Accident Analysis and Prevention 187 (2023) 107038

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

Leveraging probe data to model speeding on urban limited access highway segments: Examining the impact of operational performance, roadway characteristics, and COVID-19 pandemic

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ARTICLE INFO

Keywords:
Speeding
Traffic density
Probe data
COVID-19
Statistical modeling
Mixed effect binomial model

ABSTRACT

Stay-at-home orders - imposed to prevent the spread of COVID-19 - drastically changed the way highways operate. Despite lower traffic volumes during these times, the rate of fatal and serious injury crashes increased significantly across the United States due to increased speeding on roads with less traffic congestion and lower levels of speed enforcement. This paper uses a mixed effect binomial regression model to investigate the impact of stay-at-home orders on odds of speeding on urban limited access highway segments in Maine and Connecticut. This paper also establishes a link between traffic density and the odds of speeding. For this purpose, hourly speed and volume probe data were collected on limited access highway segments for the U.S. states of Maine and Connecticut to estimate the traffic density. The traffic density was then combined with the roadway geometric characteristics, speed limit, as well as dummy variables denoting the time of the week, time of the day, COVID-19 phases (before, during and after stay-at-home order), and the interactions between them. Density, represented in the model as Level of Service, was found to be associated with the odds of speeding, with better levels of service such as A, or B (low density) resulting in the higher odds that drivers would speed. We also found that narrower shoulder width could result in lower odds of speeding. Furthermore, we found that during the stay-at-home order, the odds of speeding by more than 10, 15, and 20 mph increased respectively by 54%, 71% and 85% in Connecticut, and by 15%, 36%, and 65% in Maine during evening peak hours. Additionally, one year after the onset of the pandemic, during evening peak hours, the odds of speeding greater than 10, 15, and 20 mph were still 35%, 29%, and 19% greater in Connecticut and 35% 35% and 20% greater in Maine compared to before pandemic.

1. Introduction

Upon the onset of the COVID-19 pandemic, various states across the United States (U.S.) issued stay-at-home orders. The unprecedented orders in turn caused a tremendous reduction in vehicle trips, and consequently the volume of traffic on roads; at the same time, roadway fatality rates increased across the country (Doucette et al., 2021; Stiles et al., 2021; Adanu et al., 2021; Dong et al., 2022). For instance, in Connecticut, despite a 43% reduction in Vehicle Miles Traveled (VMT), the rate of fatal single vehicle crashes increased by 4.1 times in the early stages of the pandemic (Doucette et al., 2021). Initially, it was hypothesized that the increase in fatality rate and crash severity occurred mainly due to increased speeding on roadways with lower volumes and less enforcement during the stay-at-home orders (Stiles et al., 2021; Dong et al., 2022; Shahlaee et al., 2022; Wang and Cicchino, 2023). However, data from National Highway Traffic Safety Administration (NHTSA) show that the fatal crash rates were still elevated throughout 2021 and even into 2022 (Wang and Cicchino, 2023; National Center for Statistics and Analysis, 2022). Recent studies show that even when the traffic volume returned to its pre-pandemic level, the speeding behavior did not (Shahlaee et al., 2022). Due to the prevalence of speeding as a factor in severe accidents during the-stay at-home period, and the continued elevated rate of fatal crash outcomes, it is necessary to study how speeding behavior changed both during and after travel restrictions

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https://doi.org/10.1016/j.aap.2023.107038
Received 22 August 2022; Received in revised form 12 February 2023; Accepted 15 March 2023
Available online 19 April 2023

were lifted.

Speeding is a contributing factor in many fatal and serious injury crashes (Cooper, 1997; Elvik, 2005; Abegaz et al., 2014; Adanu et al., 2021; Wang, and Cicchino, 2023). Researchers found that several factors impact speeding, including but not limited to roadway geometry and functional class (Afghari et al., 2018; Eluru et al., 2013), posted speed limit (Yokoo and Levinson, 2019), time of day, time of week and holidays (Jun 2010; Heydari et al., 2020), light conditions (De Bellis et al., 2018), vehicle classification (Afghari et al., 2018), weather conditions (Kurte et al., 2019), enforcement (Hauer et al., 1982; Tay, 2005), and driver psychology or perceived risk (Tucker and Marsh, 2021). Enforcement, in particular, can have a profound impact on reducing the average speed on roadways. Hauer et al. (1982) reported the reduction of speed to a number around the speed limit upstream and downstream of sites with parked police cars; they also found that the speed reduction could continue near enforcement sites for several days, even after the removal of the police cars. Similar observations were also reported in Norway, where police cars were left on segments of roadway with 60 and 80 km/h speed limits for an average of 9 h per day over a period of 6 weeks. This was found to result in significant speed reduction, even after the vehicles were removed (Vaa, 1997). Researchers also found that speeding reduces with the implementation of speed cameras. For instance, Afghari et al. (2018) found that a 1% increase in speed cameras would correlate to about a 3.5% reduction in speeding.

The occurrence of speeding can be identified using observed vehicle speeds and speed limits. The methodology by which speed is collected, however, has evolved over time. Camera and inductive loop detectors at count stations have been and still are used by many states. This method provides volume and sometimes speed data at fixed locations but fails to capture effects across a network. As most drivers are now carrying cell phones, companies such as StreetLight[1], can capture Location-Based Services (LBS) and Global Positioning System (GPS) data from these devices to provide speed and volume data across all segments of a roadway network (Turner et al., 2020; Yang et al., 2020). The availability of these probe data has enabled the effect of traffic stream variables to be captured across the entire network, as opposed to just a handful of permanent count stations or across a specific arterial. Several existing studies have used probe data. Yokoo and Levinson (2019) used speed data collected from GPS to determine that a greater percentage of drivers exceed the speed limit at speed limits below 25 mph and over 55 mph, or at night. Kurte et al. (2019) used vehicle probe data from the city of Chicago to examine how weather events cause variations in traffic speed across the roadway network, showing how drivers slow down in response to poor weather conditions. Cai et al. (2021) used Inrix probe data to evaluate speed reduction strategies. In Connecticut, Doucette et al. (2020) used Streetlight's LBS based probe data to estimate VMT in the state before and during the COVID-19 stay-at-home order. These VMT estimates were then used with crash data to determine how the crash rates among different crash types changed with the reduction in traffic volume caused by the order.

Speed, flow, and density are three major traffic stream parameters playing crucial roles in establishing various design standards or evaluating roadway safety. According to traffic flow theory, these three parameters are interrelated; an increase or decrease in one will impact the others (Mannering, and Washburn, 2020). Although the impact of traffic flow or volume on speeding has been studied significantly, limited research has been done regarding the impact of traffic density. This is partially due to gaps in data collection and the difficulty of observing density. Density, however, can have a crucial impact on speed or speeding. In fact, the Level of Service (LOS) of basic freeway segments, which is a qualitative measure on freedom to maneuver or speed, is directly associated with the level of density on the roadway segments. With probe data technology, it is possible to find space mean speed and traffic volume on roadway segments and consequently calculate the density. We use such data to establish the relationship between speeding and different levels of density.

