Modeling the impact of the COVID-19 pandemic on speeding at rural roadway facilities in Maine using short-term speed and traffic count data

Amir Shahlaee [a], Mohammadali Shirazi [a,*], Ennis Marshall [a], John N. Ivan [b]

[a] Department of Civil and Environmental Engineering, University of Maine, Orono, ME 04469, United States
[b] Department of Civil and Environmental Engineering, University of Connecticut, Storrs, CT 06269, United States

ABSTRACT

The COVID-19 pandemic caused a significant change in traffic operations and safety. For instance, various U.S. states reported an increase in the rate of fatal and severe injury crashes over this duration. In April and May of 2020, comprehensive stay-at-home orders were issued across the country, including in Maine. These orders resulted in drastic reductions in traffic volume. Additionally, there is anecdotal evidence that speed enforcement had been reduced during pandemic. Drivers responded to these changes by increasing their speed. More importantly, data show that speeding continues to occur, even one year after the onset of the pandemic. This study develops statistical models to quantify the impact of the pandemic on speeding in Maine. We developed models for three rural facility types (i.e., major collectors, minor arterials, and principal arterials) using a mixed effect Binomial regression model and short duration speed and traffic count data collected at continuous count stations in Maine. Our results show that the odds of speeding by more than 15 mph increased by 34% for rural major collectors, 32% for rural minor arterials, and 51% for rural principal arterials (non-Interstates) during the stay-at-home order in April and May of 2020 compared to the same months in 2019. In addition, the odds of speeding by more than 15 mph, in April and May of 2021, one year after the order, were still 27% higher on rural major collectors and 17% higher on rural principal arterials compared to the same months in 2019.

1. Introduction

Speed is an important element in various traffic engineering analyses. Most importantly, vehicle speed and/or speeding (driving above speed limit) can significantly influence frequency and severity of crashes (Doucette et al., 2021; Katrakazas et al., 2020). Speeding varies under different conditions such as time of the day, time of the week, different months of the year or in holidays (Jun 2010). It also varies based on functional class or facility type (Afghari et al., 2018), geometric characteristics (Eluru et al., 2013), the level of congestion, and weather conditions (Kyte et al., 2001). Psychological or perceptual conditions can also lead to speeding. In fact, researchers found that drivers are typically regulating their speeds based on visual factors and perceived risk, so with fewer cars on the road, risk perception is decreased which consequently leads to increased speed (Tucker and Marsh, 2021). Lastly, enforcement is another factor that influences speed limit violation, with

a reduction in enforcement leading to an increase in speeding. (Hauer et al., 1982; Soole et al., 2013).

The COVID-19 pandemic has had profound impacts on all aspects of our lives, even beyond the obvious health aspects. The comprehensive shutdown of in person activities during April and May of 2020 resulted in drastic reductions in traffic volumes, especially during pre-pandemic peak travel periods. Many motorists responded to the relatively empty roads by massively increasing their travel speeds; the result of this behavioral response has been an increase in the rate and incidence of fatal or severe crashes (Tucker and Marsh, 2021). In addition to the aforementioned reductions in traffic volume, there is anecdotal evidence that speed enforcement was also reduced during the shutdown orders. This is presumably because law enforcement was attempting to limit personal contact with motorists.

This study aims to understand the impact of the COVID-19 pandemic (e.g., reduction in enforcement or change in perceived risk) on speeding

during the stay-at-home order (April and May 2020), and one year after stay-at-home order (April and May 2021) in Maine. In this study, short-term traffic count and speed data from Maine roadways were used. The data were collected every 5 min at 23 continuous count stations operated by Maine Department of Transportation (Maine DOT) located on rural major collectors, rural minor arterials, and rural non-Interstate principal arterials. A mixed effect Binominal model with logit link function was developed to model speeding as a function of traffic count, accounting for factors such as time of the day, day of the week, and month of the year, and the speed limit. Two dummy variables were included to denote the duration of the stay-at-home order implementation (April and May 2020), and one year after the onset of pandemic (April and May 2021) to understand if other factors other than traffic volume reduction impacted the increased speeding trend.

2. Background

A few recent studies evaluated the impact of the COVID-19 pandemic on speeding and safety. Adanu et al, 2021 found that speeding and driving under the influence (DUI) are the two major contributing factors in increasing fatal and injury crashes in Alabama during the COVID-19 pandemic. Doucette et al. (2021) found that while the number of fatal and severe injury crashes increased during the early stages of the stay-at-home order in Connecticut, eventually the number of these crashes returned to the pre-pandemic pattern during later stages of the order, or when the order was rescinded. Like several states in the U.S., in Greece, also, researchers found that the decline in number of fatal or injury crashes is not proportionate to the reduction in traffic volume (Sekadakis et al., 2021). Vanlaar et al. (2021) examined how roadway safety differed during the pandemic between the United States and Canada. This study used self-reported data from surveys of drivers to study risky driving behavior and observe if similar driving traits were found in the two countries. These researchers found that speeding was the most common type of risk taken by the citizens of both countries. This study also used logistic regression to model crashes and found a significant difference among the two countries in risky driving behavior. In addition, in Canada, researchers found that the fatal and injury crashes reduced significantly among older drivers during the COVID-19 pandemic (Rapoport et al., 2021). In another study, Lin et al. (2021) evaluated mobility and crash patterns among different demographics and found that despite a significant mobility decrease among all demographics, the crash rates among different demographics changed disproportionately. Furthermore, it was observed that there was a spatial shift in crashes away from higher income regions towards the lower income ones. The study used crash data from New York City and Los Angeles and found that there was an increase in crash proportions for both the "Hispanic" and "Male" demographics, as well as a shift in crashes from higher income regions to lower income ones.

