ANOVA), and an observational before-and-after study. The findings indicated that fatal crashes increased by 35.8% after the speed limit was increased from 55 to 65 mph, and 33.9% when it was increased from 65 to 70 mph.

Some studies investigated the effect of speed limit reduction on possible safety issues and crash severity. For instance, De Pauw et. al [9] assessed the safety effects of reducing the speed limit from 90 kph (56 mph) to 70 kph (43 mph) on several highways in Belgium. The study incorporated 61 road sections with a total length of 116 km (72 miles) and a control group consisting of 19 road sections with a total length of 53 km (33 miles). The authors estimated the crash modification factor for fatal and injury-related crashes from six years before and after the change in speed limit. The results showed a decrease in fatal and injury-related crashes with the reduced speed limits [9]. Similarly, Islam and El-Basyouny [10] investigated the safety effect of reducing the speed limit from 50 kph (31 mph) to 40 kph (25 mph) for eight urban residential areas in Canada using crash data from four years before and after the change. The study utilized the empirical Bayes and full Bayesian methods; the full Bayesian results showed that lowering the speed limit reduces the frequency and severity of crashes, whereas the empirical Bayes method showed the opposite.

Time series crash data is valuable to study the combined effect of speed limit change on safety. For instance, Farmer [11] examined the combined effect of changes to maximum speed limits across the United States from 1995 to 2013. The author modeled annual traffic fatality rates by states as a function of maximum speed limits. He also accounted for general time trends, unemployment, the percentage of young drivers, and alcohol sales.

The methodology used in Farmer's study was recently updated to include modeling of state-by-state annual traffic fatality rates per mile of travel as a function of time, the unemployment rate, the percentage of the driving population younger than 25-years-old, safety belt use rate, and maximum posted speed limit [1]. The outcomes showed that a 5 mph increase in the speed limit increases the fatality rate by 8.5 percent on freeways and 2.8 percent on other roadways. Altogether, the authors estimated that during the 25-year study period approximately 36,760 (13,638 on interstates and 23,122 on other roads) more traffic fatalities occurred than would otherwise have been expected with no change in the maximum speed limit [1]. Prior to the Farmer study [11], Kockelman et al. [12] investigated the impacts of speed limit change with several datasets, including Washington State Highway Safety Information System data from 1993 to 1996. They found that an increase in the speed limit resulted in higher average speeds and that higher speeds increase the probability of fatalities and severe injuries. In another approach, Donnell et al. [13] published an informational guideline for evaluating design speed and setting up speed limits. They found that higher vehicle speeds lead to more severe crashes and that the greater the change in speed at impact the greater the probability of being injured in a crash. Later, Donnell et.al [14] studied the effects of increasing the speed limit from 65 mph to 70 mph on sections of rural interstates in Pennsylvania. They developed a framework for safety performance functions for future before-and-after studies using the empirical Bayes method.

Savolainen et al. [3] conducted a longitudinal analysis of fatal crash data across the United States from 1999 to 2011 and found that higher speed limits led to more single-vehicle crashes, while lower speed limits resulted in more rear-end crashes. The study assessed state-level traffic crash data for Michigan freeways from 2004 to 2012 and showed that crash, injury, and fatality rates on freeways with higher design speeds (> 70 mph) are lower than those where speed limits are raised from 55 to 65 or 70 mph. This study highlights the significance of geometric roadway design and traffic attributes for setting higher speed limit policies. Other approaches based on different datasets (Fatality Analysis Reporting System and Texas Department of Transportation) with similar study objectives also found that increases in speed limits produce more fatal crashes and severe injuries [2], [15].

Investigating truck crash incidents, Davis et al. [16] found that states with a 70 mph speed limit experienced approximately 32 percent more truck and bus-related fatal crashes than states with 60-65 mph speed limits (see Table 2). They also found that states with 75 mph or higher speed limits have approximately 52 percent more truck and bus-related fatal crashes. Grant and Lilliard [17] plotted average truck-related fatalities by rural interstate speed limits across the country from 1991 to 2005 and found higher speed limits associated with more truck-related crash fatalities. For DSL policies, Johnson and Pawar [18] analyzed speed data from Arkansas and Illinois rural interstate highways with 70/65 mph (car/truck) and 65/55 mph (car/truck) speed limits and suggested that higher speed variance is associated with a greater risk of a crash (Table 2). Speed variance or differential is the difference in speed between cars and trucks. Notably, the interaction of speed variance with the posted speed limit for trucks and cars is still an open question. Inspired by Monsere et al. [6], we list, in Table 2, the effect of raising USL on vehicle speed measures, including design speed, mean speed, and speed variance. Some of the listed studies [3], [14], [19], [24-26] detail the effect of raising the speed limit, whereas the rest of the studies compare two different speed limits. The design speed is the 85th percentile speed of the traffic on the roadway.

Table 2. The Effect of Speed Limit Policies on Vehicle Speed Measures

States [Study Reference]	Speed Policy	Before (mph)	After (mph)	Design Speed Change (mph)	Mean Speed Change (mph)	Compliance Rate Change	Speed Variance (mph)
Texas [20]	USL	70	75	+3	< +5		
Pennsylvania [14]	USL	65	70	< +5	< +5		
Utah [19]	USL	75	80		< +5	Cars (+) Trucks (+)	
Ohio [3]	USL [a]	<65	70				5.4
Michigan [3]	DSL [a] (Car/ Truck)	<65	70/60	< +5	< +5		6.9
Indiana [3]	DSL [a] (Car/Truck)	<65	70/65	< +2.5	< +2.5		6.2
Oklahoma vs. Missouri [18]	USL [a] (Trucks)	70	75	+4	+4	+3.1%	1.08
	USL [a] (Cars)	70	75	+3	+2.2	+21.5%	-0.3
Arkansas vs. Illinois [18]	DSL [a] (Trucks)	65/55	70/65	+2	+2.5	32.5%	-0.3
	DSL [a] (Cars)	65/55	70/65	-1	+0.3	14.5%	-1.3
West Texas [21]	USL to DSL (Cars)	75	75/80		+6	-9% (> SL)	
	USL to DSL (Trucks)	75	75/80		+3	-9% (> SL)	
Idaho [22]	USL to DSL (Trucks)	75	75/65	-4.5	- 2.1	+10% (> SL)	
	USL to DSL (Cars)	75	75/65		+1.1		
Montana [23]	USL to DSL	65	70/60	+3.2	+1.6		+1.3

a-Comparing speed limits; SL-Speed Limit

To investigate the effect of speed limit policies on operational speeds across the country, Johnson and Murray [24] worked with the speed data from 19 rural interstate locations. They found that states with 75 mph truck speed limits had only a 6.3 mph higher mean truck speed than states with 55 mph truck speed limits. Similarly, states with 75 mph truck speed limits had only a 1 mph higher design speed than the states with a 70-mph limit. For passenger cars, the design speed remained somewhat the same across states with 65 and 70 mph speed limits. The mean car speed was 3.5 mph higher for speed limits of 75 mph compared to 65 mph. Notably, the analysis showed that the speed differential between cars and trucks is evident across different states regardless of speed limit policy (DSL or USL). Furthermore, Garber et al. [25] examined 17 rural interstate highways from 1991 to 2000 and found that average speed, design speed, median speed, and crash rates increased over the 10 years, irrespective of the speed limit policy (USL or DSL).

Souleyrette and Olson [26] assessed the effects of changing the speed limit from 65 mph to 70 mph in Iowa and found an increase of 2 mph in the design speed. They also found a reduction in speeding violations by 12 percent. The study also inferred that an increase in the speed limit is associated with an increase in crash frequency and severity. For instance, night-time fatal crashes increased by 52 percent, serious injury cross-median crashes increased by 25 percent, and total crashes increased by 25 percent. The effect of raising speed limits on crash severity and frequency is listed in Table 3.

Table 3. The Effect of Raising Speed Limits on Crash Frequency and Severity

Reference	Period	Scope	From	To	Fatal Crashes	Truck-Related Fatal Crashes	Frequency
Davis et al.[16]	1999-2011	US (Rural)	60-65	70	+22.2 %	+31.7 %	
			60-65	75+	+84.5 %	+51.1 %	
Kockelman [12]	1993-1996	US	55	65	+24 %		+3%
Savolainen et al. [3]	1999-2011	US	60	70	+31 %		
			65	75	+54 %		
Grant and Lilliard [17]	2005	US	--	55			-561
			--	75			+362
Farmer [11]	1993-2013	US	+5		+8.3 %		-33,000

Hu et.al [19] investigated the impact in Utah between 2010 to 2014 of raising the speed limit on rural interstate freeways from 75 mph to 80 mph. They used a log-linear regression model to estimate percentage changes in speed variance and mean speeds for passenger cars and large trucks associated with the speed limit increase. Results showed that the mean speed change for passenger cars was 8.6 percent and 5.1 percent for trucks. For large trucks, the mean speed and probability of exceeding 80 mph were higher than expected within the 80 mph zones. Notably, the results contradict the claim that increasing speed limits reduces speed variance, likely due to the small sample size and the study locations being in different states [19].

Malyshkina and Mannering [27] investigated the effect of speed limit increases (65 mph to 70 mph) in Indiana on crash frequency and severity using a multinomial logit model. A multinomial logit model can relax parameter restrictions, which allows the effect of the speed limit to vary across injury outcomes. The results showed no statistically significant correlation between a change in speed limit and a change in crash severity on interstates. In another approach, Kweon and Kockelman [28] examined the safety effects of speed limit changes on Washington State highways with a posted speed limit greater than 55 mph using a random effects negative binomial model. The speed data recorded from the highway segments were used to develop models for average speed and speed variance. These models were used to estimate speed where speed data was not available. The estimated speed data combined with speed limit information and roadway design features were used to estimate crash frequency. The findings showed all speed-related variables to be statistically insignificant for fatal crash models. However, geometric features such as wider shoulders and gentle horizontal curves were associated with fewer fatal and non-fatal crashes.

Table 4. The Effect of Changing Speed Limit Policies on Crash Frequency and Severity

Study	Period	Scope	From	To	Fatal Crashes	Truck-Related Fatal Crashes	Frequency
Davis et al. [16]	1999-2011	USA	USL	DSL	-3.3%	-24.6%	
Savolainen et al. [3]	2004-2012	Michigan (Urban)	USL (55)	DSL (70/60)	-45%		
			DSL (65-70/60)	USL (70)			Decreased
	1999-2011	USA	USL	DSL		-20.5%	
Dixon et al. [22]	1998-2011	Idaho	USL (75)	DSL (75/65)	-26%	-38%	
Korkut et al. [29]	2004-2006	Louisiana	USL (60)	DSL (60/55)	-13%	-79%	
Gates et al. [23]	2005-2014	Montana	DSL (70/60)	USL (65)			NSg
Garber et al. [30]	1991-2000	Idaho	USL	DSL			Increased
		Virginia	DSL	USL	NSg		Increased

NSg – Non-Significant

Davis et al. [16] explored traffic fatalities on rural interstate highways from 1999 to 2011 and found that states with DSL policies had 3.3% fewer total fatal crashes and 24.6 percent less truck- and bus-involved fatal crashes compared to USL states (Table 4). Similarly, Savolainen et al. [3] found that states with USL policies had 20.5 percent more truck- and bus-involved fatalities than DSL states.

Dixon et al. [22] analyzed the change from a USL policy (75 mph) to a DSL policy (75/65 mph) on rural Idaho interstates and found that crash rates for all-vehicle-involved crashes declined by 26 percent and truck-involved crashes declined by 38 percent. They developed a crash prediction model that showed truck-involved crashes decreased by 8.56 percent, with a standard deviation of 5.06percent. Differential speed limits and truck lane restriction policies were implemented on a Louisiana freeway where the results indicated that total crashes decreased by 13 percent% and truck-involved crashes decreased by 79 percent [31], [29]. Gates et al. [23] found that a change from a DSL (70/60 mph) to a USL (65 mph) on two-lane two-way rural highways in Montana in 2013 did not change the number of non-animal related crashes significantly.

A brief review of the safety impacts of USL and DSL from the various studies is provided in Table 5. The results suggest that the findings related to safety impact are not conclusive and limited by the studies' scope and locations. For this reason, a more detailed effort is required to study the safety impact of USL and DSL in the California context.

Table 5. Safety Impact of USL and DSL

Purpose / Goal	Scope	Results	Reference
Assess the impact of DSL and transition from DSL to USL	Virginia	The results showed differences between the passenger vehicle and truck speeds without any consistent safety differences.	Garber et al. [30]
Assess the speed distributions for both heavy trucks and light vehicles including DSL & USL	19 rural interstate highway sites across the USA	Mean and design speeds were relatively unaffected by the posted speed limits. The 20-mph range for the posted truck speed limits (55 to 75 mph) resulted in only a 7 mph increase in the average speed for trucks (61.7 to 68.8 mph).	Johnson and Murray [24]
Assess the safety impact of DSL	Idaho for DSL	Truck mean speeds were reduced to 65.6 mph and that in turn reduced the speed variance and violation rate. The DSL reduced crashes by 8.56 percent below the 95% confidence level.	Dixon et al. [22]
Assess the impact of raising speed limits on crash severities	Indiana; Electronic Vehicle Crash Record System (2004-2006)	For crashes in 2006, 5.78% is identified as unsafe speed, compared to 7.28% before the speed limit increase. An increase in the speed limit did not significantly affect crash severity levels.	Malyshkina and Mannering [27]

Since the primary goal of this study is to assess the safety impact of changes in truck speed limits, a brief review of the use of speed limiters is presented. A few studies have looked at the impacts on truck crashes of safety equipment such as speed limiters and lane departure warning systems, forward collision warning systems, and roll stability systems [32], [33], [34], [35], [36]. These studies found that such devices have improved safety and reduced different types of truck crashes. Table 6 shows the key findings from these studies.