This study explores the change in odds of speeding on urban limited access highways (Interstates and freeways) during and after stay-at-home orders imposed in Maine (ME) and Connecticut (CT). The information about speeding and traffic density was derived from probe data provided by StreetLight Insight®. We then used a mixed effect binomial model to establish a link between the odds of speeding and contributing factors denoting the traffic density, roadway geometric characteristics, speed limit, time-related factors, two dummy variables signifying the duration of the stay-at-home order and one year since lifting the order, and several interaction variables. Shahlaee et al. (2022) examined the odds of speeding for three rural facility types in Maine during the Covid-19 pandemic using data from a few inductive loop detectors located at the permanent count stations. The current research significantly differs from the work of Shahlaee et al. (2022) and other related studies and contributes to the current literature from multiple perspectives. First, we demonstrate the application of probe data (using hourly traffic volume and speed data from StreetLight Insight®) to analyze the odds of speeding. To the best of our knowledge, limited research, if any, has been devoted to model odds of speeding using hourly probe data. Second, unlike previous studies, we study speeding for the entire network divided into homogenous segments, instead of fixed locations or a specific arterial, taking advantage of the availability of network-level probe data. Third, using data from homogenous segments, we can include different roadway characteristics in the model, allowing to measure the effect of variables such as presence of the curve and shoulder width on odds of speeding. Fourth, we establish a link between traffic density or level of service and speeding. To our knowledge, there is also limited research on this topic due to inherent difficulties in estimating the density. However, using the hourly probe data, we can obtain detailed density information, and establish a link between level of service and speeding. Fifth, and most importantly, we investigate how the odds of speeding changed during the stay-at-home order and one year since the onset of the pandemic on urban limited access highways in Maine and Connecticut, especially in morning and evening peak hours. Finally, we explore if there are any differences in odds of speeding between Maine and Connecticut.

2. Data Description

This study uses probe data collected from the StreetLight Insight® platform to link speeding with traffic density and several other factors to investigate the impact of the stay-at-home order on speeding on urban limited access highways in two New England states, Maine and Connecticut. To compute the traffic density, the limited access roads were divided into segments with homogenous characteristics (i.e., lane width, shoulder width, speed limit, and number of lanes). Then, the traffic volume and speed data were collected in one-hour aggregated intervals from StreetLight Insight® on roadway segments with speed limits of 50 mph or above for the months of April and May of 2019, 2020, and 2021 using geographic information system (GIS) maps generated for this study. StreetLight uses LBS data collected from cellphones and combines points where devices periodically register their locations (also known as "pings") with common device IDs into trips. These trips show the routes individuals take and their speeds over the route. The platform then uses a Machine Learning algorithm fed with values from permanent count stations to estimate the volume of trips and their speeds to better reflect real values (StreetLight, 2021, StreetLight, 2022). The output data is the volume (q) (vehicle/hour) of vehicles traveling in each hour on each segment, space mean speed (v) (mph), and the distribution of speed on

[1] "StreetLight draws on big data and proprietary machine-learning algorithms to measure travel patterns and makes them available on-demand via StreetLight InSight®, the world's first SaaS platform for mobility". StreetLight InSight® powers thousands of global projects every month. For more information, please visit https://www.streetlightdata.com.

that segment in 1-mph bins.

Using the distribution of the speed, and speed limit information, the percentage of vehicles that drive a certain amount (i.e., 10, 15, and 20 mph) above the speed limit were calculated. To increase the accuracy of the volume and average speed calculation, we removed data points with fewer than 10 vehicle observations. Table 1 shows, on average, the percentage of drivers that speed by more than 10, 15, and 20 mph, during different phases of the pandemic in Maine and Connecticut on roadway segments with the same speed limit. At almost every speed limit, in both states, the percentage of vehicles that speed increased during the stay-at-home orders compared to pre-pandemic. In 2021, a year after the stay-at-home orders, while speeding decreased in some instances compared to the duration of the stay-at-home order, most of the times, it remained higher than the pre-pandemic level.

Next, the traffic density (K) (vehicle/mile/lane) was calculated using the flow, density, and speed relationship as follows (where n is the number of lanes):

$$K = \frac{q}{n \times v} \tag{1}$$

Table 2 shows the summary statistics of the traffic volume (vehicle/hour), average speed (mph), and traffic density (vehicle/mile/lane) during different times of the day (i.e., morning peak hour from 6 am to 10 am, evening peak hour from 3 pm to 7 pm, and off peak) and different years (or pandemic phases) in Maine and Connecticut. We removed data records with traffic density of 45 vehicles/mile/lane or above, since this range of density corresponds to forced-flow conditions under which speeding is very difficult to occur. As shown in Table 2, the reduction in traffic volume and density and the increase in average speed in April and May of 2020 is evident in most cases, especially during the morning and evening peak hours.

We divided the traffic density observations into five groups considering a dummy variable to denote each group. The density range of $0 < K \leq 11$ vehicles/mile/lane denotes LOS of A, $11 < K \leq 18$ vehicles/mile/lane denotes LOS of B, $18 < K \leq 26$ vehicles/mile/lane denotes LOS of C, $26 < K \leq 35$ vehicles/mile/lane denotes LOS of D, and $35 < K \leq 45$ vehicles/mile/lane denotes LOS of E. The LOS of E was considered as the base (or reference) group in the analysis. To create uniform data for modeling, the density data were combined with roadway geometric characteristics, speed limit, time-dependent variables, and two variables denoting the COVID-19 phases, one signifying the duration of the stay-at-home order and the other one year since the onset of the pandemic. We also considered a dummy variable denoting the state (i.e., Maine or Connecticut). Table 3 shows the definition of the variables used in this study.

We considered two time-dependent dummy variables in the models. One variable signifies the time of the day, and it is denoted by "M" if it indicates the morning peak hours and by "E" if it denotes the evening peak hours. The other variable signifies the time of the week, and it is denoted by "W" if it is weekend. The off-peak period and weekdays were considered as the base (or reference) groups in analysis. We also included dummy variables related to several geometric characteristics of the roadway. All roadway segments had standard 12-ft lanes, so the lane width variable was not considered in modeling. The shoulder width however varies across the segments. We considered a dummy variable to account for the effect of shoulder width that is less than 6 ft. This dummy variable was denoted by "SW". We also considered a dummy variable for the presence of a horizontal curve. This dummy variable was denoted by "HC". The speed limit in Maine varies from 50 to 70 mph. we considered a speed limit of 50 or 55 mph as the base (or reference) group, and considered dummy variables signifying speed limits of 60, 65, and 70 mph. In Connecticut, the speed limits of roadway segments are 50, 55, and 65 mph. Again, we considered the speed limits of 50 and 55 mph as the base (or reference) groups and considered a dummy variable signifying the speed limit of 65 mph. Finally, we considered two dummy variables to account for COVID-19 phases, one signifying the duration of the stay-at-home order (April and May 2020) denoted by "γ" and the other, one year since the onset of the pandemic (April and May 2021) denoted by "δ" to respectively measure the impact of pandemic during and after the stay-at-home order. These dummy variables are compared

Table 1
Percentage of speeding on Urban Limited Access Highways in Maine and Connecticut.