Although relatively limited in scope, several studies investigated how different roadway geometries affect speeding. Emerging technologies, such as GPS and location-based services (LBS), enhanced access to speed data for a greater number of roadway segments. Consequently, a few studies evaluated the effects of specific geometries on speeding, such as curves and their approaches. For instance, Dias et al., (2018) analyzed curvature information on Japanese expressways and found that an increased radius leads to a decreased reduction in speed. They also modeled speed trajectory through the curves using the minimum-jerk concept and it was found that this proved to be a strong predictor of a speed and acceleration profile for drivers through a curve, given a desired speed. Additionally, Donnell et al. (2001) considered the length and grade of the approach tangent, the radius of the horizontal curve,

and the length and grade of the departure tangent to forecast the 85th percentile truck operating speeds upstream, along, and downstream of a horizontal curve. In another study, Yokoo and Levinson (2019) used GPS data obtained over the course of a week from 152 individuals in the Minneapolis-St. Paul region of the United States. In this study, speeding was found to be more prevalent at lower (below 30mph) speed limits and higher (above 40mph) speed limit roadways. On top of this, roadways with longer links (intervals between intersections) were more conducive to speeding, as were evening hours.

Afghari et al. (2018) used speed camera data in Australia to model speeding based on variations in roadway geometry. This model was then used to investigate how alteration in the roadway characteristics would impact speeding. The researchers found that speeding would be reduced by about 3.5% if the number of covert speed cameras was increased by only 1%. Furthermore, the functional class of the road and what sort of traffic it is designed for also influenced speeding, with highway division and the percentage of heavy vehicles being noteworthy factors. The likely cause of this was that heavier vehicles traveled slower causing more drivers to pass them, which introduced additional speeding. Eluru et al. (2013) modeled the proportion of vehicles in each speed period using an ordered response formulation of a fractional split model. They developed two separate models for local roads and arterials. The model's findings demonstrated the impact of roadway characteristics, such as the number of lanes, the existence of parking, the presence of sidewalks, the vertical gradient, and the presence of a cycling route on vehicle speed proportions.

The time of day and day of the week can affect how many vehicles are on the road, why individuals are making trips, and what speeds they are trying to achieve. Heydari et al., (2020) conducted a study using data from randomly selected traffic sensors in Montreal, Quebec. It was hypothesized that speeds would increase on weekend nights, however, it was found that speeding was lower on weekend nights and instead higher during the mid-day and evening. The odds of night speeding were found to be lower on the weekend than weekdays and the probability of weekend speeding was less on one-way streets. Jun (2010) analyzed the profile of speed data during the thanksgiving week of 2006 and found that there are significant differences between the speed during the congested (lower speed) and non-congested (higher speed) times during the holidays. Several papers investigated speeding using a before/after setup and explored factors that caused people to speed less than previously. One such study, conducted in Australia, tried to qualitatively determine factors that influenced speed reduction in a social context. It found that one of the most effective social situations at reducing speeds was the presence of passengers (Fleiter et al., 2010).

This research contributes to the current literature by modeling the traffic speeding on rural facilities during the COVID-19 pandemic, using 5-min aggregated data collected at count stations during the comprehensive stay at home order and one year since its inception. We will answer if other factors other than the drastic reduction in traffic volume also influenced speeding during the stay-at-home order, and to what degree the speeding behavior continued to happen approximately-one year after the onset of the pandemic compared to before pandemic.

3. Data description

More than 80% of the roads in Maine are rural. Maine DOT has collected 5-minute traffic count and speed data at 23 active continuous count stations on rural roadways in Maine. These 23 stations are located on three different rural facility types. There are 10 stations on rural major collectors, 6 stations on rural minor arterials and 7 stations on rural non-interstate principal arterials. Fig. 1 shows the location of the stations. Loop detectors at each station collect data at both directions of
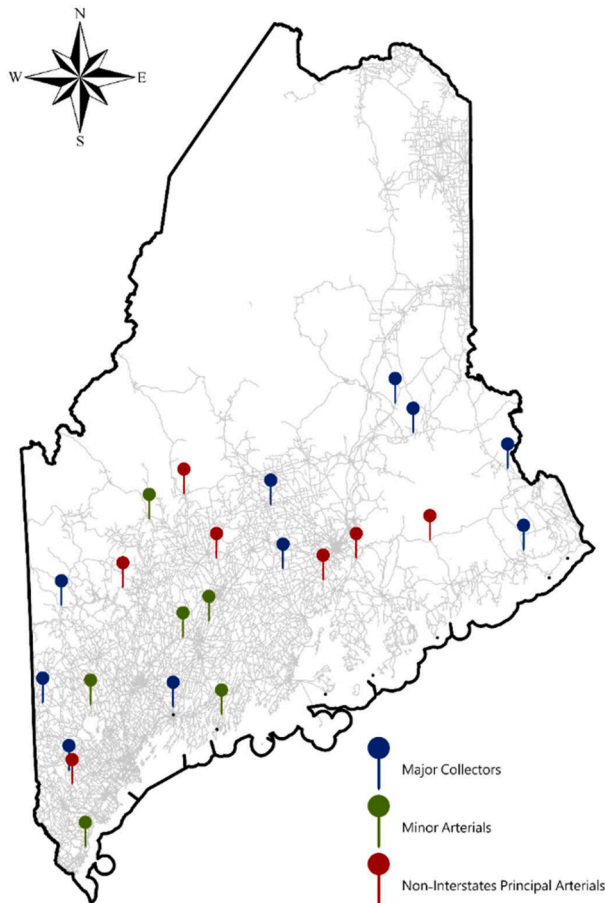
Fig. 1. Location of count stations in Maine.

the roadway. Therefore, each station provides two distinctive sets of traffic count and speed information. Data collected at these stations during the first 28 days of February, April, and May of 2019, 2020, and 2021 were respectively used to represent the duration before the pandemic (or stay-at-home order, to be exact), the stay-at-home order

duration, and one year after the order introduction. The 5-minute data collection interval allows short variations of volume and speed to be accounted for analysis. Speed limit information, necessary for determining the amount of speeding, was collected from Main DOT's Public Map Viewer[1] and Google Maps. With this data, the number of the vehicles driving 10, 15, 20 and 25 mph above the speed limit, in each 5-min time interval was found.

