Check for updates

Research Article

TRR
JOURNAL OF THE TRANSPORTATION RESEARCH BOARD

Transportation Research Record
1–13
© National Academy of Sciences:
Transportation Research Board 2021
Article reuse guidelines:
sagepub.com/journals-permissions
DOI: 10.1177/03611981211044454
journals.sagepub.com/home/trr
SAGE

Lower Volumes, Higher Speeds: Changes to Crash Type, Timing, and Severity on Urban Roads from COVID-19 Stay-at-Home Policies

Jonathan Stiles[1], Armita Kar[1], Jinhyung Lee[2], and Harvey J. Miller[1,3]

Abstract

Stay-at-home policies in response to COVID-19 transformed high-volume arterials and highways into lower-volume roads, and reduced congestion during peak travel times. To learn from the effects of this transformation on traffic safety, an analysis of crash data in Ohio's Franklin County, U.S., from February to May 2020 is presented, augmented by speed and network data. Crash characteristics such as type and time of day are analyzed during a period of stay-at-home guidelines, and two models are estimated: (i) a multinomial logistic regression that relates daily volume to crash severity; and (ii) a Bayesian hierarchical logistic regression model that relates increases in average road speeds to increased severity and the likelihood of a crash being fatal. The findings confirm that lower volumes are associated with higher severity. The opportunity of the pandemic response is taken to explore the mechanisms of this effect. It is shown that higher speeds were associated with more severe crashes, a lower proportion of crashes were observed during morning peaks, and there was a reduction in types of crashes that occur in congestion. It is also noted that there was an increase in the proportion of crashes related to intoxication and speeding. The importance of the findings lay in the risk to essential workers who were required to use the road system while others could telework from home. Possibilities of similar shocks to travel demand in the future, and that traffic volumes may not recover to previous levels, are discussed, and policies are recommended that could reduce the risk of incapacitating and fatal crashes for continuing road users.

Keywords

road safety, COVID-19, crash severity, traffic speed, transportation planning

Stay-at-home policies in response to COVID-19 reduced travel on the road networks of U.S. metropolitan areas beginning in March 2020. In Ohio, Governor DeWine announced on March 12 that the school system would not be reopening after spring break, becoming the first state to fully close schools in response to COVID-19. Several major employers in the Columbus metropolitan area were already encouraging employees to work from home. The following week, the state announced a shelter-in-place order to begin on March 23, asking residents to "stay at home or at their place of residence," with exceptions for what were deemed essential activities including some types of work (*1*). These policies, alongside additional business closures, greatly reduced travel demand, resulting in much lower volumes on arterial roads and highways that were designed for higher peak period traffic. Speed was central to this transformation, as fewer cars on the roads reduces impediments to driving at higher speeds and may encourage speeding behavior (*2*).

This unusual period of severely reduced traffic volumes under stay-at-home policies presents on opportunity to revisit the relationship of traffic volume, speed, and road system design in regard to traffic safety, and to use that reflection to prepare for possible future

[1]Department of Geography, The Ohio State University, Columbus, OH
[2]Department of Geography and Environment, Western University, London, Canada
[3]Center for Urban and Regional Analysis, The Ohio State University, Columbus, OH

Corresponding Author:
Harvey J. Miller, miller.81@osu.edu

scenarios of temporary or long-term reduced demand. This paper presents an analysis of crash data in Franklin County, Ohio—home to the city of Columbus—from February 2020 to May 2020, augmented by traffic speed and road network data. First, crash characteristics such as crash type, time of day, and intoxication are analyzed, and the extent that crash frequency declined alongside volume during the stay-at-home period is also considered. A multinomial logistic regression model to relate lower daily volume to more severe crash outcomes, and a Bayesian hierarchical logistic regression model to relate increases in average speeds to increased severity and the likelihood of a crash being fatal are constructed. Beyond confirming current understandings of the relationship of volume, speed, and safety, the findings explore the mechanisms of these relationships under the pandemic response. The findings are important because of the risks posed to essential workers who are required to use the road system while others telework from home. Two types of future scenarios are considered, one in which there is another temporary shock to travel demand, and another in which traffic volumes do not recover to previous "normal" levels because distancing practices become sustained. For both of these, policies are recommended that could improve safety.