Table 6. Impact of Speed Limiter on Safety and Truck Crashes [6]

Reference	Device	Type of Study	Key Findings
Saccomano et al. [32]	Speed Limiter	Simulation	• Increases safety in the uncongested region of traffic flow. • As volumes and percentage of trucks increases, safety gains are less pronounced. • When volume approaches capacity, reduced safety is observed. • When compliance increases, a small increase in safety is observed.
Hickman et al. [33]	Speed Limiter	Survey	• Speed limiters help in reducing the top speed of the vehicle to improve safety and fuel economy. • Some respondents reported tampering with the speed limiters (22%-27%).
Hanowski et al. [34]	Speed Limiter	Field Test	• Trucks equipped with speed limiters had a lower crash rate (50%). • The cost of technology is negligible and not cost-prohibitive.
Murray et al. [35]	Lane Departure Warning Systems	Cost-Benefit Analysis	• Significant safety benefits from reduction are single-vehicle roadway departure collisions and rollover crashes. • Positive return on investment.
	Forward Collision Warning Systems	Cost-Benefit Analysis	• Between 8,597 and 18,013 rear-end crashes are likely to be prevented using FWCS. • Positive return on investment is likely for carriers that use FWCS, which are also likely to be involved in a rear-end crash.

To summarize, an extensive review of the studies from California and other states indicates that the findings regarding the impacts of changing speed limits on crashes and operational speeds are not consistent. Notably, some of the studies that analyzed the impact of raising the speed limit on safety and operational speed (mobility) found an increase in mean speeds and fatal crashes, whereas others found no significant impact on crash severity or traffic attributes.

Data Processing

Statewide Integrated Traffic Records System (SWITRS)

The Statewide Integrated Traffic Records System (SWITRS) is a database that collects, and processes data gathered from a collision scene. See SWITRS Data Structure callout box for additional details. The Internet SWITRS application is a tool that allows California Highway Patrol, other Allied Agencies, and members of the public to request various types of statistical reports from this database in an electronic format. The application allows for the creation of custom reports requested by the user, based on different categories, including locations, dates, and collision types.

> ### *SWITRS Data Structure*
>
> The SWITRS data have a hierarchical structure, where the *collision* tables contain information on each collision and the *party* tables contain information from all parties involved in the collisions. Parties are the major players in a traffic collision, including drivers, pedestrians, bicyclists, and parked vehicles. The party information includes personal descriptors and vehicle descriptors. The *victim* tables contain information about the victims associated with each party. For example, in a motorcycle-related crash incident, a motorcyclist and his passenger are each a victim. The victims can be thought of as being nested within parties and parties can be thought of as being nested within crashes.

The preprocessing of the SWITRS data revealed an accuracy issue with numerous data points (longitude and latitude) that mapped to locations in the ocean or outside California (see Figure 5). However, the proportion of accurately mapped data from SWITRS can be identified using the Traffic Injury Mapping System (TIMS), hosted by SafeTREC, UC Berkeley. Table 7 shows that just over half of the three million records contain complete spatial data (latitude and longitude) and over 98 percent of these are within the state. This study used both TIMS and SWITRS datasets to divide the entire California dataset into several parts based on different types of roadway: (i) urban; (ii) rural; (iii) truck network; and (iv) special speed zone[1] (70 mph). These parts resulted from the spatial separation of the data points (longitude and latitude) based on the road boundaries, counties, interstates, highways, etc. Table 7 summarizes the number of records for each of these categories. The data categories were constructed using a spatial query provided with the GIS boundary data from the California Department of Transportation (Caltrans). The data covers the period from January 1, 2012, to December 31, 2018.

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[1] Caltrans and the California Highway Patrol implemented 70 mph speed limits on some interstate segments (I-5, I-8, I-10, I-15, I-40, I-205, I-215, I-505, and I-580) and non-interstate or state route segments (SR-99, SR-215) before 2019, an exception to the state's general maximum speed limit of 65 mph. Autos with trailers and trucks are still limited to 55 mph as specified in California Vehicle Code 22406.

PostGIS software was used in this study to spatially join data from other sources. To divide the dataset into urban/rural/truck network/special speed zone categories, the Caltrans Adjusted Urban Areas dataset was used. For example, the truck incidents data (points) were compared with the boundaries of California urban areas (represented spatially as polygons) to identify whether the crash occurred in an urban or a rural part of the highway system; this information was appended to the new dataset with a Boolean (yes/no) variable.

Table 7. SWITRS Data Based on Spatial Queries from 2011-2018

Data Description	Record Count
Total SWITRS Collision Records	3,061,125
Records (with / without) latitude and longitude values (spatial / non-spatial)	1,558,052 / 1,503,073
Spatial records where longitude is (negative / positive)	1,051,242 / 506,810
Spatial records (inside / outside) California	1,534,830 / 23,222
California spatial records (urban / rural)	1,230,986 / 304,248
California spatial records on Truck network	757,145
California spatial records on Interstates	436,557
California spatial records in 70 mph zones	55,901

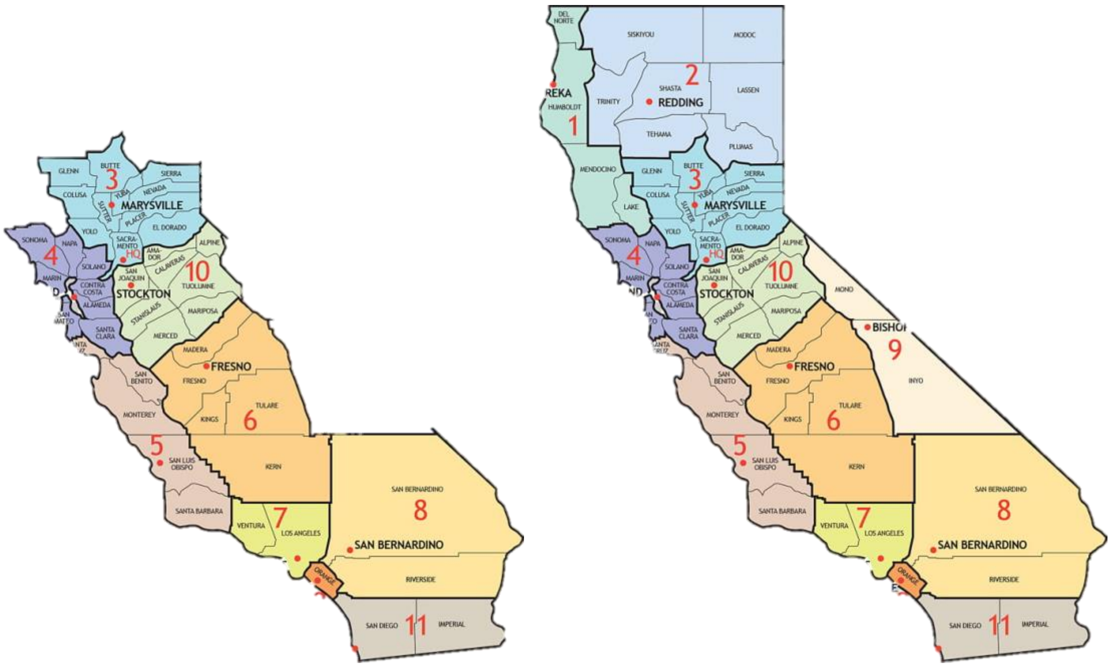
Combining Data Sources

SWITRS and PeMS

The Freeway Performance Measurement System (PeMS) in California provides an easy-to-access source of historical and real-time traffic data on highways and interstates. PeMS was initiated as a Partners for Advanced Transit and Highways (PATH) research project at the University of California, Berkeley. The data processing task from PeMS involved identifying the nearest vehicle detecting station (VDS) from the crash site and recording traffic speed, volume and other associated data from that station for the hour before the crash incident. The difficulty arose in finding the station located along the appropriate side of the freeway (i.e., with the correct direction of traffic) and linking it with the respective crash site.

The “station metadata” dataset stored in the Data Clearinghouse section of PeMS contains the location (longitude, latitude), unique identification, and direction of the VDSs. The Data Clearinghouse section provides a single access point for downloading PeMS data sets by district, month, and format. The hourly aggregates of average speed, total flow, average occupancy, direction, and other attributes with a unique station identifier are recorded in the “station hour” dataset. Preliminarily the stations were paired with the location (longitude and latitude) and hourly aggregate traffic data on different interstates and state highways. Next, the complete station dataset was used to match the nearest possible crash locations from SWITRS within four kilometers of the VDSs. Unfortunately, the PeMS only stores data for Caltrans

District 3 to 12, so data points from Caltrans Districts 1, 2, and 9 were excluded from the study area for the modeling portion of the study (Figure 2).



(a) Study Area (District 3–8, and 10–12) (b) Caltrans Districts (1–12)

Figure 2. California Department of Transportation (Caltrans) Districts

The process of matching the location and speed data from PeMS with the crash data from SWITRS was as follows.

- Extract the *"station metadata"* containing station location, identification, and direction (North, East, South, West) data from PeMS.
- Extract the *"station hour"* data for the study period across all the available Caltrans Districts (3 to 12) to incorporate traffic attributes such as "average speed," "average occupancy," "total flow," etc., in the hour before the crash incident. Data from the hour before the crash incident was used to assess the general condition of the traffic before the crash since the crash itself will likely affect the hourly aggregate flow, speed, etc., during the incident hour.
- Merge the two datasets *("station metadata"* and *"station hour")* to form a complete dataset with necessary location, unique identifier, and traffic attributes in an hourly aggregate format.
- Run the nearest distance algorithms based on the location (longitude and latitude), date, time (hour), and direction to find the nearest possible VDS from the crash location.
- Extract and merge all the relevant traffic attributes from the selected or nearest VDS, based on the matched crash data from SWITRS. After matching and uniquely identifying each vehicle involved in a crash incident, there were about 146,000 data points available for modeling.

Rationality of Using Partial Data of California

For this study, Caltrans Districts 1, 2, and 9 were excluded since there is no “station hour” and “station metadata” data from PeMS for these locations. Thus, the dataset for modeling consists of approximately 150,000 data points from 2014 to 2018, after filtering and pre-processing for any anomalies and missing values. Notably, there are few studies that have worked with operational traffic attributes (speed, flow, etc.) compared to road attributes, collision factors, and other relevant variables. Since the primary objective of this study is related to the speed limit (observed speed), and flow (operational capacity) on the roadway, the Caltrans Districts 3 to 8, and 10 to 12 provide sufficient information to develop a basic model that is applicable across California. The statewide crash data from SWITRS, when coupled with PeMS traffic attributes, provide a comprehensive dataset to predict the probability of fatalities and collisions when the average speed of the traffic stream is increased by 5, 10, or 15 mph. Moreover, it is possible to identify whether the involved vehicle is a truck and to project the potential impact from increasing the average traffic speed to evaluate the potential impact of different speed policies.

Data Description

This section describes some parts of the data used for modeling purposes. The modeling dataset consists of the combined data from SWITRS and PeMS. The merging technique and steps are discussed in the previous section. Table 8 lists the continuous variables involved in the modeling and provides a statistical description consisting of mean, minimum, maximum, and standard deviation. These parameters help to identify the breadth and frequency of the variables in the dataset. In addition, the descriptions help to understand any modeling-related errors or bias generated from these variables.

Table 8. Statistical Description of the Continuous Variables

Variable	Number of Datapoints	Statistical Description				
		Mean	Standard Deviation	Min	Max	Range
Number killed	146751	0.0194	0.1575314	0	5	5
Number injured	146751	1.60887	1.05978	0	30	30
Party count	146751	2.40499	1.05196	1	23	22
Count of severe injuries	146751	0.0613079	0.279076	0	7	7
Count of visible injuries	146751	0.331923	0.606742	0	12	12
Count of complaint of pain	146751	1.21564	1.05696	0	30	30
Crash Hour	146751	16	0	16	16	0
Crash Year	146751	2015.817	1.0889	2014	2018	4

Variable	Number of Datapoints	Statistical Description				
		Mean	Standard Deviation	Min	Max	Range
Crash Month	146751	6.4343	3.4592	1	12	11
Crash Day	146751	15.70536	8.73	1	31	30
Average speed	146751	56.473	10.672	30	81.6	51.6
Total flow	146751	2949.675	2383.724	0	15707	15707
Average Vehicle Occupancy	146751	0.094662	0.08533	0	0.9994	0.9994
Distance to Station (meters)	146751	459.68	713.0507	0.184315	3999.525	3799.341

The plot of the speed-flow relationship is presented in **Figure 3**. The plot shows that most of the fatal crashes are clustered in the vehicle-to-vehicle crash category compared to all other types of crashes.