A uniform dataset was created with speeding, traffic count, and speed limit information, as well as variables that reflect time of the day (i.e., off peak, morning peak hour, evening peak hour), time of the week (i.e., weekend, and not-weekend) and month of the year (i.e., February, April, May), along with two dummy variables. One dummy variable was set equal to one in April and May 2020 to denote the stay-at-home order, and the other set to one during these times in 2021 to distinguish after the order. Table 1 shows the description of the variables used in this study. The impact of the speed limit variable was modeled as a dummy variable, with the speed limit of 45 mph or less as the reference variable. The time of the day, time of the week, and month of the year variables were also considered as dummies. The off-peak period, weekdays (Monday through Friday), and the month of February were used as reference variables.

After a careful review of the data, we removed data records with interrupted flows, such as those affected by construction zones. Table 2 shows the summary statistics of the 5-minute aggregated traffic count data. As expected, minor and principal arterials carry more traffic compared to major collectors. In addition, the traffic counts are greater during the morning and evening peak periods compared to the off-peak period. The reduction in traffic is also apparent during the COVID-19 stay-at-home order duration (e.g., April and May 2020) for all three facility types at all times. For example, the maximum 5-min traffic count on minor arterials reduced from 115 to 59 vehicles in April 2020 compared to the same month in 2019.

Table 3 shows the distribution of speed at locations with a speed limit of 55 mph on major collectors, minor collectors, and principal arterials. As is evident from this table, the percentage of vehicles driving at higher speeds increased significantly in 2020 and 2021 compared to 2019. For example, the percentage of vehicles driving 5 mph above the speed limit at a location on a major collector roadway increased from 41.17%, to 59.72% during the morning peak period and from 45.02% to 55.21% during evening peak period in April 2020 compared to April 2019. In April 2021, one year after the comprehensive stay-at-home order, the percentage of vehicles driving at 5 mph above speed limit remains at a significantly higher percentage of 58.98% and 57.56% at this location during morning and evening peak periods respectively.

Table 1
Data description.

Variables		Variable Definition
Traffic Count	Ln (Traffic Count)	The natural log of 5-min traffic count
Time of day	Off Peak (=0)	Data collected during Off Peak (10am-3 pm and 7 pm to 6am)
	Morning Peak Period	Data collected during Morning Peak Hour (6am-10am)
	Evening Peak Period	Data collected during Evening Peak Hour (3 pm-7 pm)
Time of Week	Not Weekend (=0)	Data collected in weekdays (Monday to Friday)
	Weekend	Data collected in weekends
Month	February (=0)	Data collected in February (February 2019, 2020, and 2021)
	April	Data collected in April (April 2019, 2020, and 2021)
	May	Data collected in May (May 2019, 2020, and 2021)
Stay-at-Home Order	Before Order (=0)	February, April and May of 2019 and February 2020
	During Order	April and May of 2020 (when stay at home was in place)
	Post Order	February, April and May of 2021
Speed Limit	≤ 45 mph (=0)	Speed limit less than or equal to 45 mph
	= 50 mph	Speed limit equals to 50 mph
	= 55 mph	Speed limit equals to 55 mph

Table 2
Summary Statistics of the five-minute aggregated traffic count data.

Time Period			Major Collectors				Minor Arterials				Principal Arterials*			
			Mean	S.D.	Min	Max	Mean	S.D..	Min	Max	Mean	S.D.	Min	Max
Morning Peak Period	Feb	2019	5.8	5.7	1	59	14.1	12.3	1	113	12.3	10.4	1	71
(6 a.m. to 10 a.m.)		2020	5.8	5.8	1	59	14.3	12.3	1	113	12.4	10.5	1	73
		2021	5.6	5.5	1	52	12.9	10.4	1	84	11.4	9.8	1	72
	April	2019	6.1	6.0	1	53	15.6	13.3	1	115	13.3	11.1	1	73
		2020	4.4	3.9	1	31	9.6	7.6	1	59	8.6	6.9	1	47
		2021	6.1	5.8	1	55	15.0	11.5	1	90	12.9	11.1	1	83
	May	2019	6.6	6.3	1	49	17.5	14.3	1	118	14.7	12.4	1	77
		2020	5.2	4.7	1	37	12.5	9.8	1	70	10.6	8.6	1	53
		2021	6.7	6.2	1	56	17.0	12.7	1	85	14.4	12.3	1	87
Evening Peak Period	Feb	2019	7.3	6.9	1	54	17.8	13.8	1	104	15.8	13.3	1	90
(3p.m. to 7p.m.)		2020	7.3	7.0	1	49	17.9	13.6	1	102	16.0	13.5	1	88
		2021	6.9	6.6	1	45	16.5	12.6	1	92	14.4	12.4	1	96
	April	2019	7.7	7.3	1	53	20.0	15.0	1	106	16.8	13.8	1	84
		2020	5.6	5.3	1	43	12.5	9.8	1	76	11.0	9.4	1	62
		2021	7.8	7.1	1	54	20.1	14.4	1	94	16.6	14.0	1	75
	May	2019	8.4	7.5	1	52	22.7	16.3	1	107	18.9	15.7	1	88
		2020	7.2	6.4	1	46	17.5	12.8	1	97	14.9	12.2	1	69
		2021	8.5	7.3	1	48	23.1	16.1	1	101	18.8	15.7	1	93
Off peak	Feb	2019	4.4	4.5	1	39	9.1	10.0	1	82	8.2	9.2	1	80
		2020	4.5	4.7	1	65	9.2	10.3	1	80	8.3	9.4	1	83
		2021	4.5	4.7	1	46	9.2	10.4	1	68	8.1	9.5	1	86
	April	2019	4.6	4.7	1	46	10.3	11.3	1	77	8.8	9.8	1	66
		2020	4.1	4.1	1	36	7.6	8.2	1	63	6.6	7.5	1	57
		2021	5.0	5.2	1	48	11.0	12.3	1	82	9.0	10.5	1	81
	May	2019	5.1	5.2	1	72	11.8	13.1	1	86	9.9	11.3	1	84
		2020	4.9	5.0	1	39	10.0	11.1	1	78	8.4	9.7	1	64
		2021	5.3	5.4	1	72	12.5	14.1	1	84	10.0	11.8	1	87