Background

Volume, Speed, and Traffic Crashes

"Traffic volume" refers to the number of vehicles passing through a road segment during a defined time period. Research on the relationship of volume and safety dates to the 1950s with a study showing rates of multi-vehicle car crashes increasing with both volume and speed (*3*). Urban and rural contexts differ in the variability of volume over the course of a day. Rural low-volume roads are seen as a distinct safety challenge, which numerous studies and guides seek to address (*4–6*). For urban roads, much focus is on the effects of congestion during high-volume periods on both crash frequency and severity. Gwynne analyzed Newark, New Jersey, crash data against hourly volumes, and found that crash rates were higher in lower-volume and higher-volume periods, compared with mid-range volumes (*7*). A recent review of the literature found that, while most studies showed a positive relationship in which volumes increase crash rates, larger studies tended to find this U-shaped effect in which low and high volumes are more correlated with crashes than middle volumes (*8*). A Maryland study of arterial roads and highways found that, while crash frequency increased with congestion, severity of crashes during congested periods was lower (*9*). A UK highway study disaggregated traffic volume (number of vehicles) from congestion (delays), and included both in a model, finding that volume was associated with less-severe crashes, while delays had no effect on crash severity, suggesting that traffic flow is more important than volume (*10*). Golob and Recker compared different types of congestion, showing how more severe crashes happen with lower density of vehicles and freer flow (*11*). The effects of congestion on severity may also be contingent on the built environment in dense settings (*12*).

Speed is well known as strongly associated with higher crash severity (*13*). It is also associated with higher crash rates when controlling for congestion or volume (*14*). Traffic volumes at peak times, through congestion, can act as a limiter of maximum speed. But even against these limits, what causes some drivers to operate at illegal speeds? Drivers who choose to speed are more likely to be male, younger, and with lower levels of education (*15*). Speeding may also be habitual, especially among those who perceive speeding not to be a reckless behavior or problematic for society (*16*). The choice to speed has additionally been framed as a trade-off between perceptions of risk and perceptions of time saved (*17*). However, Ellison and Greaves estimate that the average speeding driver saves only seconds per day and argue this saving comes at the cost of fatalities (*18*). Raising speed limits on roadways can increase crash severity (*19*). However, through an analysis of speeding and fatality rate data, Lave shows that higher variance of speeds around the speed limit—both faster and slower—are correlated with increased fatal crashes, which point to the role of speed limits in coordinating traffic (*20*).

Planning of Urban Road Networks in the U.S

Road capacities, speeds, designs, and network shape are derived through a process of regional planning. Road networks in U.S. metropolitan areas consist of streets of varying widths and speed limits, ranging from wider, faster high-volume highways to narrower, slower low-volume local roads. This division of streets into a hierarchy emerged from conceptions of ideal community design that still shape their layout today. The influential "neighborhood unit" of the 1920s separated residences and schools from shopping and business centers and connected them with different types of highways and arterial roads (*21*). This hierarchy further developed as engineers created new methods of analysis and forecasting. The first travel surveys emerged in the 1940s, and an understanding of the relationship between urban land uses and travel demand led to the development of a federally mandated urban transportation planning process beginning in the 1960s (*22*). Modern transportation planning is thus part of a regional decision-making process in which current land uses and traffic volumes, and expectations of future land uses, inform decisions about new and adjusted roads (*23*). New development and resulting road designs combine to shape traffic volume and speed limits of the road network which then play a role in determining safety outcomes (*24*). Some land use patterns are more dangerous for travelers than others. For example, the siting of large retail land uses on urban arterials, such as big box shopping complexes, rather than smaller parcels on more pedestrian-friendly local roads, has negative safety outcomes, likely as a result of the higher speeds on arterials (*25*).