State[1]	Speed Limit (mph)	Year[2]	Off Peak			Morning Peak (6-10am)			Evening Peak (3–7 pm)		
			+10 mph Speeding	+15 mph Speeding	+20 mph Speeding	+10 mph Speeding	+15 mph Speeding	+20 mph Speeding	+10 mph Speeding	+15 mph Speeding	+20 mph Speeding
ME	**50**	2019	28.0%	12.0%	4.7%	29.3%	13.0%	5.0%	26.9%	11.3%	4.4%
		2020	25.9%	12.8%	5.7%	29.3%	15.5%	7.1%	29.2%	14.7%	6.5%
		2021	34.6%	13.7%	4.3%	40.0%	17.8%	5.9%	37.1%	15.4%	4.9%
	55	2019	30.2%	13.5%	4.4%	31.0%	13.4%	4.3%	32.2%	14.9%	4.9%
		2020	33.7%	16.7%	6.8%	35.4%	17.5%	7.2%	40.2%	21.2%	9.1%
		2021	40.3%	19.4%	6.9%	43.7%	21.8%	7.6%	45.0%	23.2%	8.7%
	60	2019	11.9%	4.4%	1.7%	14.8%	5.6%	2.0%	13.9%	5.0%	1.8%
		2020	13.4%	5.6%	2.5%	16.3%	7.2%	3.2%	16.1%	6.9%	3.1%
		2021	14.0%	4.5%	1.2%	17.7%	6.0%	1.6%	16.1%	5.2%	1.4%
	65	2019	22.2%	7.2%	2.0%	23.2%	7.6%	2.1%	24.9%	8.1%	2.2%
		2020	22.1%	8.6%	3.2%	23.8%	9.6%	3.7%	27.4%	11.2%	3.9%
		2021	25.3%	8.5%	1.9%	26.5%	9.0%	2.0%	29.2%	10.3%	2.3%
	70	2019	8.3%	2.3%	0.7%	9.6%	2.6%	0.8%	8.9%	2.4%	0.7%
		2020	9.2%	3.5%	1.3%	11.9%	4.7%	1.9%	10.8%	3.9%	1.5%
		2021	10.6%	2.8%	0.6%	11.4%	2.9%	0.6%	11.7%	3.0%	0.6%
CT	**50**	2019	48.9%	30.2%	15.3%	52.4%	34.2%	18.2%	49.1%	31.0%	15.8%
		2020	54.7%	35.9%	20.0%	59.4%	40.8%	23.8%	59.3%	40.4%	23.2%
		2021	54.2%	33.7%	17.2%	58.6%	38.4%	20.5%	55.1%	35.3%	18.3%
	55	2019	40.9%	21.6%	9.0%	44.9%	25.9%	11.3%	40.2%	21.8%	9.0%
		2020	47.5%	28.4%	13.9%	51.2%	32.4%	16.8%	51.4%	32.3%	16.2%
		2021	45.0%	24.6%	10.2%	49.5%	29.3%	12.9%	44.8%	25.1%	10.5%
	65	2019	17.3%	5.9%	1.9%	19.4%	6.6%	2.0%	17.3%	5.7%	1.8%
		2020	22.5%	9.5%	3.8%	25.3%	11.1%	4.4%	26.3%	11.4%	4.5%
		2021	22.7%	7.9%	2.1%	26.5%	9.5%	2.4%	24.3%	8.5%	2.2%

1 Speeding percentage calculated by taking a weighted average of speeding percentage on roadway segments with the same speed limit in each state.
2 2019 denotes April and May of 2019 (Pre-Pandemic); 2020 denotes April and May of 2020 (Stay-at-Home Order), and 2021 denotes April and May of 2021 (one year after the order).

Table 2
Summary Statistics of Traffic Volume, Average Speed and Traffic Density.

State	Speed Limit (mph)	Year[1]	Off Peak[2]			Morning Peak (6am-10am)[2]			Evening Peak (3 pm-7 pm)[2]		
			Volume Mean (S.D.)	Speed Mean (S.D.)	Density Mean (S.D.)	Volume Mean (S.D.)	Speed Mean (S.D.)	Density Mean (S.D.)	Volume Mean (S.D.)	Speed Mean (S.D.)	Density Mean (S.D.)
ME	**50**	**2019**	1658 (867.9)	51.37 (4.104)	14.21 (7.83)	1790 (899)	52.63 (4.696)	15.29 (8.59)	2486 (861.6)	51.11 (4.474)	21.58 (8.671)
		2020	1195 (467.5)	50.73 (7.328)	10.61 (5.173)	1153 (416)	51.93 (7.27)	10.03 (4.578)	1312 (498.5)	51.58 (7.623)	11.49 (5.531)
		2021	1732 (906.5)	55.02 (4.09)	13.91 (7.773)	1417 (551.5)	56.31 (4.303)	11.21 (5.02)	2272 (809.5)	55.53 (3.912)	18.15 (7.5)
	55	**2019**	1355 (751.3)	58.16 (5.592)	10.25 (5.828)	1374 (740.4)	59.28 (5.031)	10.61 (6.792)	2172 (844)	58.68 (6.022)	16.51 (7.126)
		2020	1007 (436.2)	59.69 (5.489)	7.544 (3.478)	947.2 (382.4)	60.2 (4.923)	7.253 (3.416)	1237 (529.2)	60.85 (5.654)	9.037 (4.13)
		2021	1393 (770.8)	62.01 (4.921)	9.907 (5.585)	1141 (482.8)	63.03 (4.37)	8.198 (4.023)	2000 (736.1)	62.83 (4.95)	14.12 (5.68)
	60	**2019**	1031 (484.1)	54.84 (6.583)	8.875 (4.512)	985.1 (440.5)	55.9 (6.722)	8.317 (3.981)	1369 (566.8)	55.81 (6.526)	11.61 (5.255)
		2020	894.7 (362.4)	56.39 (5.699)	7.427 (3.264)	732.1 (249.4)	57.61 (6.045)	5.959 (2.219)	1009 (389.3)	57.25 (5.762)	8.264 (3.485)
		2021	1061 (532.9)	58.16 (5.679)	8.561 (4.538)	897 (357.1)	59.45 (6.13)	7.087 (3.079)	1361 (538.2)	58.9 (5.701)	10.86 (4.618)
	65	**2019**	1141 (629.3)	66.22 (5.903)	7.986 (4.082)	1138 (555.7)	66.74 (6.192)	8.137 (4.342)	1499 (685.8)	66.99 (6.036)	10.54 (4.611)
		2020	838.2 (365.1)	66.01 (6.365)	5.933 (2.538)	822.2 (328)	66.45 (6.305)	5.833 (2.504)	930.6 (405.3)	67.01 (6.443)	6.54 (2.82)
		2021	1140 (682.5)	67.96 (5.524)	7.817 (4.404)	993.7 (463.5)	68.59 (5.259)	6.822 (3.151)	1402 (680.2)	68.92 (5.431)	9.579 (4.35)
	70	**2019**	955.4 (362.6)	65.8 (6.005)	7.299 (2.783)	915 (316.2)	66.28 (6.206)	6.968 (2.552)	1160 (387.8)	66.54 (6.161)	8.828 (3.217)
		2020	745.3 (248.9)	66.02 (6.017)	5.71 (2.039)	678.1 (209.5)	66.31 (6.481)	5.178 (1.744)	805.7 (269.4)	66.94 (5.879)	6.104 (2.255)
		2021	958.3 (411.2)	67.83 (5.543)	7.096 (3.063)	840.9 (324.6)	68.63 (5.598)	6.178 (2.488)	1149 (374.8)	68.91 (5.236)	8.431 (2.972)
CT	**50**	**2019**	2705 (1513)	59.08 (5.955)	17.23 (9.757)	3219 (1447)	60.13 (6.673)	20.65 (10.03)	4214 (1378)	57.75 (7.579)	27.4 (9.098)
		2020	2042 (1100)	61.3 (5.504)	12.69 (7.453)	2191 (979.6)	63.12 (5.18)	13.24 (6.459)	2782 (1237)	62.73 (4.743)	16.93 (8.188)
		2021	2684 (1497)	60.75 (5.638)	16.61 (9.419)	2859 (1276)	62.32 (5.287)	17.58 (8.541)	4045 (1411)	59.95 (7.141)	25.51 (9.131)
	55	**2019**	2873 (1720)	62.02 (5.456)	18.45 (10.91)	3577 (1626)	62.36 (6.87)	23.48 (10.7)	4442 (1367)	60.49 (7.09)	29.64 (9.192)
		2020	2290 (1389)	63.92 (5.114)	13.99 (8.274)	2564 (1383)	65.4 (4.674)	15.41 (7.414)	3235 (1530)	64.84 (4.833)	20 (9.013)
		2021	2905 (1765)	63.42 (5.351)	18.18 (10.8)	3335 (1552)	63.91 (6.561)	21.21 (9.738)	4295 (1517)	61.9 (7.379)	28.29 (9.739)
	65	**2019**	2308 (1322)	66.37 (4.439)	13.93 (8.197)	2680 (1282)	66.86 (5.246)	16.34 (8.162)	3686 (1435)	65.82 (5.364)	22.41 (8.671)
		2020	1751 (853.2)	67.81 (4.224)	10.44 (5.747)	1761 (732.1)	68.73 (3.879)	10.33 (4.496)	2195 (977.8)	68.81 (4.025)	13.03 (6.37)
		2021	2347 (1345)	68.19 (4.261)	13.81 (8.132)	2301 (1027)	69.35 (3.769)	13.5 (6.442)	3445 (1375)	68.44 (4.447)	20.31 (8.451)