*Non-Interstates Principal Arterials.

Table 3
Distribution of Speed in 2019, 2020, and 2021 at locations with speed limit of 55 mph.

Facility	Time Period				Speed			
					>50 mph	>60 mph	>70 mph	>80 mph
Major Collectors	Morning	April	2019		90.06%	41.17%	2.24%	0.30%
(Speed Limit = 55 mph)	Peak Period		2020		94.07%	59.72%	5.79%	0.50%
	(6 a.m. to 10 a.m.)		2021		94.79%	58.98%	5.53%	0.60%
		May	2019		93.17%	46.02%	2.97%	0.37%
			2020		93.01%	57.77%	5.43%	0.74%
			2021		95.39%	60.09%	5.11%	0.59%
	Evening	April	2019		91.07%	45.02%	2.57%	0.28%
	Peak Period		2020		90.70%	55.21%	5.11%	0.51%
	(3 p.m. to 7 p.m.)		2021		92.90%	57.56%	5.00%	0.49%
		May	2019		91.58%	46.80%	2.90%	0.39%
			2020		91.23%	58.23%	5.58%	0.66%
			2021		93.20%	59.36%	5.01%	0.61%
	Off peak	April	2019		87.73%	38.33%	2.42%	0.32%
			2020		90.56%	54.26%	5.38%	0.73%
			2021		91.53%	53.35%	4.61%	0.55%
		May	2019		89.49%	42.26%	2.98%	0.43%
			2020		89.96%	52.59%	4.66%	0.60%
			2021		92.50%	54.07%	4.51%	0.52%
Minor Arterials	Morning	April	2019		89.04%	36.72%	2.48%	0.07%
(Speed Limit = 55 mph)	Peak Period		2020		92.16%	42.42%	3.97%	0.20%
	(6 a.m. to 10 a.m.)		2021		93.19%	33.86%	2.00%	0.15%
		May	2019		94.18%	40.77%	2.70%	0.17%
			2020		94.04%	43.10%	4.15%	0.29%
			2021		92.83%	33.24%	2.14%	0.25%
	Evening	April	2019		91.10%	39.15%	2.05%	0.06%
	Peak Period		2020		90.62%	38.41%	3.03%	0.17%
	(3 p.m. to 7 p.m.)		2021		92.93%	38.89%	2.09%	0.25%
		May	2019		91.82%	38.15%	1.69%	0.05%
			2020		92.92%	41.35%	3.06%	0.17%
			2021		91.45%	32.90%	1.47%	0.23%
	Off peak	April	2019		88.59%	33.84%	1.86%	0.08%
			2020		88.70%	34.43%	2.89%	0.15%

Table 3 (*continued*)

Facility	Time Period			Speed			
				>50 mph	>60 mph	>70 mph	>80 mph
			2021	89.42%	31.20%	2.06%	0.17%
		May	2019	88.91%	32.29%	1.71%	0.06%
			2020	90.96%	35.89%	2.84%	0.17%
			2021	88.70%	27.47%	1.52%	0.13%
Principal Arterial*	Morning	April	2019	96.33%	39.21%	2.84%	0.25%
(Speed Limit = 55 mph)	Peak Period		2020	97.87%	45.82%	3.59%	0.29%
	(6 a.m. to 10 a.m.)		2021	97.17%	46.07%	4.79%	0.53%
		May	2019	96.21%	38.47%	3.06%	0.31%
			2020	97.67%	44.86%	4.30%	0.33%
			2021	97.17%	45.01%	4.83%	0.43%
	Evening	April	2019	96.37%	43.28%	4.02%	0.22%
	Peak Period		2020	96.00%	48.92%	6.24%	0.90%
	(3 p.m. to 7 p.m.)		2021	98.65%	50.05%	5.77%	0.68%
		May	2019	97.05%	41.01%	3.07%	0.23%
			2020	97.84%	47.94%	6.24%	0.60%
			2021	98.42%	51.72%	6.13%	0.64%
	Off peak	April	2019	94.79%	36.71%	2.60%	0.22%
			2020	96.42%	40.61%	3.48%	0.36%
			2021	96.51%	42.58%	4.29%	0.42%
		May	2019	95.73%	34.93%	2.74%	0.29%
			2020	96.32%	40.31%	4.13%	0.42%
			2021	96.62%	40.66%	4.24%	0.49%