This paper takes the drop in travel demand on Franklin County, Ohio, roads starting in March 2020 as an opportunity to observe a natural experiment in the effects of drastically reduced volume on traffic speeds and crashes on planned urban road networks. As theory predicts, it is expected to find that lower volumes are associated with more severe crashes. Yet it is also hypothesized that, while number of crashes will decrease, there will be increases in speeding behavior, intoxication, and types of crashes that together increase the per-crash risk of incapacitating injury and death for those who continue to use the road network, such as essential workers. It is also intended to explore the relationships of crash frequency with lower volumes, and higher speeds with different road types. The findings contribute to understandings of the relationship of volume, congestion, and speed on arterials and highways, as well as showing the implications to resilience of the mobility-oriented planning decisions that shaped the current network and its large capacity. Furthermore, the findings provide evidence for a need to take action on reconfiguring the road network in the event that decreased travel demand related to social distancing is a lasting phenomenon, and to be prepared for future shocks.

Data

Crash and Volume Data

The analyses in this paper combine crash, traffic volume, and real-time road speed data. The Ohio Department of Public Safety compiled crash data from reports; these data are available via the Ohio Department of Transportation (ODOT) website. In the study area of Franklin County during February 1 to May 8, 2020, there were 5,294 crashes. The crash dataset provides variables on crash type, severity of injury, the actions of participants, time, location (latitude, longitude), road characteristics (e.g., number of lanes, functional road class [FRC]), and crash-specific characteristics (e.g., demographics, driving behavior). Specific traffic volumes by road and time of day were not available for the majority of crash points. Therefore, to capture the degree to which volumes decreased as a result of COVID-19 pandemic restrictions, daily measurements of traffic volume on an urban interstate in Franklin County are used to create an index varying between 0 and 100 showing relative daily differences in volumes over the study period.

Speed Data

Speed information for this time period is derived using INRIX real-time traffic data on INRIX XD road segments, which capture immediate changes in networks resulting from the addition of infrastructures (e.g., new roads), policy interventions (e.g., congestion charging), and system-wide (e.g., COVID-19) as well as local events (e.g., music concerts). There are two types of speed data: observed real-time and reference speeds. To determine the extent to which speeds were higher than was typical (indicating freer-flow), the difference between the average observed daily real-time speed and a reference speed is calculated for each road segment. Here, average daily real-time speed is an average of the speeds observed by INRIX for each day (considering 24 h) for each segment. The reference speed is not the posted speed limit, but, rather, the average speed of traffic that is typically observed by INRIX on a given segment (*26*). Crash data is joined to INRIX road segments based on the date of crash occurrence, location, and road functional class. An issue when linking crashes to INRIX road segments is the discrepancy in functional class coding scheme between ODOT and INRIX. To maintain consistency between crash and speed datasets, ODOT codes were matched to INRIX as shown in Table 1.

Methods

Multinomial Logistic Regression Model of Crash Severity in Relation to Volume

Given that injury scales are widely used to classify crashes, ordinal logistic regression models are commonly applied to understand factors that influence crash severity. However depending on setting and context of a study, the required proportional odds assumption is often unmet. In such cases, researchers have applied alternative approaches, such as generalized ordered

Table 1. Matching of Ohio DOT (ODOT) and INRIX Functional Road Class (FRC) Codes for Speed Data

ODOT FRC codes	INRIX FRC codes
Interstate (1), freeway (2)	Highways and intersections (1)
Principal artery (3)	Major arteries (2)
Minor artery (4) or major collector (5)	Major roads (3)
Minor collector (6) or local road (7)	Neighborhood roads (4)

logistic regression, that relax this assumption (*10*, *27*). Another approach is multinomial logistic regression, which allows flexibility for different degrees and even directions of effects on different categories of the dependent variable (*28*). Given the exploratory goal of investigating outcomes related to a new phenomenon—COVID-19 stay-at-home restrictions—the flexibility of multinomial logistic regression was opted for. Furthermore, the multinomial approach yielded a better model fit than ordered alternatives.