[1] The average and standard deviation of traffic volume (vehicle/hour), average speed (mph), and density (vehicle/mile/lane) were calculated using data from roadway segments with the same speed limit.
[2] 2019 denotes April and May of 2019 (Pre-Pandemic); 2020 denotes April and May of 2020 (Stay-at-Home Order), and 2021 denotes April and May of 2021 (one year after the order).

with the pre-pandemic duration (April and May 2019).

As a closing note to this section, it is worth pointing out that the stay-at-home period in Maine and Connecticut started in the middle of March 2020, when states issued orders for non-essential workplaces, dining, lodging non-essential retail, and schools to close or work remotely. Furthermore, both states limited maximum gathering sizes. In Maine, these restrictions began to be eased on June 1, 2020. In Connecticut, outdoor dining as well as some non-essential retail and museums were allowed to reopen from May 20, 2020; however, schools and workplaces remained closed and remote during the entire month of May; we considered data from the months of April and May for analysis, where major daily or commuter trips such as those to work and school remained restricted.

3. Methodology

We used a mixed effect binomial regression model with a logit link function to correlate the odds of speeding with a set of dummy variables described in Table 3. The mixed effect model was used to account for location heterogeneity and repeated observations for each segment over time. Let us assume q_{is} and y_{is} respectively denote the traffic volume (vehicle/hr.), and the number of vehicles that speed by more than a certain amount (e.g., 10, 15, or 20 mph) above the speed limit on segment "s" during the i-th one-hour time interval. Likewise, let us assume P_{is} denotes the probability of speeding on segment "s" during the same i-th time interval. Then, the binomial model can be written as described in Eq. (2):

Table 3
Data Description.

Variables	Classes	Definition
Traffic Density	LOS A ($0 < K \leq 11$)	Density of 0 to 11 vehicle/mile/lane denoting LOS of A
	LOS B ($11 < K \leq 18$)	Density of 11 to 18 vehicle/mile/lane denoting LOS of B
	LOS C ($18 < K \leq 26$)	Density of 18 to 26 vehicle/mile/lane denoting LOS of C
	LOS D ($26 < K \leq 35$)	Density of 26 to 35 vehicle/mile/lane denoting LOS of D
	LOS E ($35 < K \leq 45$) (=0)	Density of 35 to 45 vehicle/mile/lane denoting LOS of E
Time of the Week	Weekday (=0)	Weekdays (Monday-Friday)
	Weekend	Weekend (Saturday-Sunday)
Time of the Day	Off Peak (=0)	Off peak hours (10 am-3 pm and 7 pm-6 am)
	Morning Peak Period	Moring Peak hours (6 am-10 am)
	Evening Peak Period	Evening peak hours (3 pm-7 pm)
COVID-19 Phases	Before Stay-at-Home (=0)	Data collected in April and May of 2019
	Stay-at-Home	Data collected in April and May of 2020
	Post Stay-at-Home	Data collected in April and May of 2021
Speed Limit	Speed Limit ≤ 55 (=0)	Segments with speed limit less than or equal to 55 mph
	Speed Limit = 60 mph	Segment with a speed limit of 60 mph
	Speed Limit = 65 mph	Segment with a speed limit of 65 mph
	Speed Limit = 70 mph	Segment with a speed limit of 70 mph
Presence of Curve	No Curve (=0)	No curve (straight alignment)
	Curve Presence	Presence of horizontal curve
Shoulder Width	Wide Shoulder (=0)	Shoulder wider ≥ 6 feet
	Narrow Shoulder	Shoulder wider < 6 feet
State	Maine	Data collected on limited access roads in Maine
	Connecticut (=0)	Data collected on limited access roads in Connecticut

$$y_{is} \sim \text{Binomial}(P_{is}, q_{is}) \equiv \binom{q_{is}}{y_{is}} P_{is}^{\,q_{is}-y_{is}} (1 - P_{is})^{y_{is}} \tag{2}$$

A logit link function was used to correlate the odds of speeding $\left(\frac{P_{is}}{1-P_{is}}\right)$ with a set of dummy variables as shown in Eq. (3).

$$\begin{aligned}\text{Logit}(P_{is}) &= \text{Ln}\left(\frac{P_{is}}{1-P_{is}}\right)\\ &= \pi + (K_A \times I_{A,\ is} + K_B \times I_{B,\ is} + K_C \times I_{C,\ is} + K_D \times I_{D,\ is})\\ &+ (SL_{60} \times I_{SL60,s} + SL_{65} \times I_{SL65,s} + SL_{70} \times I_{SL70,s} + HC \times I_{HC,\ s} + SW \times I_{SW,s})\\ &+ (W \times I_{W,i} + M \times I_{M,i} + E \times I_{E,i}) + (\gamma \times I_{\gamma,i} + \delta \times I_{\delta,i})\\ &+ (M\gamma \times I_{M\gamma,\ i} + E\gamma \times I_{E\gamma,\ i} + M\delta \times I_{M\delta,\ i} + E\delta \times I_{E\delta,\ i}) + \varepsilon_s\end{aligned} \tag{3}$$

Where.

π : common intercept (constant)

K_A, K_B, K_C, and K_D: Coefficients on dummy variables denoting LOS of A, B, C, and D, respectively.

$I_{A,\ is}$, $I_{B,\ is}$, $I_{C,\ is}$, and $I_{D,\ is}$: Dummy variables, respectively, denoting LOS of A, B, C, and D, on segment “s” during the i-th time interval (=1 if LOS is “A”, “B”, “C”, or “D”, and = 0 otherwise.).

SL_{60}, SL_{65}, and SL_{70}: Coefficients on dummy variables denoting speed limit of 60 mph, 65 mph, and 70 mph, respectively.

$I_{SL60,s}$, $I_{SL65,s}$, and $I_{SL70,s}$: Dummy variables, respectively, denoting speed limit of 60 mph, 65 mph, and 70 mph on segment “s” (=1 if speed limit is 60 mph, 65 mph, or 70 mph, and = 0 otherwise.).

HC: Coefficient on dummy variable denoting the presence of the horizontal curve.