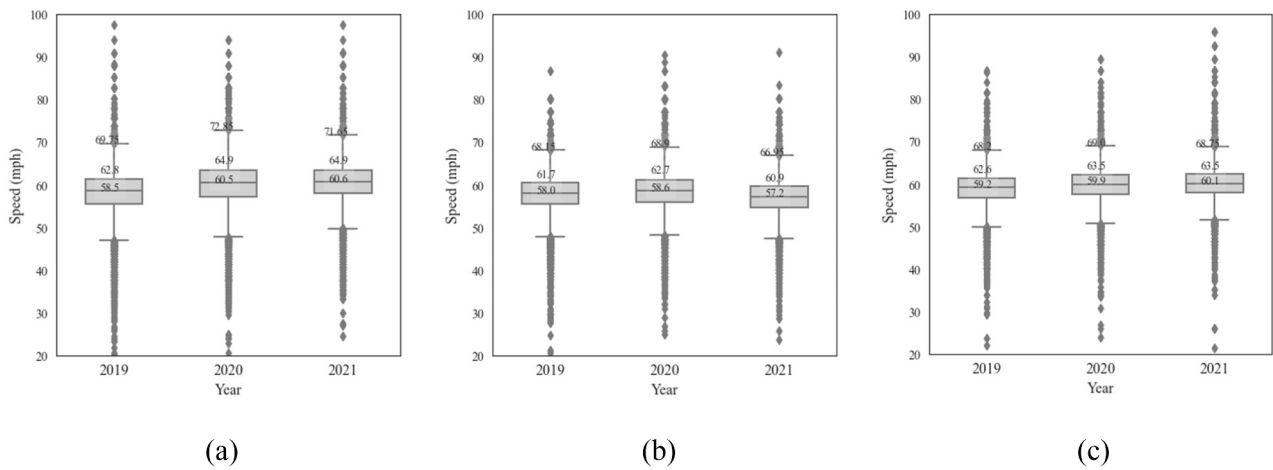*Non-Interstates Principal arterials.

Fig. 2. Distribution of speed at (a) major collectors, (b) minor arterials, and (c) non-interstates principal arterials.

Fig. 2 shows the distribution of speed at the three locations documented in Table 3, considering data collected in April and May of 2019, 2020, and 2021. As is evident from this figure, driving at higher speeds had increased significantly in 2020. Although the speed seems to return to the normal condition on the minor arterial location, the figure further illustrates that speed remains high in 2021 for the major collector and none-interstate principal arterial locations.

4. Methodology

Let us consider the number of cars passing each count station in a short duration of time (here 5 min). During each period, *n* cars pass the station; *y* out of *n* cars speed by more than a certain amount (e.g., 10, 15, 20, and 25 mph) with probability of *p* and $(n - y)$ cars do not speed with probability of $(1 - p)$. This would result in a binomial model with odds of $p/(1 - p)$. A generalized linear mixed effect Binomial regression model with a logit link function was used to model the odds of speeding for vehicles that drive 10, 15, 20, and 25 mph above speed limit. The random effect term (ε_k) was used to account for the unobserved location heterogeneity at each k-th station. The Binomial probability distribution

function is defined as (Hilbe, 2014):

$$p(y_{ik}|p_{ik}, n_{ik}) = \binom{n_{ik}}{y_{ik}} p^{y_{ik}} (1 - p_{ik})^{n_{ik} - y_{ik}} \tag{1}$$

where, n_{ik} is the traffic count at the i-th 5-min interval and k-th station, and y_{ik} is the number of vehicles driving at certain number of miles per hour (i.e., 10, 15, 20, and 25 mph) above the speed limit at the same i-th interval and k-th station. A logit function was used to link the speeding percentage (p_{ik}) to the variables described in Table 1. Equation (2) shows the link function.

$$\mathrm{Ln}\left(\frac{p_{ik}}{1 - p_{ik}}\right) = \beta_0 + \alpha \mathrm{Ln}(V_{ik}) + \sum_{j=1}^{m} \beta_j X_{j,ik} + \gamma_0 I_{d,ik} + \delta_0 I_{p,ik} + \varepsilon_k \tag{2}$$

where,

β_0: Common intercept.

α: Coefficient on the natural log of traffic count.

β_j: Coefficient on the j-th control variable.

γ_0: Coefficient on the Dummy representing stay-at-home order.

δ_0: Coefficient on the Dummy representing after-stay-at home order.

Ln(V_{ik}): Natural log of 5-min traffic count at location k for i-th observation.

$X_{j,ik}$: The value of the j-th control variable at location k for i-th observation.

$I_{d,ik}$: Stay-at-home indicator (equal to one if the i-th observation at the k-th station occurred during the stay-at-home order.).

$I_{p,ik}$: Post stay-at-home indicator (equal to one if the i-th observation at the k-th station occurred after the stay-at-home order.).

ε_k : Error term (random effect) at the k-th station.

m: The number of variables in the model.

Specifically, the model included 5-min traffic count (V), a dummy accounting for observations during the stay-at-home order (γ_0), and a dummy accounting for observations after stay-at-home order (δ_0) and a set of variables denoting time-of-day (off-pick, morning peak period, and evening peak period), time of the week (weekend and not weekend), month of the year (February, April, and May), and speed limit as control variables. The model was implemented using the "glmer" package (version 1.1–27.1) (Lee and Grimm, 2018) in R statistical software. Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and log-likelihood test statistics were used to evaluate the fit of the models.

5. Modeling results

The mixed effect Binomial model described in Section 4 was used to model odds of speeding for three rural facility types in Maine. Tables 4-6 show the modeling results for major collectors, minor arterials and principal arterials (non-Interstates), respectively. For each facility type, four speeding models were developed to estimate the number of vehicles that drive 10, 15, 20, and 25 mph above the speed limit. The corresponded odds ratios were also calculated and are shown in the tables. For each dataset, the Variance Inflation Factors (VIF) were estimated to test the existence of multicollinearity; the VIF metric was between 1 and 2; hence, no multicollinearity exists among the variables. The final models include variables that are significant at 95% confidence interval.