Two multinomial logistic regression models were fitted to show how the effects of stay-at-home policies on crash severity are related to reduced traffic volumes. These models were developed using 4,422 crash data points that were not missing any information about crash type and location. They have identical specifications, except that the role of stay-at-home policies is measured by a different variable in each. Both models control for crash type, driver actions (speeding, impairment, distraction), road characteristics (location, width, speed limit), and crash time (weekday peak period, weekend, weather conditions). In the first model, stay-at-home policies are represented by a binary independent variable indicating for each crash, if it occurred after the start of a defined period of COVID-19-related stay-at-home policies, between March 15 and May 8. In the second model, this variable is replaced with a variable whose value for each crash represents a scale of daily traffic volume relative to other days in the entire study period of February 1 to May 8. Selected insignificant independent variables are maintained as controls in models, because many of these, such as alcohol use and inclement weather, are considered important to crash modeling. It is also hoped to provide a complete picture of factors that do and do not influence crash severity.

Multinomial logistic regression coefficients represent the change in the log odds of a particular severity outcome in comparison with a base category; however, coefficients are also converted to odds ratios (OR) using ($\exp(\beta)$) for easier interpretation. The OR of a covariate represents the factor by which the dependent variable will be multiplied with a unit increase in the coefficient. Therefore, a value of less than one indicates a negative relationship between the response variable and covariate, whereas a value greater than one indicates a positive relationship. For these models, ORs represent increases or decreases in the likelihood of a particular severity outcome.

Hierarchical Binary Logistic Regression Model of Fatal Probability in Relation to Speeds

Past studies suggest that the average level of speeding in major cities of Ohio increased dramatically during the stay-at-home phases of 2020, compared with the same time period in 2019 (*2*). Columbus is one of these major cities where the average speed level increased from 4.49 km/h to 17.65 km/h between 2019 and 2020 (*2*). This study developed two separate hierarchical models for non-stay-at-home and stay-at-home periods to understand the influence of speed on the crash severity in respective study periods. The hierarchical models explore the severity levels of a crash in relation to being fatal or non-fatal, given that the crash has already occurred. Moreover, the models predict the probability of a crash being fatal considering its variance at different FRCs.

The dataset contains 2,457 data points for the non-stay-at-home period and 792 data points for the stay-at-home period that had speed data available. A one-sided Fisher's exact test was performed to identify the significance of changes in the proportion of fatal crash occurrence between non-stay-at-home and stay-at-home periods. However, the hierarchical model specifications do not evaluate the statistical significance of the differences in model coefficients over the study periods. Therefore, the changes in the influence of variables on predicting a crash being fatal over time may occur by chance and do not reflect any statistical significance.

A two-tiered hierarchical model for the datasets of each time period was applied. In the model, the average daily real-time speed above the reference speed limit of each road segment was considered as a population-level indicator (Level 1), and road classes were considered as a group-level indicator (Level 2). The dependent variable was categorized as non-fatal and fatal. Therefore, a binary logistic distribution is used (*29*). In the binary logistic distribution, the probability (p) of a crash being fatal (y) at a road segment (i) can be denoted as:

$$y_i \sim Binary(p_i)$$

$$p_i = Pr(y_i = 1)$$

$$logit(p_i) = log(\frac{p_i}{1-p_i}) = \alpha + \beta x_i + \epsilon_i \quad (1)$$

where

x_i = average daily speed above the reference speed limit of road segment (i);

α = average probability of a crash being fatal (population-level intercept);

β = the magnitude of influence of x_i on the outcome variable (slope);

ϵ_i = random error.