$I_{HC,s}$: Dummy variable denoting the presence of the horizontal curve on segment “s” (=1 if present, and = 0 if not present.).

SW: Coefficient on dummy variable denoting a narrow (less than 6ft) shoulder width.

$I_{SW,s}$: Dummy variable denoting a narrow shoulder width for segment “s” (=1 if shoulder width is less than 6ft, and = 0 otherwise.)

W, M , and E: Coefficients on dummy variables denoting the weekend, morning peak hour, and evening peak hour, respectively.

$I_{W,i}$, $I_{M,i}$, and $I_{E,i}$: Dummy variables, respectively, denoting the weekend, morning peak hours, and evening peak hours at the i-th time interval (=1 if weekend, morning, or evening peak, and = 0 otherwise.).

γ: Coefficient on dummy variable denoting the stay-at-home order.

$I_{\gamma,i}$: Dummy variable denoting the stay-at-home order at the i-th time interval (=1 if stay-at-home order, and = 0 otherwise.)

δ: Coefficient on dummy variable denoting the post stay-at-home order.

$I_{\delta,i}$: Dummy variable denoting the post stay-at-home order at the i-th time interval (=1 if post stay-at-home order, and = 0 otherwise.)

$M\gamma$: Coefficient on dummy variable denoting the interaction of the morning peak hours and stay-at-home order.

$E\gamma$: Coefficient on dummy variable denoting the interaction of the evening peak hours and stay-at-home order.

$M\delta$: Coefficient on dummy variable denoting the interaction of the morning peak hours and post stay-at-home order.

$E\delta$: Coefficient on dummy variable denoting the interaction of the evening peak hours and post stay-at-home order.

$I_{M\gamma,\ i}$: Dummy variable denoting the interaction of the morning peak hours and stay-at-home order at the i-th time (=1 if stay-at-home order and morning peak hours, and = 0 otherwise.)

Table 4
Modeling Results for Urban Limited Access Highways in Maine.

Category	Variables	+10 mph Speeding		+15 mph Speeding		+20 mph Speeding	
		Mean (S.E.)[1]	Odds Ratio	Mean (S.E.)[1]	Odds Ratio	Mean (S.E.)[1]	Odds Ratio
Intercept	**Constant (π)**	−1.437 (0.03180)	–	−2.619 (0.03460)	–	−3.750 (0.03280)	–
Traffic Density (or LOS)	**LOS A ($0 < K \leq 11$) (K_A)**	0.689 (0.00084)	1.99	0.739 (0.00120)	2.09	0.655 (0.00200)	1.93
	LOS B ($11 < K \leq 18$) (K_B)	0.6237 (0.00083)	1.89	0.658 (0.00120)	1.93	0.533 (0.00190)	1.71
	LOS C ($18 < K \leq 26$) (K_C)	0.472 (0.00083)	1.60	0.466 (0.00120)	1.59	0.345 (0.00190)	1.41
	LOS D ($26 < K \leq 35$) (K_D)	0.257 (0.00087)	1.29	0.228 (0.00130)	1.26	0.135 (0.00210)	1.15
Time Variables	**Morning Peak Period (M)**	0.161 (0.00027)	1.18	0.152 (0.00040)	1.17	0.116 (0.00068)	1.12
	Evening Peak Period (E)	0.174 (0.00024)	1.19	0.163 (0.00035)	1.18	0.127 (0.00060)	1.14
	Weekend (W)	0.357 (0.00014)	1.43	0.366 (0.00020)	1.44	0.332 (0.00033)	1.40
Pandemic phases	**Stay-at-Home (γ)**	0.032 (0.00027)	1.03	0.182 (0.00038)	1.20	0.373 (0.00060)	1.45
	Post Stay-at-Home (δ)	0.258 (0.00021)	1.29	0.220 (0.00031)	1.25	0.061 (0.00053)	1.06
Pandemic Phases and Time of the day	**Morning Peak × Stay-at-Home ($M\gamma$)**	0.034 (0.00046)	1.04	0.065 (0.00064)	1.07	0.104 (0.00010)	1.11
	Evening Peak × Stay-at-Home ($E\gamma$)	0.110 (0.00040)	1.12	0.123 (0.00056)	1.13	0.129 (0.00088)	1.14
	Morning Peak × Post Stay-at-Home ($M\delta$)	0.009 (0.00039)	1.01	0.025 (0.00055)	1.03	0.033 (0.00095)	1.03
	Evening Peak × Post Stay-at-Home ($E\delta$)	0.044 (0.00033)	1.05	0.077 (0.00046)	1.08	0.118 (0.00080)	1.13
Segment Features	**Curve Presence (HC)**	−0.316 (0.00014)	0.73	-0.266 (0.0500)	0.77	−0.195 (0.05400)	0.82
	Shoulder Width < 6ft. (SW)	–[2]	–	–[2]	–	–[2]	–
	Speed Limit = 60 (SL_{60})	−1.32 (0.04200)	0.27	−1.33 (0.05800)	0.26	−1.196 (0.06200)	0.30
	Speed Limit = 65 (SL_{65})	−0.65 (0.05300)	0.56	−0.91 (0.03700)	0.40	−1.10 (0.04200)	0.33
	Speed Limit = 70 (SL_{70})	−1.84 (0.06100)	0.16	−2.07 (0.23100)	0.13	−2.21 (0.08700)	0.11
Goodness-of-Fit Metrics	**AIC**	63,579,918		89,288,802		111,434,338	
	BIC	63,580,147		89,289,030		111,434,566	
	log-Likelihood	−31789940		−44644382		−55717150	

[1] Standard errors.
[2] Insignificant at 95% Confidence Interval.

$I_{E\gamma,i}$: Dummy variable denoting the interaction of the evening peak hours and stay-at-home order at the i-th time (=1 if stay at-home-order and evening peak hours, and = 0 otherwise.)

$I_{M\delta,i}$: Dummy variable denoting the interaction of the morning peak hours and post stay-at-home order at the i-th time (=1 if post stay-at-home order and morning peak hours, and = 0 otherwise.)

$I_{E\delta,i}$: Dummy variable denoting the interaction of the evening peak hours and post stay-at-home order at the i-th time (=1 if post stay at home order and evening peak hours, and = 0 otherwise.)

ε_s : The random effect component for segment "s" (normally distributed).

To compare speeding in Maine and Connecticut, we also developed models with combined Maine and Connecticut data, with dummy variables that denote Maine (I_{ME}), interaction of Maine and stay-at-home order ($I_{ME,\gamma}$) and interaction of Maine and post stay-at-home order ($I_{ME,\delta}$) variables. Due to differences in speed limit in Connecticut and Maine, we only used a dummy variable that denotes the speed limit of 65 mph and greater (i.e., =1 if speed limit is 65 mph or above, and = 0 otherwise). Therefore, the following link function (Eq. (4) was used to model data.

$$
\begin{aligned}
\mathrm{Logit}(P_{is}) &= \mathrm{Ln}\left(\frac{P_{is}}{1-P_{is}}\right) \\
&= \pi + \left(K_A \times I_{A,\ is} + K_B \times I_{B,\ is} + K_C \times I_{C,\ is} + K_D \times I_{D,\ is}\right) \\
&+ \left(SL_{\geq 65,s} \times I_{SL \geq 65,s} + HC \times I_{Hc,\ s} + SW \times I_{SW,s}\right) \\
&+ \left(W \times I_{W,i} + M \times I_{M,i} + E \times I_{E,i}\right) + \left(\gamma \times I_{\gamma,i} + \delta \times I_{\delta,i}\right) \\
&+ \left(M\gamma \times I_{M\gamma,\ i} + E\gamma \times I_{E\gamma,\ i} + M\delta \times I_{M\delta,\ i} + E\delta \times I_{E\delta,\ i}\right) \\
&+ \left(ME \times I_{ME} + ME\gamma \times I_{ME,\gamma} + ME\delta \times I_{ME,\delta}\right) + \varepsilon_s
\end{aligned}
\quad (4)
$$

4. Modeling results

This section documents the modeling results. First, the data in Maine and Connecticut were used separately to develop models for these states. Then, the data in both states were combined and used in an aggregated model to explore the difference in speeding between Maine and Connecticut. We used log-likelihood, AIC, and BIC metrics to select the final model. We analyzed both correlation and multicollinearity among explanatory variables, and no significant correlation or multicollinearity was observed in data. Variables reported in final models are significant at 95% Confidence Interval.