5.1. Major collectors

Table 4 shows the modeling results for the major collectors. As expected, the traffic count and speeding exhibit a negative association; as the number of vehicles increases, the odds of speeding decreases. Intuitively, it is expected to see fewer vehicles speed by more than 25 mph than 20 mph than 15 mph than 10 mph as the number of vehicles increases, which was well reflected in the modeling results. The odds of speeding by more than 10 mph or 15 mph above the speed limit decreases by about 4% as the natural log of traffic count increases by one unit. The increase in traffic count also has a significant impact on the number of vehicles that are driving 20 and 25 mph above the speed limit. As the natural log of traffic count increases by one unit, the odds of speeding by more than 20 and 25 mph decreases by 38% and 39% respectively.

Time of the day (off peak vs morning peak period vs evening peak period), day of the week (weekends vs weekdays), and different months (e.g., February vs April vs May) can significantly influence the speeding behavior. The modeling results show that the odds of speeding by more than 10, 20, 20, and 25 mph increases by around 8–10% during the weekends compared to weekdays. Speeding is also more common during the peak periods, especially morning peak periods, presumably because drivers are often in hurry during these times. This hypothesis is well reflected in modeling results. As shown in Table 4, the odds of speeding by more than 10, 15, and 20 mph increases by 20%, 25%, and 16% respectively during the morning peak period, and by 13%, 11%, and 4% during the evening peak periods. The impact of morning and evening peak periods on speeding over 25 mph was insignificant; presumably, this observation is due to higher traffic volume during peak periods that limits the possibility of extreme speeding. It is also worth pointing out that in Maine, the month of February often sees significant snowfall and

Table 4
Modeling results for rural major collectors.

Variables	+10 mph Speeding		+15 mph Speeding		+20 mph Speeding		+25 mph Speeding	
	Mean (S.E.)[1]	Odds Ratio	Mean (S.E.)	Odds Ratio	Mean (S.E.)	Odds Ratio	Mean (S.E.)	Odds Ratio
Intercept	−1.565 (0.120)		−2.851 (0.122)		−4.122 (0.155)		−5.955 (0.172)	
Ln (Traffic Count)	−0.047 (0.002)	0.954	−0.041 (0.003)	0.960	−0.479 (0.007)	0.619	−0.502 (0.014)	0.606
Weekend	0.074 (0.003)	1.077	0.092 (0.004)	1.096	0.076 (0.011)	1.079	0.081 (0.022)	1.084
Morning Peak Period	0.1834 (0.003)	1.201	0.224 (0.005)	1.251	0.149 (0.012)	1.161	−[2]	–
Evening Peak Period	0.125 (0.003)	1.133	0.103 (0.005)	1.109	0.0414 (0.012)	1.042	−[2]	–
April	0.283 (0.003)	1.327	0.270 (0.005)	1.311	0.375 (0.014)	1.454	0.465 (0.028)	1.591
May	0.276 (0.003)	1.317	0.252 (0.005)	1.286	0.3869 (0.014)	1.472	0.520 (0.028)	1.682
Stay-at-Home (γ_0)	0.237 (0.003)	1.267	0.295 (0.006)	1.343	0.432 (0.014)	1.540	0.509 (0.027)	1.664
Post Stay-at-Home (δ_0)	0.193 (0.003)	1.212	0.237 (0.005)	1.267	0.357 (0.012)	1.429	0.458 (0.023)	1.581
Speed Limit = 50 mph	−1.478 (0.249)	0.228	−1.555 (0.235)	0.211	−0.993 (0.214)	0.371	−0.547 (0.283)	0.579
Speed Limit = 55 mph	−0.757 (0.133)	0.469	−1.270 (0.174)	0.281	−1.272 (0.268)	0.280	−[2]	–
AIC	2,057,063		1,063,567		326,235		115,692	
BIC	2,057,206		1,063,709		326,378		115,799	
Log-Likelihood	−1,028,520		−531,771		−163,106		−57,837	

[1] Values written in parenthesis are standard errors.
[2] Insignificant variables at 95% confidence level.

Table 5
Modeling results for rural minor arterials.

Variables	+10 mph Speeding		+15 mph Speeding		+20 mph Speeding		+25 mph Speeding	
	Mean (S.E.)[1]	Odds Ratio	Mean (S.E.)	Odds Ratio	Mean (S.E.)	Odds Ratio	Mean (S.E.)	Odds Ratio
Intercept	−2.494 (0.076)		−3.443 (0.147)		−4.704 (0.294)		−6.697 (0.238)	
Ln (Traffic Count)	−0.262 (0.003)	0.769	−0.478 (0.005)	0.620	−0.850 (0.012)	0.427	−0.892 (0.018)	0.410
Weekend	0.184 (0.004)	1.203	0.140 (0.009)	1.150	0.189 (0.023)	1.209	0.217 (0.039)	1.242
Morning Peak Period	0.3421 (0.004)	1.408	0.357 (0.010)	1.429	0.131 (0.028)	1.140	−[2]	–
Evening Peak Period	0.224 (0.004)	1.251	0.264 (0.010)	1.302	0.103 (0.029)	1.109	−[2]	–
April	0.318 (0.005)	1.375	0.433 (0.011)	1.542	0.454 (0.031)	1.574	0.467 (0.052)	1.596
May	0.208 (0.005)	1.231	0.336 (0.011)	1.400	0.434 (0.031)	1.544	0.477 (0.052)	1.611
Stay-at-Home (γ_0)	0.288 (0.004)	1.333	0.274 (0.011)	1.316	0.396 (0.029)	1.487	0.401 (0.049)	1.493
Post Stay-at-Home (δ_0)	−[2]	–	−0.031 (0.010)	0.970	0.084 (0.026)	1.087	0.200 (0.044)	1.222
Speed Limit = 50 mph	−1.373 (0.127)	0.253	−1.675 (0.225)	0.187	−1.077 (0.437)	0.341	−0.687 (0.289)	0.503
Speed Limit = 55 mph	−[2]	–	−1.075 (0.193)	0.341	−0.844 (0.313)	0.430	0.790 (0.279)	2.204
AIC	1,232,140		389,743		90,947		37,895	
BIC	1,232,255		389,881		91,085		38,009	
Log-likelihood	−616,060		−194,859		−45,461		−18,937	