Equation 1 is updated to a random intercept model to estimate the variation in the average probability of a crash being fatal among road classes. Therefore, the probability (p) of a crash being fatal (u) on a road segment (i) within road class (j) can be expressed as:

$$u_{ij} = logit(p_{ij}) = \alpha_j + \beta x_i + \epsilon_{ij} \tag{2}$$

$$\in_{ij} \sim Normal(0, \sigma_e{}^2)$$

$$\alpha_j \sim Normal(0, \sigma_\alpha{}^2)$$

where α_j is the road class-specific random effect assumed to be normally distributed at the group level with unknown variance $\sigma_\alpha{}^2$. The population-level error term $\in_{ij}$ is assumed to be normally distributed with unknown variance $\sigma_e{}^2$ (*29*).

Bayesian Inferences

For this paper, a hierarchical model was developed using a full Bayesian approach derived from the Monte Carlo Markov Chain (MCMC) algorithm (*30*). Bayesian inference is an algorithm that summarizes fitted probability of a dataset so that prediction on new data can be obtained using the probability distribution of model parameters (*31*). In other words, Bayesian inferences take into account a prior set of knowledge, and develop a posterior set of knowledge based on the information contained within the dataset. Its posterior distribution is proportional to the product of the prior information on the parameters and the likelihood measures of the data samples (*29*). The Bayesian framework defines unknown quantities as random variables, and explains them as probability distributions. Therefore, the Bayesian inferences assume random effect distributions of hierarchical models as the prior distribution, and predict the outcomes of the dependent variable (u_{ij}) as normally distributed around a mean (μ_{ij}) with an error term ($\sigma_e{}^2$). Therefore, Equation 2 can be rewritten as:

$$u_{ij} = logit(p_{ij}) = Normal(\mu_{ij}, \sigma_e{}^2) \tag{3}$$

$$\mu_{ij} = \alpha_j + \beta x_i$$

$$\alpha_j \sim Normal(\alpha, \sigma_\alpha{}^2)$$

where α_j is the mean response variable assigned to each road class (j) and follows a Gaussian distribution with the mean α (population-level intercept) and standard deviation σ_α (of group-level intercepts) (*29*).

The model was fitted using the BRMS package, which models Bayesian inferences in an RStudio environment (*32*). The model was designed based on unknown, uninformative priors, where the regression coefficients were assumed to have a normal distribution with a mean equal to zero and a standard deviation that follows a HalfCauchy Distribution with a scale parameter equal to 10 (*10*). The posterior distributions were estimated using 10,000 iterations of four Markov chains.

Model Interpretation and Assessment

Binary logistic model estimations are in a log-odd scale. For better interpretation, both population-level and group-level intercepts were recalculated in a logit inverse scale where the probability of response variable is measured by $p = exp(\alpha)/(1 + exp(\alpha))$ (*30*). Additionally, OR estimates for the independent variables were calculated, as for the previous model (exp(β)). The 95% Bayesian credible interval (BCI) was used as an indicator of significance for the covariates. The coefficients are considered as significant if their 95% BCIs do not include zero, or their ORs do not include 1 (*32*).

Group level variation is examined with the intra-class correlation coefficient (ICC), representing the proportion of overall residual group-level variance. Here, ICC can be defined as $\sigma_\alpha{}^2/(\sigma_\alpha{}^2 + \sigma_e{}^2)$. The population-level variance ($\sigma_e{}^2$) in a logistic distribution can be presented as $\pi^2/3 = 3.29$ (*32*, *33*). ICC value close to zero signifies very small variation among groups, while a larger value shows greater variation and justifies the use of a hierarchical model instead of an ordinary binary model (*34*). Since additional data were not available to evaluate the predictive abilities of the hierarchical models, cross-validation techniques were applied for model validations. The Bayesian leave-one-out (LOO) cross-validation information criterion, along with their standard errors, were estimated for each model (*35*). Model comparisons were performed between ordinary logistic regression and hierarchical logistic regression to examine how model performances have changed with consideration of group-level indicators.