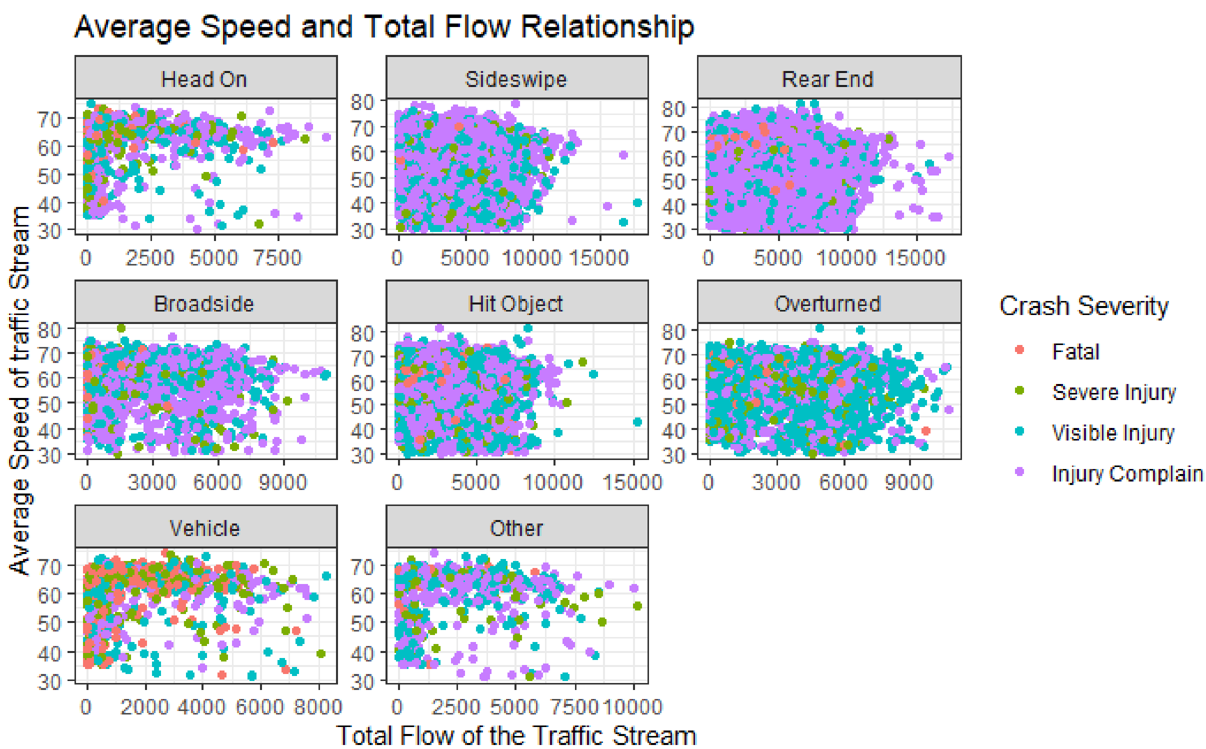


Figure 3. The relationship between speed (mph) and flow (vehicle/hour) for different types of Collisions and Crash Severity

Modeling Analysis

Two types of statistical models were developed in this study, binary logit models and an ordered logit model. This section highlights the scope of the three different binary logit models which were applied to the four types of roadway segments detailed in Table 9.

Based on various input variables, the three models determine whether the incident was more or less likely to involve a 1) truck-related crash, 2) a speeding-related crash, or 3) a fatal crash. Each model was developed (trained) based on a sample set and then tested on a separate sample to determine the model fitness for all four segments (urban, rural, truck network, special speed zone). This portion of the modeling effort was limited to binary logit models, mainly due to the dichotomous (yes/no) nature of the dependent or response variables. For instance, the "Fatal Crashes" logit model simply predicts the probability of a crash as being fatal or not. It does not differentiate the severity of the injuries resulting from the crash (from a mere complaint of pain to a fatal crash) as does the ordered logit model (which is described in a later section of this report). For the "Speeding-related Crashes" model, the term speeding means driving at an unsafe speed exceeding the posted speed limit.

Table 9. Details of the Modeling Segments for the Study

Dependent or Response Variable (Y)	Model Type	Modeling Scope			
		Urban	Rural	Truck Network	Special 70/55 Speed Zone
Truck Crashes	Binary Logit (BL)	x	x	x	x
Speeding-related Crashes	Binary Logit (BL)	x	x	x	x
Fatal Crashes	Binary Logit (BL)	x	x	x	x

Because of the dichotomous (yes/no) nature of the first three response variables (*"fatal-crash," "truck-crash," "unsafe-speed"*), a binary logit model was adopted for each instance. For this study, the logit models reflect whether (0 or 1) a crash is fatal or not, truck-related or not, and unsafe-speed related or not, based on predictor variables. These types of models are designed to overpredict the number of such crashes to ensure a margin of safety in setting policy.

Since the study builds on three different logit models to investigate and infer the relationships between various predictor variables (such as traffic average speed, flow, alcohol influence, etc.) and response variables (truck-related crashes, speeding-related crashes, fatal crashes, and collision severity), it is possible to compare the effects of different predictor variables on the response variables across models. For instance, in the fatal crash model, crashes involving trucks have a greater probability of being fatal than do passenger car-related crashes, which is also reflected in the "numbers killed" predictor variable in the truck crash model.

The methodological approach was to develop the logit models with a portion of the historic crash data (2014-2018) and use them to predict (on the complete dataset) the number of crashes being fatal or not, truck-related or not, and unsafe-speed-related or not. Once validated, those models can be used to estimate changes in the response variables from changes in the speed limit policies. More details on the prediction part of the modeling are discussed in the policy analysis section.

The framework of the binary logit model used in this study is defined as follows.

$$P(y_n) = \frac{e^x}{1+e^x} \tag{1}$$

$$X = \beta_0 + \beta_1 x_1 + \beta_x x_2 + \ldots + \beta_N x_N \tag{2}$$

Where, $P(y_n)$ is the probability of n, x denotes the predictive variables which determine the probability of a discrete outcome for n, β_N denote estimating parameters, N defines the number of independent parameters and X represents the linear function of multiple explanatory variables. The odds ratio (OR) is obtained from the exponential of the logit model coefficients. It denotes the odds that an outcome will occur given an exposure, compared with the odds of the outcome happening in the absence of that exposure.

For example, let's say that among the accidents that involve a truck (i.e., are positive for the outcome "truck-related crash") the number **with** and the number **without** an "unsafe lane change" (i.e., the *exposure* or *predictor variable*) are *p* and *q*, respectively. Also, among the causes of accidents that do **not** involve a truck (i.e., are negative for the outcome), the number with and the number without an "unsafe lane change" (exposure) are *r* and *s*, respectively. The OR is calculated as follows:

$$OR = \frac{p/r}{q/s} = \frac{ps}{qr} \tag{3}$$

If the OR is greater than 1, the presence of the exposure (for instance, an unsafe lane change) is associated with higher odds of the crash being truck related. On the other hand, if the OR is less than 1, the presence of an unsafe lane change is associated with a lower probability of a truck being involved in the crash. In other words, an OR greater than 1 indicates that the predictor variable has a positive impact on the probability of the outcome (response variable). On the other hand, an OR lower than 1 indicates that the predictor variable has a negative impact on the outcome.

The next sections describe the results of each of these models and how some of the key predictor variables are related to the response variables, specifically whether they are more or less likely to be present in truck crashes, unsafe-speed related crashes, and those involving fatalities. The final section of this study reports on what the models can infer about the likelihood of fatal crashes from increasing speed limits consistent with the various scenarios presented above.

Truck Crash Model

The logit model of a truck-related crash is divided into four different types of roadway segments (urban, rural, speed zone, truck network) with several continuous and categorical predictor variables (upper and lower sections of Table 10, respectively). The categorical variables consist of groups of two or more individual variables describing the specifics of the crash incident (cause of the crash, type of collision, road and weather conditions, etc.).

The results are reported for the urban, rural, special speed zone, and truck network segments. Notably, the number of crashes for rural roads is considerably less than for urban roads by approximately 86,000. This is likely due to crashes being rarer in rural surroundings compared to more crowded urban areas. Similarly, the special speed zone area has relatively few truck crashes, possibly because it makes up a small proportion of the interstate network, designed to specifically handle merging traffic from several locations. Since the special speed zone provision was enacted in 2016 and ended in 2019, it has three years of crash data compared to the 5 years of data for the other segments (urban and rural).

Each of the predictor variables has a distinct impact on the outcome—i.e., the probability that a crash involves a truck or "is truck-related." The values for the truck-related crash model in Table 10 represent the exponential form of the actual model estimates (i.e. the log odds of the predictor variables for the response variable) which are equal to the odds ratio (OR) described above (see Equation 3). An odds ratio greater than one indicates that the predictor variable has a positive impact on the response variable (or outcome)—that is, whether the crash involves a truck—whereas an odds ratio less than one indicates a negative impact or association. For convenience in interpretation, the positive impact on the probability of the response variable can be denoted as a positive association. This terminology has been used throughout the report when actual numbers are not stated in the model description.

For truck-related crashes, the injury predictors including "visible injury" and "severe injury" have a positive impact on the probability of a crash being truck-related. This implies that certain types of injuries ("visible injury" and "severe injury") are more likely to occur in truck-related crashes than in other types. We can interpret the model coefficients directly as odds ratios, so for example, for every unit increase in the count of a "visible injury" or a "severe injury" in a crash, the odds of the crash being truck-related increases by a factor of 1.061 and 1.015, respectively for rural areas. Similar results are observed in other areas (urban, truck network) except for special speed zone, where the visible injury count has a negative impact (less than one) on the probability of a crash being truck related.

Similarly, a higher "average speed" of traffic shows a positive impact on the probability of crash being truck-related: for every unit increase in average traffic speed in a crash, the odds of the crash being truck-related increase by a factors of 1.012, 1.023, 1.011, and 1.014 for urban, rural, special speed zone, and the truck network, respectively. Since the model does not differentiate between average car and truck speed, the operational impact of differential changes in those speed limits may require further investigation using microscopic simulation analysis or other techniques.

Although the influence of alcohol is statistically significant, it shows a negative impact on the probability of whether the crash involves a truck. In other words, for every unit increase in alcohol influenced crashes, the odds of the crash being truck-related decrease by a factor of 0.764, 0.599, and 0.676 in urban, rural, and special speed limit areas, respectively. This suggests that the influence of alcohol is not a primary factor in truck-related crashes. Notably, while truck-related crashes may be linked with higher average highway speeds, speeding or unsafe speed itself (driving above the posted speed limit) is not the primary collision factor for truck-related crashes.

Table 10. Binary Logit Model for Truck Related Crashes

Predictor Variable	Odds Ratio (Effect on Truck Crash Probability)			
	Urban (65/55)	**Rural (65/55)**	**Speed Zone (70/55)**	**Truck Network (65/55)**
CONTINUOUS VARIABLES				
Complaint of Injury Count [a]	0.879	0.755	0.805	0.870
Visible Injury Count [a]	1.045	1.061	0.967	1.078
Severe Injury Count [a]	1.212	1.015	1.088	1.213
Number Killed [a]	1.969	1.563	1.835	1.947
Average Speed [a]	1.012	1.023	1.011	1.014
Total Flow [a]	1.000	1.000	1.000	1.000
CATEGORICAL VARIABLES				
Primary Collision Factors				
Alcohol Influence [a]	0.764	0.599	0.676	0.645
Speeding / Unsafe Speed [a]	0.614	0.651	0.725	0.547
Unsafe Lane change [a]	1.144	1.144	1.742	1.034
Improper Turning [a]	1.115	1.286	1.892	1.070
Following Closely	0.558 [a]	0.456	0.259	0.465 [a]
Unsafe Starting and Backing	0.931 [a]	0.879 [b]	1.668 [a]	1.144 [a]
Improper Passing	0.859 [a]	0.832	2.736 [a]	0.830 [a]
Other Hazardous Vehicle [a]	1.432	3.436	1.624	1.813
Other than Driver [a]	1.510	1.608	1.690	1.414
Weather Condition				
Weather - Clear	-	-	-	-
Weather - Cloudy [a]	1.017	1.023	0.955	0.980
Weather - Raining [a]	1.203	1.412	1.350	1.192
Road Surface				
Dry Surface	-	-	-	-
Wet Surface [a]	1.124	0.899	0.998	1.031
Collision Type				
A - Head-On	-	-	-	-
B - Sideswipe [a]	2.676	5.258	3.879	3.174
C - Rear End [a]	1.674	4.444	3.562	2.132
D - Broadside [a]	1.697	3.716	3.211	2.286
E - Hit Object	0.420 [b]	1.021 [b]	0.454	0.495 [a]
F - Overturned	0.541 [a]	0.859 [c]	0.406	0.613 [a]

Predictor Variable	Odds Ratio (Effect on Truck Crash Probability)			
	Urban (65/55)	Rural (65/55)	Speed Zone (70/55)	Truck Network (65/55)
CATEGORICAL VARIABLES				
G - Vehicle	0.707 [a]	5.000 [a]	2.152 [a]	0.943 [a]
H – Other [a]	1.499	2.902	2.163	1.960
Lighting				
A - Daylight	-	-	-	-
B - Dusk - Dawn [a]	0.739	1.316	1.244	0.859
C - Dark - Street Lights [a]	0.795	1.059	0.802	0.721
D - Dark - No Street Lights [a]	1.046	1.387	1.280	1.268
E - Dark - Street Lights Not Functioning [a]	0.773	4.400	3.516	0.999
Observations	91,617	8,287	6,120	77,063

a: $p < 0.01$; b: $p < 0.05$; c: $p < 0.1$

The values for categorical variables used as a predictor in a logit model are expressed with respect to a reference level. For instance, for the “collision type” predictor variables in the truck-crash logit model, the reference level for comparison is the “head-on” type collision, indicated by dashes (“-“) in Table 10. The odds ratio of model estimates shows that among different types of collisions, “sideswipe” crashes have a positive impact on the probability of a crash being truck-related in rural and urban areas. In rural areas “sideswipe” type collisions are highly associated with truck-related crashes. Likewise, the “rear end” and “broadside” collisions are significant and positively associated with the probability of a crash being truck-related for all the segments. This impact is considerable for rural and special speed zones, where for every unit increase in “rear end” and “broadside” collisions, the odds of a crash being truck-related increase by a factor greater than three (Table 11).