[1] Values written in parenthesis are standard errors.
[2] Insignificant variables at 95% confidence level.

Table 6
Modeling results for rural principal arterials (Non-Interstates).

Variables	+10 mph Speeding		+15 mph Speeding		+20 mph Speeding		+25 mph Speeding	
	Mean (S.E.)[1]	Odds Ratio	Mean (S.E.)	Odds Ratio	Mean (S.E.)	Odds Ratio	Mean (S.E.)	Odds Ratio
Intercept	−0.751 (0.122)		−2.097 (0.120)		−3.324 (0.159)		−4.387 (0.214)	
Ln (Traffic Count)	−0.130 (0.001)	0.879	−0.260 (0.002)	0.771	−0.426 (0.003)	0.653	−0.687 (0.007)	0.503
Weekend	0.219 (0.002)	1.245	0.260 (0.003)	1.297	0.296 (0.005)	1.344	0.287 (0.012)	1.332
Morning Peak Period	0.105 (0.002)	1.111	0.124 (0.003)	1.132	0.168 (0.006)	1.183	0.162 (0.014)	1.175
Evening Peak Period	0.099 (0.002)	1.105	0.101 (0.003)	1.106	0.081 (0.006)	1.085	0.081 (0.014)	1.085
April	0.194 (0.002)	1.214	0.213 (0.003)	1.237	0.155 (0.007)	1.168	0.151 (0.015)	1.163
May	0.154 (0.002)	1.167	0.168 (0.003)	1.183	0.082 (0.007)	1.086	0.117 (0.015)	1.124
Stay-at-Home (γ_0)	0.326 (0.003)	1.385	0.415 (0.004)	1.514	0.503 (0.007)	1.653	0.600 (0.015)	1.823
Post Stay-at-Home (δ_0)	0.067 (0.002)	1.072	0.161 (0.003)	1.174	0.224 (0.006)	1.251	0.311 (0.013)	1.364
Speed Limit = 50 mph	−2.171 (0.100)	0.114	−1.970 (0.196)	0.140	−2.753 (0.459)	0.064	−3.379 (0.350)	0.034
Speed Limit = 55 mph	−0.962 (0.258)	0.382	−1.648 (0.513)	0.193	−1.727 (0.392)	0.178	−1.061 (0.361)	0.346
AIC	2,658,315		1,452,673		614,863		227,587	
BIC	2,658,455		1,452,813		615,003		227,727	
Log-likelihood	−1,329,145		−726,325		−307,419		−113,781	

[1] Values written in parenthesis are standard errors.

adverse weather conditions, resulting in reduced speeds. The snowfall and adverse weather conditions are significantly less prevalent in the months of April and May. As shown in Table 4, the odds of speeding 10, 15, 20, and 25 mph above the limit increases by 32%, 31%, 45%, and

59% respectively in April compared to February and by 31%, 29%, 47%, and 68% in May compared to February.

Most importantly, both dummy variables, which represent the periods during and after the stay-at-home order, are significant with a

positive value. This shows that it is not just the reduction in traffic volume that resulted in increased speed during or after the order, but other variables played a role as well. In particular, the odds of speeding by more than 10, 15, 20, and 25 mph increased by 27%, 34%, 54%, and 66% respectively during the order. This observation could be due to reduced traffic enforcement during this time in Maine. Even one year later, the odds of speeding by more than 10, 15, 20, and 25 mph are still 21%, 27%,43% and 58% higher than before the order during the same months. Although these odds are slightly less than during the stay-at-home order (possibly due to resumed enforcement), the results show that drivers have become used to speeding on major collectors during the COVID-19 pandemic.

5.2. Minor arterials

Table 5 shows the modeling results for rural minor arterials. Again, the number of vehicles significantly influences the odds of speeding. In particular, as the natural log of the traffic count increases by 1 unit, the odds of speeding by more than 10, 15, 20, and 25 mph decreases by 23%, 38%, 57%, and 59% respectively. The reduction in traffic count has a greater impact on minor arterials compared to major collectors. Since minor arterials are designed to carry more traffic, a reduction in traffic gives drivers more opportunities to speed. Like the modeling results for the major collectors, speeding increases during the weekend, morning, and evening peak periods. In particular, the odds of speeding by more than 10, 15, 20, and 25 mph increases by 20%, 15%, 21%, and 24% during the weekends compared to weekdays. When compared to off peak, the odds of speeding by more than 10, 15, and 20 mph increases by 41%, 43%, and 14% respectively during morning peak periods and by 25%, 30%, and 11% respectively during evening peak periods. As noted previously, it is expected to observe higher number of speeding cases during peak periods, especially during the morning peak periods, as drivers could be in hurry during these times. As with major collectors, the peak period variable is insignificant for the 25 mph and above model, possibly due to the increased volume reducing opportunities for speeding. Additionally, the modeling results show that a greater number of vehicles speed during the month of April and May compared to February, due to improved weather conditions.