Table 5
Modeling Results for Urban Limited Access Highways in Connecticut.

Category	Variables	+10 mph Speeding		+15 mph Speeding		+20 mph Speeding	
		Mean (S.E.)[1]	Odds Ratio	Mean (S.E.)[1]	Odds Ratio	Mean (S.E.)[1]	Odds Ratio
Intercept	**Constant (π)**	−0.745 (0.005000)	–	−1.73 (0.016000)	–	−2.88 (0.005300)	–
Traffic Density (or LOS)	**LOS A ($0 < K \leq 11$) (K_A)**	0.565 (0.000051)	1.76	0.631 (0.000061)	1.88	0.778 (0.000085)	2.18
	LOS B ($11 < K \leq 18$) (K_B)	0.539 (0.000045)	1.72	0.560 (0.000055)	1.75	0.646 (0.000078)	1.91
	LOS C ($18 < K \leq 26$) (K_C)	0.389 (0.000042)	1.48	0.392 (0.000051)	1.48	0.447 (0.000072)	1.56
	LOS D ($26 < K \leq 35$) (K_D)	0.206 (0.000041)	1.23	0.209 (0.000050)	1.23	0.240 (0.000073)	1.27
Time Variables	**Morning Peak Period (M)**	0.207 (0.000048)	1.23	0.260 (0.000059)	1.30	0.274 (0.000083)	1.32
	Evening Peak Period (E)	0.052 (0.000050)	1.05	0.072 (0.000064)	1.08	0.096 (0.000091)	1.10
	Weekend (W)	0.385 (0.000026)	1.47	0.346 (0.000030)	1.41	0.307 (0.000042)	1.36
Pandemic Phases	**Stay-at-Home (γ)**	0.236 (0.000042)	1.27	0.331 (0.000050)	1.39	0.416 (0.000069)	1.52
	Post Stay-at-Home (δ)	0.230 (0.000036)	1.26	0.203 (0.000045)	1.23	0.132 (0.000065)	1.14
Pandemic Phases and Time of the day	**Morning Peak × Stay-at-Home ($M\gamma$)**	−0.005 (0.000074)	1.00	−0.024 (0.000087)	0.98	−0.013 (0.00012)	0.99
	Evening Peak × Stay-at-Home ($E\gamma$)	0.201 (0.000070)	1.22	0.206 (0.000085)	1.23	0.196 (0.00012)	1.22
	Morning Peak × Post Stay-at-Home ($M\delta$)	0.012 (0.000067)	1.01	−0.00055 (0.000082)	1.00	−0.002 (0.00011)	1.00
	Evening Peak × Post Stay-at-Home ($E\delta$)	0.064 (0.000066)	1.07	0.051 (0.000083)	1.05	0.039 (0.00012)	1.04
Segment Features	**Curve Presence (HC)**	−0.059 (0.008600)	0.94	–[2]	–	–[2]	–
	Shoulder Width < 6 ft. (SW)	−0.163 (0.014000)	0.85	−0.175 (0.032000)	0.84	−0.188 (0.016000)	0.83
	Speed Limit = 65 (SL_{65})	−1.42 (0.008800)	0.24	−1.75 (0.01800)	0.18	−2.01 (0.007300)	0.13
Goodness-of-Fit Metrics	**AIC**	2,115,114,525		1,658,782,658		1,193,904,392	
	BIC	2,115,114,786		1,658,782,919		1,193,904,638	
	log-Likelihood	−1057557245		−829391311		−596952179	

[1] Standard errors.
[2] Insignificant at 95% Confidence Interval.

4.1. Maine models

Table 4 shows the modeling results for urban limited access highways in Maine. The odds of speeding in Maine increased as the LOS of roadways improves. For speeding of 10 mph or more, the odds of speeding increases by 29% for a LOS of D, 60% for a LOS of C, 89% for a LOS of B, and 99% for a LOS of A when compared to a LOS of E. Similarly, for speeding of 15 mph or more, the odds of speeding increases by 26% for a LOS of D, 59% for a LOS of C, 93% for a LOS of B, and 2.09 times for a LOS of A compared to a LOS of E. Lastly, for speeding of 20 mph or more, the model shows that the odds of speeding increases by about 15%, 41%, 71%, and 93% for LOS of D, C, B, and A respectively compared to LOS of E.

In addition to an increase in the odds of speeding for lower traffic densities (better levels of service), the model also shows that the odds of speeding during the morning and evening peak hours are greater than one, even before the pandemic. This indicates that the odds of speeding increases during peak hours compared to off-peak. In particular, before the pandemic, the odds of speeding by more than 10, 15, and 20 mph (controlling for the other factors) increased by 18%, 17%, and 12% respectively during the morning peak hours and by about 19%, 18%, and 14% respectively during the evening peak hours, compared to off peak hours. In addition, the odds of speeding in Maine also increases during the weekend, with the odds of speeding by more than 10, 15, and 20 mph increasing by 43%, 44%, and 40% respectively compared to weekdays.

Most importantly, the modeling results show an increase in the odds of speeding during and after the COVID-19 stay-at-home order implementation. During the COVID-19 restriction, at the off-peak hours, the odds of speeding increased by 3% for speeding of at least 10 mph, 20% for speeding of at least 15 mph and 45% for speeding of at least 20 mph. Furthermore, the odds ratio of speeding increases by an additional factor (in addition to the increase during the off-peak hours) of 1.04, 1.07, and 1.11 times during the morning, and 1.12, 1.13-, and 1.14- times during evening peak hours for speeding by more than 10, 15 and 20 mph. This will result in increased odds of 7%, 28% and 61% during the morning peak hours, and 15%, 36% and 65% during the evening peak hours for speeding by more than 10, 15 and 20 mph respectively, compared to pre pandemic.

Likewise, even after almost one year since the time that the stay-at-home order was lifted, during the off-peak hours, the odds of speeding continued to be above pre-pandemic levels by 29% for speeding of at least 10 mph, 25% for speeding of at least 15 mph, and 6% for speeding of at least 20 mph. In addition, the odds ratio of speeding increased by additional factor (in addition to observed increase during off-peak hours) of 1.01, 1.03, and 1.03 times during the morning and 1.05, 1.08 and 1.13 times during the evening peak hours. This results in an increased odds of 31%, 29%, and 9% during the morning and 35%, 35% and 20% during the evening for speeding greater than 10, 15, and 20 mph respectively compared to before pandemic. The results show that although the odds of speeding by more than 20 mph reduced compared to during the stay-at-home order, the odds of speeding by more than 10

Table 6
Modeling Results for Urban Limited Access Highways in Maine and Connecticut.