Compared to “clear weather,” a unit increase in crashes involving “rainy weather” increases the odds of the crash being truck-related by factors of 1.203, 1.412, 1.350, and 1.192 for urban, rural, special speed zone, and truck network segment roads, respectively.

Crashes occurring on wet road surfaces compared to a regular dry surface increases the odds of the crash being truck-related in urban areas by a factor of 1.124. The lighting of the surrounding areas plays a role in the probability of a crash being truck related. Compared to “daylight” conditions, “dark areas with faulty streetlights” are statistically significant and have a considerable impact in rural areas and special speed zones, where the odds of the crash being truck-related increases by a factor of 4.40, and 3.516, respectively.

The model diagnostics of the truck-related crashes for different road types (urban, rural, speed zone, and truck network) including pseudo-rho-square (McFadden R-square), AIC, true positive rate (TPR), false-positive rate (FPR), and AUC-ROC are reported in Table 11.

Table 11. Model Diagnostics for Truck Crashes

Model Diagnostics	Model Scope			
	Urban	*Rural*	*Speed Zone*	*Truck Network*
Training Sample	65 %	80 %	85 %	65 %
Testing Sample	35 %	20 %	15 %	35 %
Misclassification Error	0.045	0.1248	0.1332	0.0518
Sensitivity (True Positive Rate)	0.0956328	0.04778	0.07317	0.07052686
Specificity	0.6941427	0.7935883	0.8387097	0.6843843
False Positive Rate	0.3058573	0.2064117	0.16129	0.31561
Model Precision	0.45	0.528571	0.6625	0.4333
Area Under Receiver Operating Curve (AUROC)	0.4811	0.5807	0.631	0.4846
Akaike Information Criteria (AIC)	43,367.350	6,257.611	6,448.473	38,396.000
McFadden R-square	0.0624890	0.127952	0.135239	0.0769942
Total Observations (Sample)	94,325	8,315	8,625	78,892

The models' accuracy can be tested. The confusion matrix (Figure 4) provides a clear concept of modeling accuracy. Here, for example, the number of truck crashes accurately classified can be expressed as the proportion of true positives relative to the number of predicted (true and false) positives. A higher precision value is associated with a better model. The predictive power of the Truck Crashes model is satisfactory according to the precision value in Table 11 for each of the different road types.

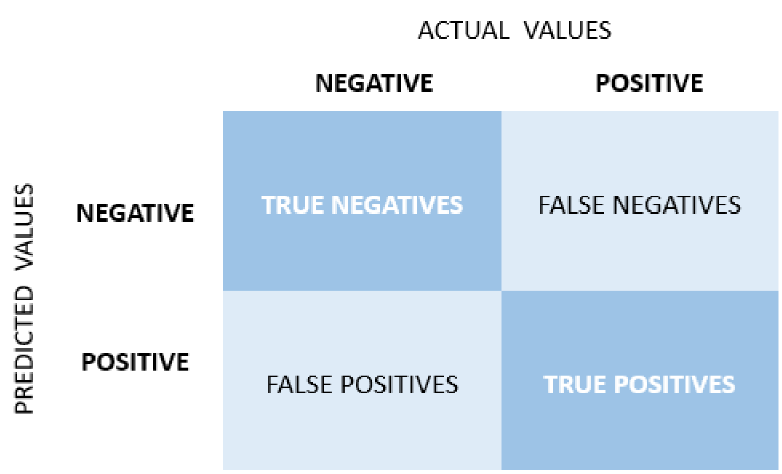


Figure 4. Confusion Matrix for the Binary Logit Model

$$\text{Precision} = {TP}/{(TP + FP)}$$

Speeding-related Crash Model

Like the truck crash model, the logit model for speeding-related crashes is divided into four segments representing different road types (urban, rural, speed zone, truck network) with several continuous and categorical predictor variables. Speeding-related crashes occur when the unsafe speed of a vehicle is the primary collision factor for the crash. The urban, rural, special speed zone, and truck network segments are the primary classifications used to describe the spatial and temporal effects of similar predictor variables on speeding-related crashes. As in the Truck Crash model, the model estimates (log odds) for the crash model are not shown in the results; rather the exponential form of the model estimates (odds ratio or OR) is reported for easier interpretation in Table 12.

For speeding-related crashes, the injury predictors including "visible injury" and "severe injury" have a negative impact on the probability of a crash being speeding-related. This implies that certain types of injuries are less likely to occur in speeding-related crashes. Again, we can interpret the model coefficients as odds ratios, where for every unit increase in the injury count (visible/severe injury) in a crash, the odds of the crash being speeding-related decreases by a factor of 0.917, and 0.701, respectively for rural areas. In urban, truck network, and special speed zone segments, a unit increase in a fatalities (number killed) increases the odds of a crash being speeding-related by factors of 1.332, 1.146, and 1.261, respectively.

The influence of alcohol is not statistically significant and shows a negative impact on the probability of whether the crash is speeding-related. In other words, for every unit increase in alcohol influenced crashes, the odds of the crash being speeding-related decrease by factors of 0.033, 0.042, 0.040, and 0.032 in urban, rural, special speed zone, and truck network segments, respectively. This suggests that the influence of alcohol is not a primary factor in speeding-related crashes.

The "vehicle type at fault" variable describes the vehicle type responsible for the crash in the model. Where motorcycles are responsible, there is a high probability of speeding-related crashes, by a factor greater than five in all study segments (urban, rural, special speed zone, and truck network). In general, motorcycles are more likely responsible for speeding-related crashes than other vehicle types in the study segments. Trucks are the next most likely cause of crashes resulting from unsafe speed in all the study segments.

For the "collision types" predictor variable in the speeding-related crash model, the reference level for comparison is the "head-on" type collision. The odds ratio of model estimates shows that among different types of collisions, "rear-end" crashes are significant and have a considerable impact on the probability of a crash resulting from unsafe speed in all the study segments. This implies that the "rear-end" type of collisions are more likely to occur from unsafe speeds than other types of collisions.

A crash occurring on a "wet road surface" compared to a regular "dry surface," increases the odds of the crash being speeding-related in rural and special speed zone segments by factors of 4.104, and 4.017. In other words, unsafe speed is the primary collision factor for crashes occurring in wet road surfaces in rural and special speed zone segments. Similar results are also observed in urban and truck network segments. The lighting of the surrounding areas also plays a role in speeding-related crashes. Compared to "daylight" conditions, "dark areas with faulty streetlights" are a statistically significant and have a considerable impact in rural areas and special speed zone, where the odds of the crashes occurring due to unsafe speed increases by factors of 3.438, and 3.644, respectively.

Table 12. Logit Model related to Speeding Related Crash

Predictor Variable	Odds Ratio (Car speed limit / Truck speed limit)			
	Urban (65/55)	Rural (65/55)	Speed Zone (70/55)	Truck Network (65/55)
CONTINUOUS VARIABLES				
Complaint of Injury Count [a]	1.181	1.124	1.118	1.171
Visible Injury Count [a]	0.836	0.917	0.862	0.833
Severe Injury Count [a]	0.713	0.701	0.679	0.683
Number Killed [a]	1.332	0.821	1.247	1.146
Average Speed [a]	0.992	0.988	0.986	0.993
Flow [a]	1.000	1.000	1.000	1.000
Alcohol Influence	0.033	0.042	0.040	0.032
CATEGORICAL VARIABLES				
Weather Condition				
Weather - Clear	-	-	-	-
Weather - Cloudy [a]	1.033	0.963	1.122	1.007
Weather - Raining [a]	1.463	0.911	1.221	1.345
Vehicle Type at Fault				
Truck [a]	3.051	2.374	1.498	2.757
Passenger Car [a]	2.460	1.511	1.430	2.349
Motorcycle [a]	6.041	7.192	6.406	5.612
Pickup [a]	2.877	1.359	1.436	2.640
Road Surface				
Dry Surface	-	-	-	-
Wet Surface [a]	3.200	4.104	4.017	3.960
Collision / Crash Type				
A - Head-On	-	-	-	-
B - Sideswipe	0.243 [a]	0.568	0.112	0.237
C - Rear End [a]	6.329	7.594	4.307	5.714
D - Broadside	0.544	0.770 [c]	0.281	0.584
E - Hit Object	0.404 [a]	0.722 [c]	0.112	0.373[a]
F – Overturned	0.535 [a]	0.636	0.101	0.455 [a]
G - Vehicle	0.584 [a]	0.964	0.172	0.642 [a]
H - Other	0.334	0.663	0.032	0.312

Predictor Variable	Odds Ratio (Car speed limit / Truck speed limit)			
	Urban (65/55)	Rural (65/55)	Speed Zone (70/55)	Truck Network (65/55)
CATEGORICAL VARIABLES				
Lighting				
A - Daylight	-	-	-	-
B - Dusk - Dawn [a]	0.969	0.849	1.150	0.890
C - Dark - Street Lights [a]	0.943	0.868	0.980	0.974
D - Dark - No Street Lights [a]	0.943	0.995	1.222	0.945
E - Dark - Street Lights Not Functioning [a]	0.945	3.438	3.644	0.885
Observations	91,617	8,287	6,120	77,063

a: $p < 0.01$; b: $p < 0.05$; c: $p < 0.1$

The diagnostics of the speeding-related crash logit model for different segments including pseudo-rho-square (McFadden R-square), AIC, true positive rate (TPR), false-positive rate (FPR), and AUC-ROC are reported in Table 13. The predictive power of the model is accurate in determining the probability of a crash from unsafe speeds for all segments according to the model precision score noted in the diagnostic table. The model also has the highest accuracy, compared to the truck-related and fatality models, for predicting speeding-related crashes due to a larger number of recorded data points in the dataset.

Table 13. Model Diagnostic of Speeding Related Crash Logit Model

Model Diagnostics	Model Segments (Car / Truck Speed Limit)			
	Urban (65 / 55)	Rural (65 / 55)	Speed Zone (70 / 55)	Truck Network (65 / 55)
Training Sample	75 %	75 %	75 %	75 %
Testing Sample	25 %	25 %	25 %	25 %
Misclassification Error	0.0885	0.1102	0.1013	0.0875
Sensitivity (True Positive Rate, TPR)	0.640073	0.695885	0.794905	0.625843
Specificity	0.57945	0.679531	0.745118	0.582799
False Positive Rate, FPR	0.0.1809	0.139616	0.153037	0.176617
Model Precision	0.87798	0.829424	0.826490	0.876704
Area Under Receiver Operating Curve (AUROC)	0.6466	0.719	0.8291	0.6485
Akaike Information Criteria	62,061.93	6,002.252	3,981.752	52,356.96
McFadden R-square	0.501615	0.478330	0.535134	0.501819
Total Observations (Sample)	91,617	8,287	6,120	77,063

Fatal Crash Model

The fatal crash model is also divided into four different parts reflecting the different types of roadway segments (urban, rural, special speed zone, truck network) with several continuous and categorical predictor variables. Although the urban and rural segments are the primary classifications used to describe the spatial and temporal effect of similar predictor variables on fatal crashes, the special speed zone also provides an insight where the speed difference between cars and trucks is 15 mph. The exponential form of the model estimates denoted as the odds ratio (OR) are reported in Table 14.

In the fatal crash model, the injury predictors such as “severe injury” have a positive impact on the probability of a crash being fatal. This implies that severe injuries are more likely to result in fatal crashes. We can again interpret the model coefficients as odds ratios, where for every unit increase in the severe injury count in a crash, the odds of the crash being fatal increase by a factors of 1.190, 1.945, 1.136, and 1.038, respectively for urban, rural, speed zone, and truck network segments. However, for all the study segments other injury predictors including “complaint of injury” and “visible injury” show a negative impact on the probability of a crash being fatal. This observation is consistent with the real-world since fatal crashes mostly involve severe injuries.