The two dummy variables, one signifying times during the stay-at-home order and the other the times after the order, both, denote positive coefficients. The first of these two is significantly large, showing that speeds on minor arterials were significantly affected during the stay-at-home order. As shown in Table 5, the odds of speeding by more than 10, 15, 20, and 25 mph increased by 33%, 31%, 49%, and 49% respectively during the order. This observation is likely due to reduced enforcement during this period. In April and May of 2021, speeding by more than 10, and 15 mph seems to return to pre-stay-at-home conditions, but aggressive driving (i.e., speeding by more than 20, and 25 mph) still happens at higher odds. That said, it happens with significantly less frequency than when observed during the order. In particular, the odds of speeding by more than 20 and 25 mph on minor arterials were still 9% and 22% higher than before, even after one year since the order was issued.

5.3. Principal arterials

Table 6 shows the modeling results for stations located at rural principal arterial (non-Interstates) facilities. As the natural log of traffic count decreases by one unit, the odds of speeding by more than 10, 15, 20, and 25 mph decreases by 12%, 23%, 35%, and 50%. Similar trends are also observed regarding the time of the week (i.e., weekends), time of the day (i.e., morning, and evening peak periods), and months of the year (i.e., April and May) as the other two facilities. specifically, the odds of speeding by more than 10, 15, 20, and 25 mph increases by 25%, 30%, 34%, and 33% during the weekends compared to weekdays. When compared to off peak, the odds of speeding by more than 10, 15, 20, and

25 mph increases by 11%, 13%, 18% and 17% respectively during morning peak periods and by 11%, 11%, 9% and 9% respectively during evening peak periods. Higher odds of speeding in April and May compared to February is also evident from the results, due to improved weather conditions.

Most importantly, the modeling results show increased odds of speeding during the stay-at-home order. Compared to before, the odds of speeding by more than 10, 15, 20, and 25 mph increased by 39%, 51%, 65%, and 82% respectively. For non-interstates principal arterials, the modeling results show that speeding behavior continues to happen, though to a lesser degree, even one year after the comprehensive order. In particular, the odds of speeding by more than 10, 15, 20, and 25 mph are still 7%, 17%, 25%, and 36% higher than before pandemic.

As a closing note to this section, it is worth pointing out that the modeling results show decreased odds of speeding at higher speed limits (i.e., 50 or 55 mph). The speed limit variable was used as a control variable in the models, but these results are also expected as people intuitively are more inclined to speed on roads with lower speed limits as shown in previous studies (Afghari et al., 2018).

6. Summary and conclusions

The rate of fatal and severe crashes in Maine has been increased during the COVID-19 pandemic. During the comprehensive stay-at-home order implemented in Maine, the traffic volume decreased drastically. Drivers responded to this change by increasing their speed. A Binomial mixed effect model was used to model the 5-minute data collected at count stations to understand the impact of the pandemic on speeding. The results show that the odds of speeding by more than 10, 15, 20, and 25 mph on rural major collectors increased by 27%, 34%, 54%, and 66% respectively in April and May of 2020 in comparison to these same months in 2019. Similarly, the odds of speeding by more than 10, 15, 20, and 25 mph increased by 33%, 32%, 49%, and 49% on minor arterials and by 39%, 51%, 65%, 82% on principal arterials during the same duration compared to before. The results also show that the odds of speeding by more than 10, 15, 20, and 25 mph in April and May of 2021 (one year after the stay-at-home order) was still 21%, 27%, 43%, and 58% higher on rural major collectors than the same period before pandemic. The odds of speeding by more than 10, 15, 20, and 25 mph in April and May of 2021on principal arterials is also 7%, 17%, 25%, and 36% higher than the same period in 2019. These results show that many drivers have become accustomed to speeding.

Maintaining system operational efficiency of transportation infrastructure, including both traffic flow and safety, is becoming more and more of concern in the face of diminishing funds available to transportation agencies for construction and maintenance. Recent history suggests that system operational efficiency is increasingly challenged by unexpected disruptions in traffic demand caused by natural disasters and other emergencies, such as the COVID-19 pandemic. Transportation agencies will need to be prepared for the safety and operational impacts of such disruptions in traffic volume as they manage system operational efficiency. This study found that in addition to drastic reduction in traffic volume, other factors (presumably, reduction in speeding enforcement or change in perceived risk) also influenced the increase in operational speed (or speeding, to be exact) during the comprehensive stay-at-home order. In addition, speeding continued to happen in Maine even after one year since the onset of the pandemic stay-at-home order. Speeding is a contributing factor in many fatal or severe crashes, so recognizing that speeding has significantly increased suggests the importance of exploring countermeasures or interventions to reduce the speed. These results also show that the massive disruption in travel demand, or traffic volume, can have a profound impact on the operational speed or speeding that can have lasting effects long after the disruption has ceased. Roadway operating agencies should consider this likelihood of increases in drivers speeding whenever unexpected reductions in travel demand or traffic volume occur, and properly plan for

such incidents where possible to reduce the expected increases in fatal crashes.

In this study, we used a binomial model, due to its flexibility to model binary response variables, and interpreted the results using the change in odds of speeding. Other methods such as time series models (e.g., multivariate timeseries) can also be used and are suggested for future studies. The variables denoting the number of COVID-19 cases or death were not considered in this study due to their limited variations in Maine. It is recommended to use these variables in states where the number of COVID-19 cases or death fluctuate significantly from one day to another. Future studies are also recommended to compare the change in odds of speeding in states with different population or density.

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.

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