Category	Variables	+10 mph Speeding		+15 mph Speeding		+20 mph Speeding	
		Mean (S.E.)[1]	Odds Ratio	Mean (S.E.)[1]	Odds Ratio	Mean (S.E.)[1]	Odds Ratio
Intercept	**Constant** (π)	−0.800 (0.015000)	–	−1.79 (0.003600)	–	−2.93 (0.0042)	–
Traffic Density (or LOS)	**LOS A** ($0 < K \leq 11$) (K_A)	0.568 (0.000050)	1.76	0.632 (0.000060)	1.88	0.778 (0.000085)	2.18
	LOS B ($11 < K \leq 18$) (K_B)	0.541 (0.000045)	1.72	0.562 (0.000054)	1.75	0.647 (0.000077)	1.91
	LOS C ($18 < K \leq 26$) (K_C)	0.390 (0.000041)	1.48	0.393 (0.000050)	1.48	0.448 (0.000072)	1.57
	LOS D ($26 < K \leq 35$) (K_D)	0.207 (0.000041)	1.23	0.210 (0.000050)	1.23	0.240 (0.000073)	1.27
Time Variables	**Morning Peak Period (M)**	0.206 (0.000047)	1.23	0.258 (0.00040)	1.29	0.272 (0.000083)	1.31
	Evening Peak Period (E)	0.057 (0.000049)	1.06	0.076 (0.000061)	1.08	0.098 (0.000090)	1.10
	Weekend (W)	0.384 (0.000025)	1.47	0.346 (0.000030)	1.41	0.307 (0.000041)	1.36
Pandemic Phases	**Stay-at-Home** (γ)	0.236 (0.000042)	1.27	0.331 (0.000049)	1.39	0.415 (0.000069)	1.52
	Post Stay-at-Home (δ)	0.230 (0.000036)	1.26	0.207 (0.000038)	1.23	0.131 (0.000065)	1.14
Pandemic Phases and Time of the day	**Morning Peak × Stay-at-Home** ($M\gamma$)	−0.004 (0.000073)	1.00	−0.022 (0.000076)	0.98	−0.012 (0.000120)	0.99
	Evening Peak × Stay-at-Home ($E\gamma$)	0.196 (0.000069)	1.22	0.203 (0.000083)	1.23	0.194 (0.000120)	1.21
	Morning Peak × Post Stay-at-Home ($M\delta$)	0.012 (0.000066)	1.01	–[2]	–	−0.002 (0.000110)	1.00
	Evening Peak × Post Stay-at-Home ($E\delta$)	0.063 (0.000065)	1.07	0.052 (0.000078)	1.05	0.040 (0.000120)	1.04
Segment Features	**Curve Presence (HC)**	−0.100 (0.017000)	0.90	−0.074 (0.004200)	0.93	−0.041 (0.006200)	0.96
	Shoulder Width < 6ft. (SW)	−0.073 (0.028000)	0.93	−0.081 (0.008100)	0.92	−0.097 (0.006500)	0.91
	Speed Limit ≥ 65 ($SL_{\geq 65}$)	−1.270 (0.017000)	0.28	−1.60 (0.004900)	0.20	−1.86 (0.005600)	0.16
State	**Maine (ME)**	−0.566 (0.031000)	0.57	−0.733 (0.007700)	0.48	−0.862 (0.004200)	0.42
	Maine × Stay-at-Home ($ME\gamma$)	−0.210 (0.000180)	0.81	−0.146 (0.000250)	0.86	−0.046 (0.000390)	0.96
	Maine × Post-Stay-at-Home ($ME\delta$)	0.023 (0.000150)	1.02	0.039 (0.000210)	1.04	−0.032 (0.000360)	0.97
Goodness-of-Fit Metrics	**AIC**	2,227,274,597		1,748,556,563		1,257,706,411	
	BIC	2,227,274,902		1,748,556,854		1,257,706,717	
	log-Likelihood	−1113637277		−874278261		−628853185	

[1] Standard errors.
[2] Insignificant variable at 95% confidence Interval.

mph increased in the state after stay-at-home order, presumably due to increased perceived risk by drives after the order.

Examining geometric characteristics, the model shows that the impact of a narrower shoulder width (less than 6 ft.) on the odds of speeding by more than 10, 15 and 20 mph is insignificant. Furthermore, the results show 27% reduction in odds for speeding of more than 10 mph, 23% for speeding of more than 15 mph, and 18% for speeding of more than 20 mph on curves compared to tangents. The modeling results also showed decreased odds of speeding when speed limit is greater than 60 mph (i.e., it is 60, 65, or 70 mph) compared to smaller speed limits of 50 and 55 mph.

4.2. Connecticut models

Table 5 shows the modeling results for urban limited access highways in Connecticut. As Shown in Table 5 the odds of speeding increases as traffic density decreases (or as the level of service improves). In particular, the odds of speeding by more than 10 mph increases by 23% at LOS of D, by 48% at LOS of C, by 72% at LOS of B and 76% at LOS of A compared to a LOS of E. Likewise, the odds of speeding by more than 15 mph increases by 23% at LOS of D, by 48% at LOS of C, by 75% at LOS of B and by 88% at LOS of A compared to LOS of E. Finally, the odds of speeding by more than 20 mph increases by 27% at LOS of D, 56% at LOS of C, 91% at LOS of B and 2.18 times at LOS of A.

The modeling results show that in Connecticut, even before pandemic, the odds of speeding during the morning and evening peak hours were higher than the off-peak hours. Specifically, speeding by more than 10, 15, and 20 mph respectively increases by 23%, 30% and 32% during the morning and by 5%, 8% and 10% during the evening peak hours compared to off-peak hours. In addition, in Connecticut, the odds of speeding increases during the weekend compared to weekdays. Specifically, speeding by more than 10, 15 and 20 mph increases by 47%, 41% and 36% during the weekends compared to weekdays. The modeling results show a significant increase in odds of speeding in Connecticut during the COVID-19 pandemic. Specifically, the odds of speeding by at least 10 mph increased by 27%, speeding by at least 15 mph by 39%, and speeding by at least 20 mph by 52% during off-peak hours. The model also included variables to determine the increases in odds of speeding during the morning and evening peak hours. The odds of speeding during the morning peak hours increased at almost the same rate as the off-peak hours during the pandemic. During the evening peak hours, however, the odds ratio of speeding by more than 10, 15, and 20 mph increased by an additional factor (in addition to the increase during the off-peak hours) of 1.22, 1.23, and 1.22 during the stay-at-home order, and additional factor of 1.07, 1.05, and 1.04 one year since the stay-at-home order. This will result in increased odds of 55%, 71% and 85% during the stay-at-home order, and 35%, 29%, and 19% one year after lifting the order for speeding greater than 10, 15, 20 mph during the evening peak hours.

The dummy variable denoting the presence of curves was only significant for speeding by more than 10 mph. Specifically, the odds of speeding by 10 mph decreases by about 6% on curves compared to tangents on limited access highways in Connecticut. The shoulder width dummy variable was shown to be significant in Connecticut. The modeling results show that the narrower shoulder (less than 6 ft.) results in decreased odds of speeding. Specifically, the odds of speeding by more than 10, 15 and 20 mph decrease by 15%, 16% and 17% respectively when the shoulder is narrower than 6 ft. As noted earlier, in Connecticut, Most Freeways and Interstates have a Speed limit of 65 mph; there are no segments with a speed limit of 60 mph, or 70 mph or above. Therefore, we only considered a dummy variable for speed limit of 65 mph. Similar to the results in Maine, The odds of speeding decreases at higher speed limits of 65 mph. As shown in Table 5, the odds of speeding by more than 10, 15 and 20 mph are respectively 76%, 82% and 87% lower on segments with speed limits of 65 mph compared to segments with lower speed limits.