The “average speed” of the traffic is statistically significant and indicates that fatal crashes are associated with higher average speeds for all study segments. This is relatable to the real-world since higher speeds tend to increase the degree of injury in a crash.

The influence of alcohol is statistically significant and shows a positive impact on the probability of the crash being fatal. From modeling estimates, this indicates that for a unit increase in alcohol influenced crashes, the odds of the crash being fatal increase by factors of 1.585, 2.022, 1.360, and 1.357 for iurban, rural, speed zone, and truck network segments, respectively. .

Except for the truck network segment, unsafe speed-related crashes are likely to be fatal on urban, rural, and special speed zone roads. For other primary collision factors “improper turning” is statistically significant. For every unit increase in such a crash, the odds of the crash being fatal increase by factors of 1.187, 2.488, 1.634, and 1.179 on urban, rural, speed zone, and truck network roads, respectively.

Truck involved crashes are also more likely to be fatal. The model results show that for a unit increase in truck-involved crashes, the odds of the crash being fatal increase by a factorsof 2.633, 1.744, 1.825, and 2.693 on urban, rural, speed zone, and truck network roads,respectively. The effect is substantial on urban and truck network roads, indicating that truck crashes on these segments are more likely to be fatal than on other segments.

For the “collision types” predictor variable in the fatal crash model, the reference level for comparison is the “rear-end” type collision. The odds ratios of model estimates shows that among different types of collisions, “head-on,” “broad-side,” and “vehicle-related” crashes are significant and have a considerable impact on the probability of a crash being fatal in all the study segments (urban, rural, speed zone, and truck network). Among these, "vehicle-related" collisions are far more likely to be fatal. The results show that for a unit increase in "vehicle-related" collisions, the odds of the crash being fatal increase by factors of 6.878, 5.504, 5.818, and 6.614 on urban, rural, speed zone, and truck network roads, respectively.

A crash occurring in "cloudy weather" compared to regular "clear weather," increases the odds of the crash being fatal by factors of 1.254, 1.306, and 1.144, respectively, in urban, special speed zone, and truck network segments. The lighting of roadway areas plays a critical role in crashes being fatal. Except for the "streetlight not functioning" case, all other lighting conditions are statistically significant and have a positive impact on the probability of crashes being fatal in all the study segments.

Table 14. Logit Model Related to Fatal Crash

Predictor Variable	**Odds Ratio (Car speed limit / Truck Speed Limit)**			
	Urban (65/55)	***Rural (65/55)***	***Speed Zone (70/55)***	***Truck Network (65/55)***
CONTINUOUS VARIABLES				
Complaint of Injury Count	0.046	0.242	0.097	0.102
Visible Injury Count [a]	0.085	0.509 [a]	0.317 [a]	0.184 [b]
Severe Injury Count [a]	1.190	1.945	1.136	1.038
Average Speed [a]	1.025	1.006	1.022	1.030
Flow [a]	1.000	1.000	1.000	1.000
CATEGORICAL VARIABLES				
Primary Collision Factors				
Alcohol Influence [a]	1.585	2.022	1.360	1.357
Speeding [a]	1.011	1.211	1.256	0.752
Unsafe Lane change	0.718 [a]	1.119 [a]	0.468 [c]	0.678 [a]
Improper Turning [a]	1.187	2.488	1.634	1.179
Unsafe Starting and Backing	0.683	2.730 [a]	-	0.682
Follow Closely	0.209	1.126	-	0.361
Truck Involved Crash [a]	2.633	1.744	1.825	2.693
Vehicle Type at Fault				
Passenger Car [a]	0.929	0.771	0.679	0.922
Motorcycle	1.836	0.807	0.842 [b]	1.589
Pickup [a]	1.285	0.842	0.607 [c]	1.221
Weather Condition				
Weather - Clear	-	-	-	-
Weather - Cloudy [a]	1.254	0.946	1.306	1.144
Weather - Raining [a]	0.880	0.383	0.927	0.741
Road Surface				
Dry Surface	-	-	-	-
Wet Surface [a]	0.791 [a]	0.584	0.747 [c]	0.853 [a]

Predictor Variable	Odds Ratio (Car speed limit / Truck Speed Limit)			
	Urban (65/55)	***Rural (65/55)***	***Speed Zone (70/55)***	***Truck Network (65/55)***
CATEGORICAL VARIABLES				
Collision Type				
A - Head-On [a]	3.550	5.784	2.695	4.066
B - Sideswipe	0.913 [a]	0.696 [b]	1.211 [a]	0.806 [a]
C - Rear End	-	-	-	-
D - Broadside [a]	2.478	2.495	2.151	2.821
E - Hit Object [a]	1.501	1.179	1.140	1.381
F – Overturned [a]	0.963	1.410	1.635	1.347
G – Vehicle [a]	6.878	5.504	5.818	6.614
H - Other	1.727 [a]	1.870 [a]	1.950 [b]	1.661 [a]
Lighting				
A - Daylight	-	-	-	-
B - Dusk – Dawn [a]	1.547	1.594	1.334	1.604
C - Dark - Street Lights [a]	1.615	1.467	1.416	1.372
D - Dark - No Street Lights [a]	1.883	1.546	1.611	1.766
E - Dark - Street Lights Not Functioning	1.372 [a]	0.011	0.015	0.953 [c]
Observations	91,617	8,287	6,120	77,063
Akaike Information Criterion	9,290.447	2,223.165	1,317.048	9,227.758
McFadden R-square	0.320724	0.202557	0.271293	0.282530

a: $p < 0.01$; b: $p < 0.05$; c: $p < 0.1$;

The diagnostics of the fatal crash logit model for different segments including pseudo-rho-square (McFadden R-square), AIC, TPR, FPR, and AUC-ROC are reported in Table 15. The model predicts a smaller number of fatal crashes than the actual number of fatal crashes recorded in the database segments. According to the model precision values noted in Table 15, the fatal crash model performs well in predicting whether a crash is fatal or not.

Table 15. Model Diagnostic of Fatal Crash Logit Model

Model Diagnostics	Odds Ratio (Car / Truck Speed Limit)			
	Urban (65/55)	Rural (65/55)	Speed Zone (70/55)	Truck Network (65/55)
Training Sample	75 %	75 %	75 %	75 %
Testing Sample	25 %	25 %	25 %	25 %
Misclassification Error	0.0118	0.0416	0.0279	0.0142
Sensitivity (True Positive Rate, TPR)	0.1533923	0.07692308	0.115161	0.1857585
Specificity	0.88919	0.87634	0.86616	0.89853
False Positive Rate (FPR)	0.02536	0.01434	0.00965	0.03254
Model Precision	0.8756	0.5385	0.8712	0.802
Area Under Receiver Operating Curve (AUROC)	0.8356	0.7861	0.7214	0.8409
Akaike Information Criteria (AIC)	9,290.447	2,223.165	1,317.048	9,227.758
McFadden R-square	0.320724	0.202557	0.271293	0.282530
Total Observations (Sample)	91,617	8,287	6,120	77,063

Speed Policy Discussion

This section describes the results of using the models described above to estimate the safety implication of changing the speed limit on fatal and speeding-related crashes for urban and rural segments of the highway system. Changes in speed limits has been shown to have a direct impact on the average speed of the traffic ([3], [14], [19]). As noted in the literature review, for a 5 mph increment in the speed limit the average speed of the traffic tends to increase within a range of 2-4 mph (Table 2). To be conservative, we modeled the safety implication of changing the speed limit by assuming it would result in the same the increment or decrement in average speed (for instance, a 5 mph change in the speed limit is assumed to produce a 5 mph change in the average traffic speed on the highway). The speed policy analysis is divided into two parts. The first part discusses the safety implication of raising the speed limit of trucks to a uniform speed limit (Table 16). The second part discusses the safety implication from varying the current differential speed limit (Table 17).

The fatal crash and speeding-related (unsafe speed) crash models were used to predict the number of such crashes in the crash records. For this purpose, we used 70 percent of the crash records for model development and used the models to predict the specific crash probability on the entire crash dataset. This section estimates the increase or decrease in the number of specific crashes (fatal, unsafe speed) in the crash dataset fora given level of probability that the crash will produce the particular result at issue. For example, if we count all accidents where there is at least a 5 percent chance that a fatality will result under the existing speed level **Policy A** (55/65 mph) there is there could be as many a 6768 annual fatal crashes. If we raise the threshold to better than even odds (p > 50%) that any particular crash will produce a fatality then only 368 fatalities will likely result. The tables below reflect the estimated number of fatalities and speed-related crashes for four given probability ranges (p > 5%, p > 10%, p > 20%, and p > 50%) for all roads, and for urban, rural and special speed zone roads for each of the different speed policy alternatives.

Again, using eqivalent changes in the average speed as a proxy for changing the speed limit provides a conservative estimate of the probability of additional fatal crashes and unsafe-speed crashes from increasing the speed limit since raising the speed limit typically results in a smaller actual increase in average traffic speed (so a 5 mph increase in the posted speed limit, for instance, will result in a smaller increase in average speed and thus likely result in fewer actual crashes). The policy alternatives used for analysis in this section are listed below.

A. Existing differential speed policy for cars (65 mph) and trucks (55 mph).
B. Raising the speed limit on interstates (urban and rural) for trucks from 55 to 65 mph.
C. Raising the speed limit on interstates (urban and rural) from 55 to 75 mph for trucks and from 65 to 75 mph for cars.
D. Lowering the existing differential speed on interstates (urban and rural) from 55 to 50 mph for trucks and from 65 to 60 mph for cars.
E. Raising the existing differential speed on interstates (urban and rural) from 55 to 70 mph for trucks and 65 to 80 mph for cars.

Policy A is the current speed policy (DSL) scenario, which is used as a base case for comparison with the other alternatives. **Policy B** and **Policy C** reflect changing the speed limit (average speed) to a uniform speed or USL scenarios (Table 16), whereas **Policy D** and **Policy E** represent scenarios for differential speed or DSL alternatives (Table 17). For each probability level the predicted changes (+/-) in the estimated number of fatal crashes and speeding-related crashes resulting from the modeled change in the average speed of traffic from the various policy scenarios compared to the predicted values based on the historical crash data (2014-2018) under the current differential speed **Policy A**, are presented in the following tables along with the associated percentage changes (+/- n%).

USL Policy Alternatives

For USL policy alternatives, **Policy B** raises the truck speed limit (55 mph) to the level of passenger cars (65 mph) to attain a uniform speed limit. This policy is instituted in two stages: B1(60/65 mph), and B2(65/65 mph). The estimates derived for the first stage of Policy B, defined as **Policy B1,** were obtained by incrementing the average speed of the traffic in truck-related crashes by 5 mph to simulate raising the speed limit to 60 mph for trucks. This approach is used because the database only contains information on the average traffic speed, not the average speeds of cars and trucks separately. It, in effect, assumes that only truck speeds will increase under this scenario and thus only counts the additional fatalities or speeding related crashes involving trucks due to raising the average traffic speed for all vehicles (not just for trucks). While it is not a perfect substitute, it represents a reasonable simplifying assumption given the lack of more specific data on average truck and car speeds.

Modeling for the second stage, defined as **Policy B2,** involved incrementing the average traffic speed of the in truck-related crashes from **Policy B1** by an additional 5 mph to simulate a 65 mph speed limit for trucks. Again, this approach models changing only the average speed of the traffic in truck-related crashes to make a broad estimation of the impact of changing the speed limit for trucks since the database does not classify average traffic speed by vehicle type. For the special 70 mph speed zone, while the average speed of truck-related crashes is increased by a total of 10 mph to simulate the effect of a 65 mph speed limit for trucks, the average speed for the remainer of the crashes is decreased by 5 mph to reflect a lower 65 mph speed limit for cars. This produces a gross estimation of the crashes resulting from a uniform speed limit for all traffic considering the average speed of truck-related crashes and other crashes.

Policy C reflects the scenario where the speed limit is gradually raised from 55 to 75 mph for trucks and from 65 to 75 mph for cars. This policy dictates that the truck speed limit (55 mph) is first raised to the level of passenger cars (65 mph) as in **Policy B** and then both speed limits are increased uniformly to 75 mph as part of the USL policy.

Modeling for **Policy C** was also performed in two stages, where the first stage (**Policy C1**) reflects incrementing the average speed of all traffic by 5 mph from **Policy B** to simulate a uniform speed limit of 70 mph. The second stage of **Policy C,** defined as **Policy C2,** reflects further incrementing the average speed of all traffic from **Policy C1** by 5 mph to reflect a uniform speed limit of 75 mph. For the special speed zone, the same approach used above is followed, however the average speed of the crash incidents excluding trucks is increased by 5 mph to reflect the new uniform speed limit (75 mph), whereas the average speed for truck-related crash incidents is increased by 20 mph.

Results

For **Policy B1 (60/65)**, the predicted number of fatal crashes increases across all probability levels in urban areas and special speed zones other than the most restrictive case (p > 50%) but for rural areas predicted crashes only show only a slight increase of 0.1 percent (755 fatal crashes vs. 754) for the > 10% probability level. For urban areas the increase in the predicted number of fatal crashes is as high as one percent across the different probability levels. For special speed zones the increase in predicted fatal crashes is as high as two percent among the least restrictive probability levels.