Results

Traffic Crash Characteristics Under Stay-at-Home Policies

In between the governor's announcements of school closure and stay-at-home order, daily traffic volumes in Franklin County, Ohio, declined, reaching their lowest points after the end of March, yet soon began to rise (Figure 1). As a collective social practice, it is challenging to determine a starting point for social distancing under stay-at-home guidance. For this analysis, a 55-day period is defined, beginning soon after the school closing announcement, and ending in early May when volumes began to rise in earnest from their lowest levels. However, certainly some social distancing existed before this point and beyond this point, and may even manifest in a lasting change to volumes, as will be considered in a later discussion of the implications of the findings.

During this stay-at-home period, traffic crashes changed in type, time of day, and severity as compared with both a non-stay-at-home period immediately preceding

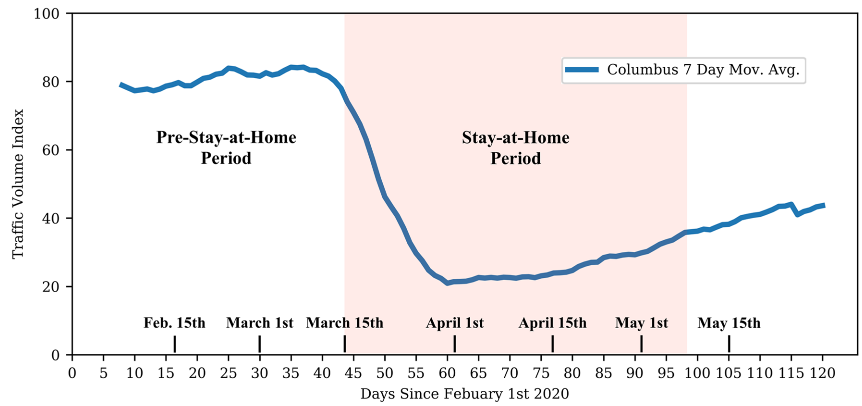

Figure 1. Changes in urban interstate traffic volume across stay-at-home and non-stay-at-home periods in Franklin County, Ohio (February–May 2020).

it, as well as a year-on-year comparison with the same 55-day period in 2019. A simple comparison of means among these groups shows some large differences in types of crashes during stay-at-home (Table 2). Rear collisions accounted for 19% of crashes, compared with 35.5% one year earlier, while crashes involving a single vehicle only were nearly doubled from 12.9% to 25.3%. Crashes in which the reporting officer cited speeding as a factor were nearly doubled under stay-at-home compared with the previous year at 15.4%. Additionally, crashes involving alcohol and drugs were both higher, being indicated in 5.3% and 3.2% of crashes, respectively. Crashes were much less frequent under the stay-at-home period, averaging only 24.4 per day compared with 75.8 per day in the prior year. Crashes per each unit of a relative index of traffic volume showing daily variations were only slightly lower in the stay-at-home period compared with the previous year. Additionally, the severity of these crashes increased, with 3.3% being incapacitating or fatal compared with 1.5% the previous year. Finally, a time analysis of the distribution of crashes throughout the day shows fewer crashes occurring in traditionally congested peak travel times, which helps explain the fewer incidents of rear collisions. Figure 2 shows that under the stay-at-home guidance, crashes were less prevalent during morning peaks and slightly less prevalent during evening peaks. Yet, they were slightly more prevalent during off-peak periods later in the day.

Relating Stay-at-Home Policies to More Severe Crashes Through Daily Traffic Volume

Table 3 shows the results from both multinomial logistic regression models, which include identical control variables. The binary variable of interest for the first model indicates if each crash occurred during a period of stay-at-home policies that is defined as being between March 15 and May 8, 2020, as depicted by the shaded time period in Figure 1. In the second model, the variable of interest is replaced with a continuous variable whose value for each crash represents daily traffic volume on that day relative to other days in the study period. The possible values for this variable comprise the moving average depicted in Figure 1.