4.3. Combined models

A model with combined Maine and Connecticut data was developed to compare the odds of speeding between the two states. The combined model included a dummy variable indicating "Maine", as well as variables that accounted for the interactions of the "Maine" variable and the variables denoting the pandemic phases (during and one year after the stay-at-home duration). Therefore, the modeling results help show how the odds of speeding were affected in the two states, compared before and after the pandemic. The results of this model are shown in Table 6. The negative sign for the coefficient on the "Maine" dummy variable indicates that the odds of speeding in Maine is lower than Connecticut. In fact, before the pandemic, the odds of speeding by at least 10 mph, 15 mph and 20 mph were respectively 43%, 52% and 58% lower in Maine compared to Connecticut. The modeling results also show that during the stay-at-home order, the odds ratios of speeding by at least 10 mph, 15 mph, and 20 mph increased at a lower rate in Maine compared to Connecticut; specifically, during the stay-at-home order, the odds for speeding greater than 10 mph, 15 mph, and 20 mph were increased respectively at 19%, 14%, and 4% lower rate in Maine compared to Connecticut. Lastly, the modeling results show that one year after the restriction period, the increased odds of speeding in Maine remained about the same as Connecticut, with a slightly increase in odds ratio for speeding greater than 10 mph (2% increase) and 15 mph (4% increase), but smaller odds for speeding of 20 mph or more (3% decrease).

5. Summary and conclusions

As the number of drivers on roadways drastically reduced with the onset of the COVID-19 Pandemic, traffic speeds increased. This study used mixed effect binomial regression models with a logit link function to correlate the odds of speeding with dummy variables indicative of traffic density, highway geometric characteristics, temporal variables such as time of the day and time of the week, phases of the stay-at-home order, and several interaction variables. Using emerging probe datasets, this study was able to provide a unique, network level perspective showing how these dummy variables affected the odds of speeding on limited access highways in Maine and Connecticut. Furthermore, since the data were collected at hourly intervals, the models are based on detailed data, improving their representation of true network conditions.

The modeling results are consistent with previous studies (see Wang and Cicchino, 2023; Shahlaee et al., 2022). Using data from probes rather than count stations, however, we were able to study speeding patterns across the highway network. In addition, we further explored the change in odds of speeding during peak hours, during the stay-at-home order and one year since that. Particularly, the results showed that during the time when stay-at-home orders were in place, the odds of speeding by more than 10, 15, and 20 mph increased by 55%, 71% and 85% respectively in Connecticut, and by 15%, 36%, and 65% respectively in Maine the during evening peak hours, compared to pre-pandemic levels. Similarly, the study showed that even after one year since the stay-at-home orders were lifted, the odds of drivers speeding remained elevated relative to where they were prior to COVID-19. One year after the lifting of restrictions, the odds of speeding greater than 10, 15, and 20 mph during the evening peak hours were still 35%, 29%, and 19% greater in Connecticut and 35% 35% and 20% greater in Maine than prior to the pandemic.

With the use of hourly probe datasets (i.e., hourly volume and space mean speed), this study was also able to include traffic density in the model, reflected as dummies for different levels of service. The modeling results show how the odds of speeding changes as the compaction of vehicles on a roadway change. It was found that compared to an LOS of E, improved LOSs of D, C, B, and A all have increased odds of speeding, with the greatest increase in odds being for speeding of 20 mph or more, as seen in Tables 4- 6. In each case, as the level of service improves, the odds of speeding increases. This establishes a link between lower traffic densities, or better roadway service, and greater speeding and potentially more severe crashes. Regarding the roadway characteristics, the modeling results show that narrower shoulder width and curve presence leads to lower odds of speeding. In Maine and Connecticut, the odds of speeding reduced for speed limits greater than 60 mph (i.e., it is 60, 65, or 70 mph) compared to smaller speed limits of 50 and 55 mph; these findings are consistent with other studies (Afghari et al., 2018; Shahlaee et al., 2022).

Since the probe data used in this study was collected from cellphones, the data covers the entire network across two states. Consequently, the difference in the odds of speeding, and the changes in these odds during and after the COVID-19 stay-at-home orders could be captured in the model in broader scale. Using a dummy to denote the "state" and modelling the interactions between the state dummy variable and the COVID-19 dummy variables, the model shows that the odds of speeding in Maine were lower pre-pandemic than the odds of speeding in Connecticut, with the odds of speeding in Maine becoming less than those of Connecticut (or, more likely, the odds of speeding in Connecticut becoming even greater) during the stay-at-home orders. Following the lifting of the stay-at-home order, the odds of speeding in Maine have been lower than the odds of speeding in Connecticut by levels about equal to pre-pandemic conditions.

The modeling results show that the odds of speeding increases during times with drastic reduction in traffic volume, such as the pandemic. These results could be used to guide agencies in deploying enforcement resources to minimize speeding should these circumstances arise again. Although the odds of speeding in 2021 is relatively smaller than in 2020, still, it is substantially above the pre-pandemic level; hence, the massive disruption in travel demand or drastic reduction in traffic volume is shown to have had a lasting effect on the operational speed and speeding behavior on roadways. Speeding is a major factor in fatal and serious injury crashes; recognizing that speeding has substantially increased, in both Maine and Connecticut, compared to pre-pandemic conditions suggests the need for exploring countermeasures or interventions to decrease speeding and raise public awareness, to enhance roadway safety. Given the models' considerations of roadway characteristics and temporal variables, the conditions, and times that the odds of speeding are greater can be identified. This allows for speeding countermeasures to be targeted accordingly, to make the most of potentially limited resources. Finally, with departments of transportation having limited budgets, the push to both increase roadway operational efficiency and safety together can pose a burden. The establishment of a link between the odds of speeding and the level of service achieved by a roadway can be helpful to these agencies in simultaneously designing capacity and safety improvements for roadways.

Although limited access roads have higher design standards compared to other facility types, they experience a significant number of severe and fatal crashes due to higher volume and speed on these roads. The higher rates of severe crashes as well as the availability and greater accuracy of probe data sources on these roads were the two primary reasons that we focused on these roads in this paper. In addition, given that the level of service on freeways depends on traffic density, we were able to establish a link between level of service on these roads and odds of speeding using probe data. Future research is recommended to explore the odds of speeding on other roadway facility types using probe data. Future studies could also examine how COVID-19 case rates, death rates, or how factors like unemployment or population density affect the odds of speeding and how higher speeds impact roadway safety.

Declaration of Competing Interest

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

Data availability

The authors do not have permission to share data.

Acknowledgements

The authors gratefully acknowledge StreetLight Data, Inc. for providing the speed and volume data that were used for the analysis. The authors would also like to thank Mr. Torail Murphy for collecting the probe data (StreetLight Insight® volume and speed data) in Connecticut. This study was funded by Region 1 UTC, Transportation Infrastructure Durability Center (TIDC), in collaboration with the Maine DOT. The authors appreciate the support from Mr. Dennis Emidy, Mr. Jeffrey Pulver, Mr. Edward Hanscom, Mr. Robert Skehan, and Mr. Dale Peabody from Maine DOT throughout the research. The content of this paper and the results reflect the view of the authors, and do not necessarily reflect those of the TIDC program, Maine DOT, or StreetLight Data, Inc.

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