Unsafe speed-related crashes show small percentage decreases (< -0.5%) in urban areas. However, in rural areas there are no or small percentage increases (< 0.5%). Despite the variation between urban and rural areas in the **Policy B1** estimates, overall the percentage of predicted unsafe speed-related crashes for all areas combined increase for all proability levels with the largest increase as high as one percent (92349 unsafe speed crashes vs. 91370) at the > 10% probability level. The largest change under **Policy B1** occurs in the special speed zone where predicted unsafe speed-related crashes increase by 1.5 percent (5208 unsafe speed crashes vs. 5124) for the least restrictive probability category (p > 5%).

For **Policy B2 (65/65)**, the predicted number of fatal crashes increases in urban areas at all probability levels and at all probability levels except the most-restrictive category (p > 50%) in the special speed zone. For rural areas, predicted crashes only increase 0.1 percent at the lowest probability level (1862 fatal crashes vs. 1859) and at the over 10 percent level (755 fatalities vs. 754). For urban areas, the increase in the predicted number of fatal crashes is as high as 1.5 percent (2313 fatal crashes vs. 2272). For the special speed zone, fatal crashes increase as much as three percent (506 fatal crashes vs. 490) at the > 10% probability level and at the > 5% percent level (1081 vs. 1044).

Unsafe speed-related crashes decrease by a small percentage (< -0.5%) in urban areas but increase slightly (< 0.5%) in rural areas. Overall, the increase is as high as 0.9 percent (92274 unsafe speed crashes vs. 91370). The increase in the special speed zone is up to 2 percent (5218 unsafe speed crashes vs. 5124).

Table 16. **Speed Limit Policy Alternatives for USL. The percentage change in the bracket is the comparison with the base case (Policy A).**

Speed Limit Policies (Truck/Car)	**Predicted Probability**	**No. of Predicted Fatal Crashes (Overall)**	**No. of Predicted Fatal Crashes (Urban)**	**No. of Predicted Fatal Crashes (Rural)**	**No. of Predicted Fatal Crashes in Special Speed Zone**	**No. of Predicted Unsafe Speed Related Crashes (Overall)**	**No. of Predicted Unsafe Speed Related Crashes (Urban)**	**No. of Predicted Unsafe Speed Related Crashes (Rural)**	**No. of Predicted unsafe Speed Crashes Special Speed Zone**
A: DSL (55/ 65 mph for Urban, Rural) & (55/70 for Special Speed Zone)	**> 5 %**	**6768**	**4656**	**1859**	**1044**	**105813**	**98221**	**7857**	**5124**
	> 10 %	**3110**	**2272**	**754**	**490**	**91370**	**86520**	**5663**	**3894**
	> 20 %	**1243**	**1074**	**252**	**181**	**77095**	**72787**	**4732**	**3641**
	> 50 %	**368**	**333**	**36**	**44**	**69188**	**65841**	**4125**	**3289**
B1: DSL 60/65 mph	> 5 %	6916 (+2%)	4700 (+0.9%)	1859 (+0%)	1067 (+2%)	106031 (+0.2%)	98181 (-0.04%)	7866 (+0.1%)	5208 (+1.5%)
	> 10 %	3184 (+2%)	2300 (+1%)	755 (+0.1%)	500 (+2%)	92349 (+1%)	86402 (-0.14%)	5664 (+0.02%)	3905 (+0.2%)
	> 20 %	1263 (+1%)	1082 (+0.5%)	252 (+0%)	184 (+1.5%)	77341 (+0.3%)	72764 (-0.03%)	4732 (+0%)	3654 (+0.3%)
	> 50 %	370 (+0.5%)	334 (+0.3%)	36 (+0%)	44 (+0%)	69666 (+0.7%)	65832 (-0.01%)	4126 (+0.02%)	3326 (+1%)
B2: USL 65/65 mph	> 5 %	7014 (+3%)	4714 (+1%)	1862 (+0.1%)	1081 (+3%)	105980 (+0.16%)	98144 (-0.08%)	7875 (+0.2%)	5218 (+2%)
	>10 %	3217 (+3%)	2313 (+1.5%)	755 (+0.1%)	506 (+3%)	92274 (+0.9%)	86335 (-0.2%)	5670 (+0.1%)	3903 (+0.2%)
	> 20 %	1274 (+2%)	1095 (+1.5%)	252 (+0%)	186 (+2.5%)	77317 (+0.3%)	72734 (-0.07%)	4732 (+0%)	3654 (+0.36%)
	> 50 %	373 (+1%)	336 (+0.9%)	36 (+0%)	44 (+0%)	69654 (+0.6%)	65823 (-0.03%)	4126 (+0.02%)	3323 (+1%)
C1: USL 70/70 mph	> 5 %	7889 (+16%)	5314 (+14%)	1864 (+0.3%)	1142 (+9%)	105689 (-0.12%)	97933 (-0.2%)	7904 (+0.6%)	5106 (+0.35%)
	>10 %	3517 (+13%)	2543 (+11%)	758 (+0.5%)	567 (+15%)	91250 (-0.13%)	85202 (-1%)	5714 (+0.9%)	3881 (-0.3%)

Speed Limit Policies (Truck/Car)	Predicted Probability	No. of Predicted Fatal Crashes (Overall)	No. of Predicted Fatal Crashes (Urban)	No. of Predicted Fatal Crashes (Rural)	No. of Predicted Fatal Crashes in Special Speed Zone	No. of Predicted Unsafe Speed Related Crashes (Overall)	No. of Predicted Unsafe Speed Related Crashes (Urban)	No. of Predicted Unsafe Speed Related Crashes (Rural)	No. of Predicted unsafe Speed Crashes Special Speed Zone
	> 20 %	1402 (+12%)	1170 (+8%)	252 (+0%)	215 (+18%)	77054 (-0.05%)	72435 (-0.4%)	4733 (+0.02%)	3639 (-0.05%)
	> 50 %	389 (+5%)	354 (+6%)	36 (+0%)	49 (+11%)	69162 (-0.04%)	65509 (-0.5%)	4133 (+0.15%)	3280 (-0.27%)
C2: USL 75/75 mph	> 5 %	8785 (+29%)	6019 (+29%)	1870 (+0.6%)	1305 (+25%)	105360 (-0.4%)	97639 (-0.6%)	7929 (+0.9%)	4947 (-3%)
	>10 %	3796 (+22%)	2752 (+21%)	762 (+1%)	657 (+34%)	90446 (-1%)	84381 (-2%)	5786 (+2%)	3849 (-1%)
	> 20 %	1537 (+23%)	1241 (+15%)	252 (+0%)	245 (+35%)	76767 (-0.4%)	72170 (-0.8%)	4735 (+0.06%)	3621 (-0.5%)
	> 50 %	414 (+12%)	378 (+13%)	36 (+0%)	51 (+15%)	68722 (-0.6%)	65008 (-1%)	4146 (+0.5%)	3235 (-1.5%)

For **Policy C1 (70/70)**, fatal crashes increase substantially in urban areas and the special speed zone at all probability levels. For rural areas, the number of predicted crashes increase as much as 0.5 percent (758 fatal crashes vs. 754) at the >5% probability level but not at all at the > 20% and > 50% levels. For urban areas the predicted increase is as high as 14 percent (5314 fatal crashes vs. 4656) and it is as much as 18 percent (215 fatal crashes vs. 181) for the special speed zone.

Unsafe speed-related crashes decrease as much as one percent (85202 unsafe speed crashes vs. 86520) in urban areas at the > 10% percent probability level but increase in rural areas as much as one percent (5714 unsafe speed crashes vs. 5663). Overall, they decline as much as -0.13 percent (91250 unsafe speed crashes vs. 91370) at the > 10% percent probability level. There are both small percentage increases and decreases (<1%) in the special speed zone.

For **Policy C2 (75/75)**, fatal crashes increase substantially in urban areas and special speed zones across all probability levels. The increases are as high as 29 percent (6019 fatal crashes vs. 4654) for urban roads and 35 percent (245 fatal crashes vs. 181) for the special speed zone. For rural areas, the maximum increase is just one percent (762 fatal crashes vs. 754) at the > 10% probability level with no increases at the >20% and >50% levels.

Usafe speed-related crashes decrease by as much as -2 percent in urban areas (84381 vs 86520) but increase by as much as two percent in rural areas. Overall, there is up to a one percent decrease. The decrease is as much as three percent in the special speed zone (4947 vs. 5124).

DSL Policy Alternatives

For DSL policy alternatives (Table 17), **Policy D** lowers the current speed limit (55/65 mph) to 50 mph for trucks and 60 mph for cars, maintaining the 10 mph differential. The model estimates are obtained by decreasing the average traffic speed values for the accidents in the database and rerunning the models to predict how many would have resulted in fatalities or involve speed related crashes under those conditions. **Policy E** would raise the current speed limit from 55 to 70 mph for trucks and from 65 to 80 mph for cars, again keeping the 10 mph differential. **Policy E** is introduced in three stages, where the first stage (**Policy E1**) increases the speed limit to 60 mph for trucks and 70 mph for cars, the second stage (**Policy E2**) raises it to 65 mph for trucks and 75 mph for cars, and the third stage (**Policy E3)** completes the full increases. For stage one, the modelling raised the average traffic speeds for all the crash data points by 5 mph to simulate the differential speed limit of 60/70 mph. The second stage increased the average traffic speeds by an additional 5 mph from **Policy E1** to simulate the differential speed limit of 65/75 mph. The final stage added another 5 mph increment to the average traffic speed to estimate the safety implications of the 70/80 differential speed. For the special speed zone, the differential speed policy alternatives (Policy D and Policy E) have a 15 mph variance between car and truck speed limits, otherwise the methodology is the same (Table 17).

Results

For **Policy D (50/60)**, fatal crashes decrease substantially in urban areas and the special speed zone across all probability levels. The decrease for urban areas is as much as -10 percent (4180 fatal crashes vs. 4656) and -13 percent (157 fatal crashes vs. 181) for special speed zones. The declines are smaller or insubstantial for rural areas, with the largest predicted decrease of -0.4 percent (751 fatal crashes vs. 754) at the > 10% probability level.

Unsafe speed-related crashes increase by as much as one percent (87759 unsafe speed crash vs. 86520) in urban areas but decrease by as much as -0.8 percent (5619 vs.5663) in rural areas. Overall, the increase in the predicted number unsafe speed-related crashes is as high as one percent (92,689 unsafe speed crashes vs. 91370). In the special speed zone, the maximum increase is also as high as one percent.

For **Policy E1 (60/70)**, fatal crashes show substantial increases in the urban and special speed zones across all probability levels. For urban areas the increase is as high as 10 percent (5145 fatal crashes vs. 4656) while for special speed zones it is as great as 12 percent (552 fatal crashes vs. 490). For rural areas, maximum increase is only 0.2 percent (753 fatal crashes vs. 754) at the > 10% probability level but there is no increase for the > 20% or > 50% probabiltiy levels.

Unsafe speed-related crashes decrease by as much as one percent (85312 unsafe speed crash vs. 86520) in urban areas. However, in rural areas they increase as much as 0.6 percent (5700 unsafe speed crashes vs. 5663). Overall there is a decrease in the predicted number of unsafe speed-related crashes by as much as -0.9 percent (90539 unsafe speed crash vs. 91370). The decrease is as much as -2 percent (4987 unsafe speed crashes vs. 5124) in the special speed zone.

Table 17. **Speed Limit Policy Alternatives Based on Fatal Crash and Unsafe-Speed related Crash. The percentage change in the bracket is the comparison with the base case (Policy A).**

Speed Limit Policies (Truck/Car)	Predicted Probability	No. of Predicted Fatal Crashes (Overall)	No. of Predicted Fatal Crashes (Urban)	No. of Predicted Fatal Crashes (Rural)	No. of Predicted Fatal Crashes in Special Speed Zone	No. of Predicted Unsafe Speed Related Crashes (Overall)	No. of Predicted Unsafe Speed Related Crashes (Urban)	No. of Predicted Unsafe Speed Related Crashes (Rural)	No. of Predicted Unsafe Speed Crashes in Special Speed Zone
A: DSL (55/ 65 mph for Urban, Rural) & (55/70 for Special Speed Zone)	**> 5 %**	**6768**	**4656**	**1859**	**1044**	**105813**	**98221**	**7857**	**5124**
	> 10 %	**3110**	**2272**	**754**	**490**	**91370**	**86520**	**5663**	**3894**
	> 20 %	**1243**	**1074**	**252**	**181**	**77095**	**72787**	**4732**	**3641**
	> 50 %	**368**	**333**	**36**	**44**	**69188**	**65841**	**4125**	**3289**
D: DSL (50/ 60 mph for Urban, Rural) & (50/65 for Special Speed Zone)	> 5 %	6063 (-10%)	4180 (-10%)	1854 (-0.3%)	944 (-9%)	106279 (+0.4%)	98399 (+0.1%)	7834 (-0.3%)	5165 (+0.8%)
	> 10 %	2866 (-7%)	2104 (-7%)	751 (-0.4%)	446 (-8%)	92689 (+1%)	87759 (+1%)	5619 (-0.8%)	3924 (+0.7%)
	> 20 %	1129 (-9%)	1007 (-6%)	251 (-0.4%)	157 (-13%)	77670 (+0.7%)	73184 (+0.5%)	4730 (-0.04%)	3655 (+0.4%)
	> 50 %	344 (-6%)	318 (-4%)	36 (+0%)	41 (-6%)	70166 (+1%)	66146 (+0.4%)	4115 (-0.2%)	3330 (+1%)
E1: DSL (60/70 mph for Urban, Rural) & (60/75 for Special Speed Zone)	> 5 %	7518 (+11%)	5145 (+10%)	1861 (+0.1%)	1134 (+8%)	105505 (-0.2%)	98018 (-0.2%)	7883 (+0.3%)	4987 (-2%)
	> 10 %	3356 (+8%)	2459 (+8%)	753 (+0.2%)	552 (+12%)	90539 (-0.9%)	85312 (-1%)	5700 (+0.6%)	3862 (-0.8%)
	> 20 %	1345 (+8%)	1144 (+6%)	252 (+0%)	200 (+10%)	76801 (-0.4%)	72482 (-0.4%)	4732 (+0%)	3623 (-0.5%)
	> 50 %	383 (+4%)	345 (+3%)	36 (+0%)	45 (+2%)	68743 (-0.5%)	65528 (-0.4%)	4133 (+0.2%)	3242 (-1%)

Speed Limit Policies (Truck/Car)	Predicted Probability	No. of Predicted Fatal Crashes (Overall)	No. of Predicted Fatal Crashes (Urban)	No. of Predicted Fatal Crashes (Rural)	No. of Predicted Fatal Crashes in Special Speed Zone	No. of Predicted Unsafe Speed Related Crashes (Overall)	No. of Predicted Unsafe Speed Related Crashes (Urban)	No. of Predicted Unsafe Speed Related Crashes (Rural)	No. of Predicted Unsafe Speed Crashes in Special Speed Zone
E2: DSL (65/75 mph for Urban, Rural) & (65/80 for Special Speed Zone)	> 5 %	8491 (+25%)	5830 (+25%)	1869 (+0.5%)	1240 (+18%)	106087 (+0.2%)	97757 (-0.4%)	7909 (+0.6%)	4976 (-2%)
	> 10 %	3633 (+16%)	2639 (+16%)	759 (+0.6%)	615 (+25%)	92452 (+1%)	85456 (-1%)	5749 (+1.5%)	3838 (-1%)
	> 20 %	1488 (+19%)	1218 (+13%)	252 (+0%)	243 (+34%)	77356 (+0.35%)	72200 (-0.8%)	4734 (+0.04%)	3606 (-0.9%)
	> 50 %	402 (+9%)	365 (+9%)	36 (+0%)	45 (+2%)	69681 (+0.7%)	65024 (-1%)	4143 (+0.4%)	3215 (-2%)
E3: DSL (70/80 mph for Urban, Rural) & (70/85 for Special Speed Zone)	> 5 %	9439 (+39%)	6470 (+38%)	1870 (+0.6%)	1374 (+31%)	105160 (-0.6%)	97421 (-0.8%)	7934 (+0.9%)	4964 (-3%)
	> 10 %	3985 (+28%)	2843 (+25%)	760 (+0.7%)	681 (+38%)	89790 (-1.5%)	84877 (-2%)	5820 (+2.5%)	3818 (-1.5%)
	> 20 %	1667 (+34%)	1303 (+21%)	252 (+0%)	263 (+45%)	76531 (-0.7%)	71900 (-1%)	4741 (+0.2%)	3596 (-1%)
	> 50 %	428 (+16%)	399 (+19%)	36 (+0%)	51 (+15%)	68401 (-1%)	65588 (-0.4%)	4153 (+0.7%)	3161 (-3%)

For **Policy E2 (65/75)**, fatal crashes increase in the urban and special speed zones across all probability levels by as much as as 25 percent (5830 fatal crashes vs. 4656) for urban areas and 34 percent (243 fatal crashes vs. 181) for special speed zones. For rural areas, the number of predicted crashes increase by no more than 0.6 percent (759 fatal crashes vs. 754) at the lowest levels of probability.

By constrast, unsafe speed-related crashes decrease in urban areas by areas as much as -1 percent (85456 unsafe speed crash vs. 86520). However, in rural areas they increase as high as 1.5 percent (5749 unsafe speed crashes vs. 5663). Overall the increase in unsafe speed-related crashes is as high as one percent (92452 unsafe speed crash vs. 91370). The estimated unsafe speed-related crashes in the special speed zone show a decrease of as much as -2 percent (4976 unsafe speed crashes vs. 5124) at the > 5% probability level.

For **Policy E3 (70/85)**, fatal crashes increase in urban areas and special speed zones across all probability levels. The increase is as high as 38 percent (6470 fatal crashes vs. 4656) for urban areas and 45 percent (263 fatal crashes vs. 181) for the special speed zone. For rural areas, the maximum increase is less than one percent (760 fatal crashes vs. 754) with no observed changes for the higher probability levels. Overall, however, fatal creashes increase as high as 39 percent (9439 vs. 6768 fatal crashes) for the least restrictive probability category.

Unsafe speed-related crashes decrease by as much as -2 percent (84877 unsafe speed crash vs. 86520) in urban areas and as much as three percent (4964 unsafe speed crashes vs. 5124) in the special speed zone. However, in rural areas there is an increase as high as 2.5 percent (5820 unsafe speed crashes vs. 5663). Overall, the unsafe speed-related crashes decline as much as -1.5 percent (89790 unsafe speed crashes vs. 91370).

Summary

The speed limit policies show a clear contrast between urban and rural areas. The percentage increase in predicted fatal crashes in rural areas is far less across all policy alternatives (USL and DSL) compared to urban areas. Although the special speed zone was only in effect for three years (2016-2018), the modelling shows the same tendencies toward higher fatal and speeding related crashes from increasing highway speeds as urban areas. Similarly, the predicted change in unsafe speed crashes shows distinct differences between urban and rural areas for both USL and DSL policy alternatives. Notably, unsafe speed-related crashes increase in rural areas for both USL and DSL policy scenarios, unlike in urban areas.

Among the USL alternatives, **Policy B2** (65/65) shows an increase in the predicted number of fatal crashes in urban areas of less than 1.6 percent across all probability levels. Notably, the increases in fatal crashes in rural areas are far less than urban areas, where the maximum increase is around 0.1 percent. Similarly, the increase in unsafe-speed-related crashes in rural areas is less than 0.3 percent. Interestingly, the predicted number of unsafe speed related crashes in urban areas exhibit a decrease of up to -0.2 percent. The special speed zone exhibits an increase as high as three percent for fatalities and two percent for unsafe speed crashes.

For the DSL alternatives, **Policy D** (50/60) shows a decrease in the predicted number of fatal and unsafe speed crashes in urban and rural areas. For DSL **Policy E1** (60/70), the increase in the predicted number of fatal and unsafe speed crashes in rural areas is limited to 0.6 percent across probability levels.

Across the country, speed limits are increasing. However, the impacts of this trend are unclear as studies differ based on the datasets and methodology used (see literature review section). On that note, data limitations play a critical role in assessing the safety implication of changing the speed limit. The primary goal of this study was to compare the safety impacts of USL and DSL on California roadways. For the DSL scenarios, the average speed of the traffic at the time of the incident, including cars and trucks was shifted (increased/decreased) to maintain the differential between car and truck speeds in the proposed change in speed limit. For USL, a uniform speed is required for both cars and trucks. Thus, to analyze a shift from the current DSL speed limit (Policy A), for instance, to a uniform speed limit for both cars and trucks at 65 mph (Policy B), the average speed of the trucks on the highway has to be increased relative to that of cars. For this reason, separate speed data for cars and trucks are required. However, the study dataset consists of aggregated average speeds for all traffic, including cars and trucks. Since the necessary speed data (car vs. truck) is not available, the average traffic speed for truck-related crashes only is used to represent the truck average speed for the USL scenarios. Although this assumption produces relatable results, without explicit model variables that describe the effect of vehicle classification (cars vs. trucks), the representative USL results may not be reliable. On the other hand, the modeling assumptions and dataset support the DSL scenarios. This suggests that an explicit comparison whether DSL scenarios are better than USL scenarios or vice-versa is not feasible because of the data limitation. Thus, according to our study scope and limitation, the results of the USL scenarios should be considered less reliable than those of the DSL scenarios.

Modeling Limitations

The models developed in this study do not contain roadway geometry information (e.g. lane width, median width, and shoulder width). The segment length for each crash is recorded as the length of the nearby vehicle detecting station (VDS). Since this study assesses the safety impact of shifting the posted speed limit (average speed) using the historical dataset, the cumulative number of crashes (fatal, unsafe speed) were the primary candidate for evaluation rather than segment specific variation.

The variable for highway speed in this study is defined as the observed average speed of the traffic in the hour before the crash. Since there is no vehicle classification data available for the VDS from PeMS, the average speed of the entire traffic stream is used rather than the separate average speeds of passenger cars and trucks.

Across the data segments and for different models, total flow values show a similar trend, which is a slightly positive impact on the outcomes (i.e., probability of a crash involving a truck, being related to speeding, or involving a fatality). There is no distinctive pattern to the model estimates that can be used to describe a different possible impact (greater or smaller) of flow on the outcome. This is associated with the high value of flow and variability along with the data segments (see **Figure 3**).

Conclusion

Speed limits promote highway safety and assist law enforcement to ensure an optimum tradeoff between safety and mobility based on the geometry of the roadway and other relevant factors. This study was undertaken to assess the impact of higher speed limits on safety to inform policymakers of the potential safety issues, based on a data-driven modeling approach. To achieve this goal the study consisted of a literature review, data collection and preprocessing, modeling analysis, and policy discussion.

The review of studies from California and other states indicated that the findings concerning the impacts of changing speed limits on crashes and operational speeds are not consistent. Notably, some of the studies that analyzed the impact of raising the speed limit found an increase in mean speeds and fatal crashes, whereas others found no significant impact on crash severity or frequency.

In this study, the multi-step process of data extraction, processing, and matching with crash data involved SWITRS, CHIPS, and PeMS datasets. First, SWITRS data was combined with CHIPS data to append more accurate data on crash locations and other relevant fields. However, this first matching effort (SWITRS and CHIPS) produced very few data points, due to mismatches of the time-window, location tag, and other attributes. Second, SWITRS data was merged with the PeMS data to match specific crashes with critical traffic attributes (average speed, flow, occupancy) which resulted in a large set of data points—approximately 150,000—for the study period of 2014 to 2018. This dataset was used for the modeling part of the study.

For the modeling approach, the dataset was divided into roadway types (urban, rural, special speed zone, and truck network). Three binary logit models (truck-related crash, speeding-related crash, and fatal crash) were developed to examine the effect of different predictor variables on the crash outcome. The model results showed some interesting and expected associations with the predictor variables. The discrepancies resulted from modeling limitations and data requirements. The primary limitation of this study is that it does not contain any road geometry information and vehicle speed classification data.

DSL and USL policy alternatives were tested by predicting the increase or decrease of certain type of crashes (fatal, unsafe speed) using the historic data by increasing or decreasing the values of the variables for average traffic speed. The primary assumption for this methodology is that the average speed of the traffic is directly linked with the posted speed limit of the roadway. The policies were then tested based on the predicted fatal and unsafe-speed related crashes in urban, rural and special speed zone areas. The proposed alternative speed limit policies result in different outcomes in the predicted number of crashes in urban and rural areas. The percentage increase in predicted fatal crashes in rural areas is far less across all policy alternatives (USL and DSL) compared to urban areas. For instance, for USL Policy B2(65/65 mph) the projected increases in fatal crashes in rural areas are less than that of urban areas (0.1 percent vs. 1.6 percent). The change (increase/decrease) in the predicted number of unsafe speed related crashes for different roadway types show a dissimilar trend. For instance, rural areas show a maximum 0.3 percent increase in unsafe speed related crashes while urban areas exhibit a decrease of 0.2 percent. The special speed zone exhibits as much as a three percent increase in fatal crashes and as many as two percent more unsafe speed crashes.

For the DSL policy alternatives (D and E), the predicted number of fatal crashes increase significantly for urban areas compared to rural areas for higher speed limits (Policy E). The special speed zone also exhibits similar increases. The number of fatal crashes decrease, however, when the posted speed limit is reduced (Policy D) for both urban and rural areas. In contrast, a small increase (< 2%) in the predicted number of speeding related crashes is observed for urban areas when the posted speed limit is lowered (Policy D). For DSL Policy E1(60/70), the increase in the predicted number of fatal and unsafe speed crashes in rural areas is limited to 0.6 percent across probability levels.

Information on the average speed of trucks compared to automobiles is needed to assess policies that would change the posted differential speed limit to a unified speed limit for both classes of vehicles. However, the traffic data available for this study did not include such information. For this reason, the USL scenarios were evaluated by using the average highway speed for the set of all truck-related crashes. Although this assumption provides relatable results, without explicit classification of the average speed according to the vehicle type the USL policy results may not be consistent. Moreover, lack of classified (cars and trucks) speed data makes the comparison between DSL and USL scenarios difficult. Considering the data limitation and study scope, the results of DSL scenarios provide more reliable estimates over the USL scenarios.

The natural extension of this study will be to address the noted model limitations by incorporating segment-based analysis with geometric information such as segment length, number of ramps, lane width, median width, shoulder width, road profile, curvature, alignment, etc., for individual crashes. Based on such data elements, the models would be more comprehensive and better able to infer the safety impact of changing the speed limit.

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Appendix

Preliminary Data Merging Effort

SWITRS and CHIPS

An attempt was made to augment the publicly available SWITRS data with real-time incident data for the years 2015 to 2018 from the California Highway Incident Processing System (CHIPS) to develop a more accurate and robust dataset for modeling. CHIPS data is acquired at regular intervals from the California Highway Patrol traffic incident information repository and hosted locally at the Road Ecology Center, UC Davis. The dataset is maintained and operated as a query-based system to scrape the relevant data points from a larger parent source. One key issue with the CHIPS dataset is the presence of multiple data points for the same event with appended or curbed information. However, this issue is partly resolved using appropriate query words and unique identifying events from the large pool of data. For instance, to identify all crashes involving trucks the query included keywords such as “truck,” “big rig,” and “tractor-trailer.” The recorded data fields include the location, date and time, incident type, and certain details of the incidents such as severity level, type of vehicle involved, etc. Though the primary objective of CHIPS is to investigate wildlife-vehicle collisions, the plethora of real-time data collected during the process provides information on other types of collisions, involving trucks, passenger cars, motorcycles, etc.

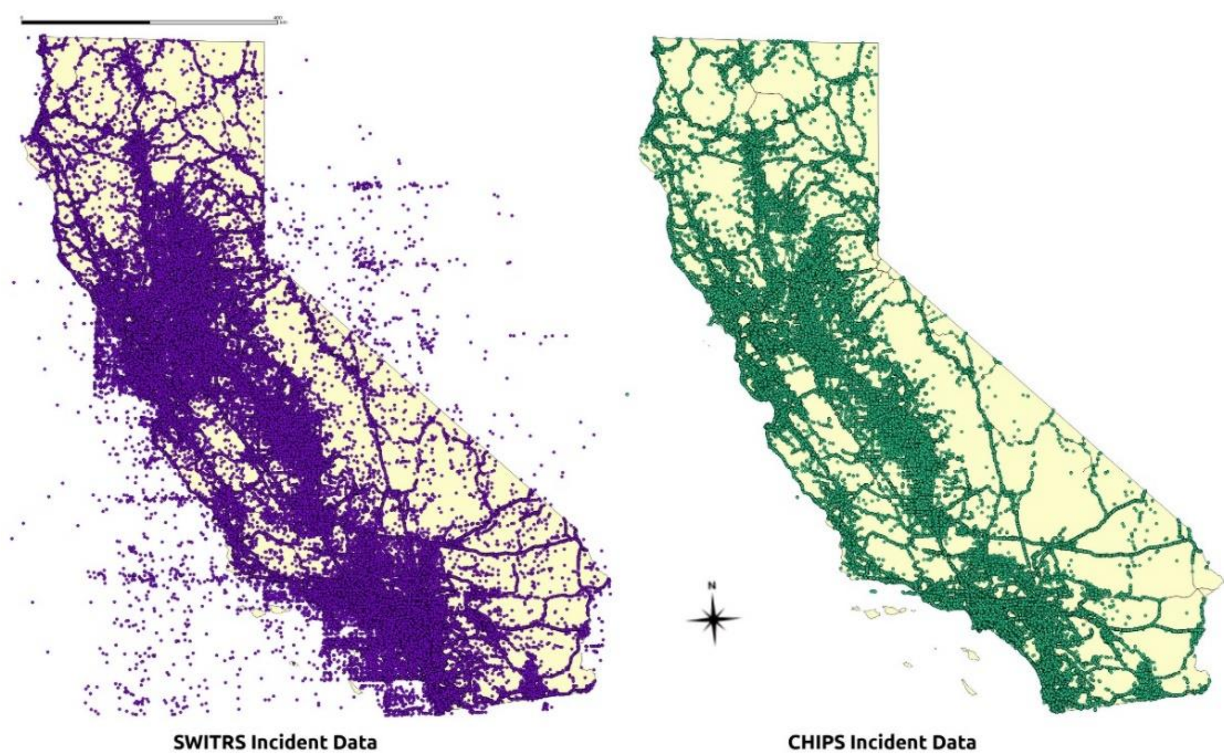

Figure 5. Visual Comparison of the SWITRS and CHIPS Datasets

There were problems, however, linking the incidents reported in the CHIPS and SWITRS datasets by matching them based on the locations reported in the two data sets. The matching process used a distance-based method, with three different distance filters: 20, 50, and 1000 meters. The SWITRS crash records consisted of 1,873,781 data points, with 107,543 marked as truck accidents, whereas there are more than 2 million records in CHIPS with 331,432 truck-related events. The high volume of records in the CHIPS dataset may have resulted from multiple records with appended information for each separate crash incident, as noted above. Unfortunately, the matched proportion of the dataset was quite small, possibly due to mismatches of time-windows, location tags, and other attributes.

Spatial-Temporal Join

Two methods were used to merge the CHIPS and SWITRS datasets: (i) a spreadsheet approach and (ii) a GIS-based approach. In the spreadsheet approach, CHIPS and SWITRS data were combined and compared with the parent datasets. SWITRS fields with critical information were selected, including incident type, vehicle make and model, severity level, number of vehicles involved, and location description (street name/ highway). Next, this information was compared with the candidate CHIPS data points describing vehicle type, involved parties, and severity level. The spreadsheet showed the results of the spatial-temporal query matches in a single row, and the values were used to identify matches, with the condition that the maximum distance between the CHIPS point and the SWITRS point was up to 1000 meters.

For the GIS-based approach, several layers of both CHIPS and SWITRS data were generated to search for potential candidates for spatial matching using ArcMap and QGIS. A query model with different data layers was generated to organize and match the CHIPS data. This model pivots on the “join table” feature to link the “chips id” with the SWITRS unique identifier (“case id”). The join was made by running the spatial-temporal query and using additional fields from both datasets to help determine appropriate matches. Since SWITRS and CHIPS contain geospatial point data in the form of latitude and longitude fields (WGS84 coordinate system), along with the date and time of the incident, a spatial-temporal query was used to associate the two datasets. The procedure was set up to do the following for each CHIPS record:

- Search for candidate SWITRS collision records that were one hour before or after the CHIPS incident date (temporal variation).
- Form the set of candidate records from SWITRS by considering points less than 1000 meters from the CHIPS recorded location.
- If there is just one matched record it was accepted as a singular candidate. In the event of multiple matching candidates, other critical data points such as collision severity, location description, vehicle type, and other relevant fields were considered to select the best candidate.
- Finally, a “crosswalk” record was generated in the join table with the best candidate from the previous step.

Once the procedure was completed, the join table was used to set up a query to extract data from both sets of data (SWITRS and CHIPS) to create a combined set.

Table 18. Matched results between CHIPS and SWITRS datasets

Distance	Matches	Average number of candidates	Candidates with one match	Number of matches Urban / Rural	Percent Urban / Rural
20 meters	4,254	1.03290	4,131	3,293 / 961	29%
50 meters	10,700	1.06040	10,127	8924 / 1776	20%
1000 meters	18,944	1.11490	17,073	16,375 / 2,569	16%

Since the *CHIPS* and *SWITRS* datasets do not share a common keyword or field to join the database tables, the spatial-temporal query creating the association was a challenging task. The assessment phase involved manually matching a candidate match from the CHIPS and SWITRS datasets as *"true positive"* and *"false positive"* for accuracy. As noted in Table 18*,* the candidate incidents with a 1000-meter distance range showed a match for less than 20% of the total SWITRS truck records and less than 6% of the CHIPS truck records. Therefore, it is important to examine the "true negatives" and "false negatives" to get some insight into the join. As noted, the SWITRS data includes many incidents with coordinates (latitude and longitude) mapped into the ocean, reducing the number of matches overall. Thus, after much effort, the combination of the SWITRS and CHIPS dataset was not used for the modeling purpose of the study. The modeling part of the study was carried out on the merged dataset of the SWITRS and PeMS dataset detailed in the following section.

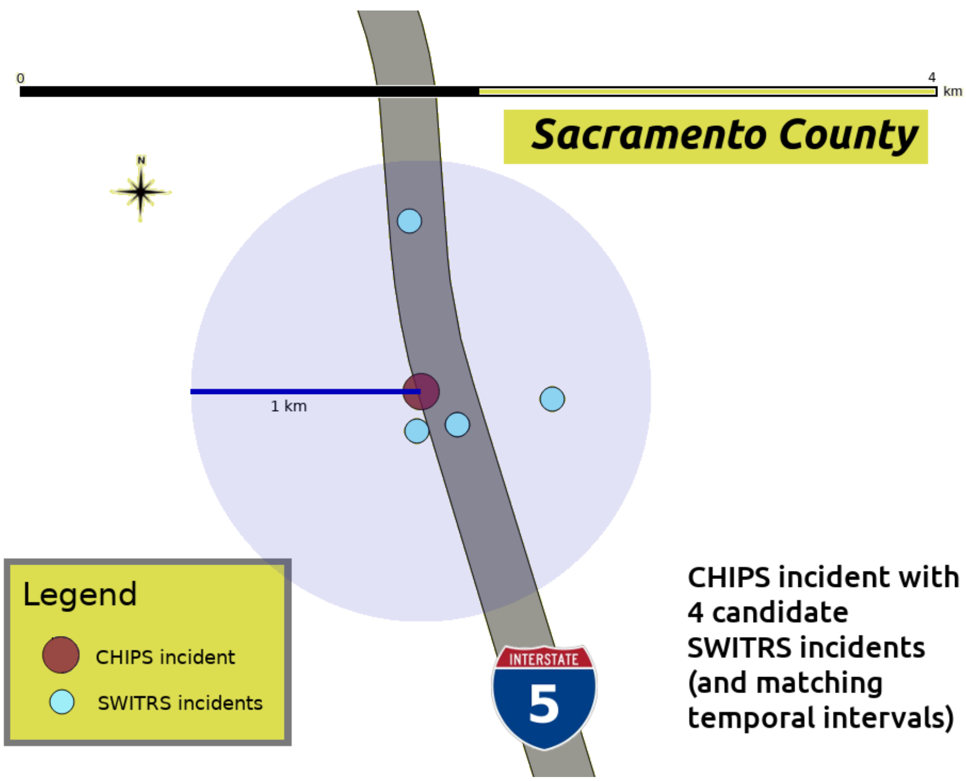

Figure 6. Sample Spatial Joining of CHIPS and SWITRS Incidents

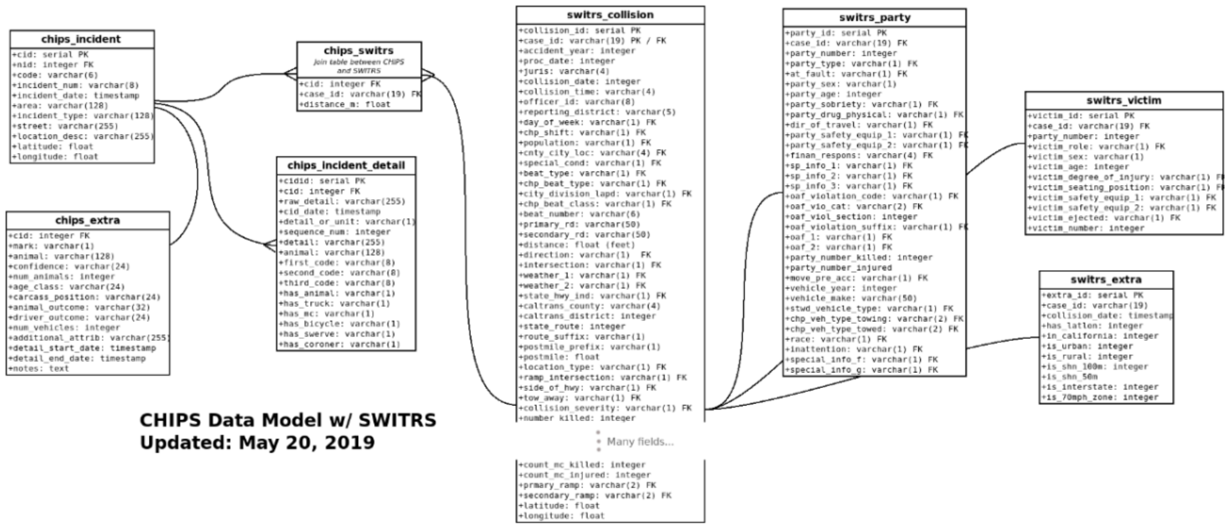

Figure 7. Joining of CHIPS model with SWITRS datapoints