In the first model, the stay-at-home time period binary variable is associated with increased severity, showing that crashes in this period were more likely to be incapacitating or fatal when controlling for other crash attributes. While relatively low, the odds of an incapacitating or fatal crash more than double under stay-at-home policies. In the second model, the daily volume scale variable is associated with a lower likelihood of an incapacitating or fatal crash, showing that higher daily volumes are associated with lower likelihood of a crash resulting in injury or death. Given the drop off in volume that characterizes the stay-at-home period, and that these variables play the same function in each model, this points to volume being fundamental to how stay-at-home policies influence the severity of crashes. For the control variables, the models show nearly identical results. Speeding (as indicated by reporting officers), higher posted speed limits, and not using seat belts are strongly associated with more severe categories of injury in both models, as are particular types of crashes, including head-on, angled, and pedestrian or cyclist. The use of drugs and being a senior driver are associated with a higher likelihood of an incapacitating or fatal crash in both specifications.

Our modeling of traffic volumes and categories of crash severity has demonstrated that lower volumes from stay-at-home policies are related to more severe crash

Table 2. Descriptive Statistics for Stay-at-Home and Non-Stay-at-Home Periods in Franklin County, Ohio (February 1–May 8)

	Year-on-year 2019	Pre-stay-at-home 2020	Stay-at-home 2020
Days in time period	55	43	55
Total crashes	4,170	3,950	1,342
Mean crashes per day	75.8	91.8	24.4
Mean daily traffic volume index (1–100)	80.1	70.6	27.0
Mean daily crashes per volume index	0.95	1.3	0.90
Severity: Fatal (%)	0.29	0.36	0.71
Incapacitating (%)	1.75	1.1	2.6
Non-incapacitating (%)	13.8	14.5	21.0
Possible injury (%)	10.7	11.0	11.2
No injury (%)	73.4	73.1	64.6
Speeding indicated (%)	7.3	8.5	15.4
Alcohol indicated (%)	4.3	4.3	5.3
Drugs indicated (%)	1.6	1.2	3.2
Distraction indicated (%)	5.1	4.1	4.9
Senior driver (%)	12.1	11.4	8.9
Young driver (%)	34.2	33.3	33.1
Unrestrained (mean occupants)	0.46	0.55	0.86
Posted speed (mean mph)	40.6	38.8	37.9
Lanes: One or two (%)	36.1	41.5	51.0
Three or four (%)	45.0	40.3	32.2
Five or more (%)	18.9	18.1	16.8
Highway (%)	23.1	19.4	19.3
Type: Rear end (%)	35.5	31.1	18.9
Head on (%)	1.5	1.8	2.1
Backing (%)	3.6	4.1	4.2
Sideswipe (%)	21.1	20.0	16.5
Angled (%)	17.0	17.9	19.1
Turning (%)	1.3	1.1	2.4
Parked car/object (%)	16.4	20.0	31.5
Pedestrian/bike (%)	2.0	2.5	3.0
Animal (%)	0.9	0.7	0.7
Other/unknown (%)	0.7	0.7	1.5
Single vehicle only (%)	12.9	14.6	25.3
Location: not an intersection (%)	73.2	70.4	70.5
Four-way intersection (%)	14.4	17.0	16.0
Other intersection (%)	8.2	9.2	8.2
Ramp (%)	3.1	2.5	3.7
Other (%)	1.1	0.9	1.5
Daylight (%)	74.1	62.2	65.6
Inclement weather (%)	15.0	24.6	21.4
Peak period (%)	32.9	29.4	22.4
Weekend (%)	23.0	23.7	26.2

Note: Crash statistics reflect crashes for which details exists, numbering 3,492, 3,305, and 1,130 for each category, respectively.

outcomes. However, the mechanism of that relationship has, as yet, not been demonstrated. It is hypothesized this mechanism to be higher average speeds on some classes of roads; this is examined below.

The Effects of Increased Road Speeds on the Severity of Crashes by Road Type

The result from one-sided Fisher exact test indicates that the proportion of fatal crashes is significantly higher during the stay-at-home period than the non-stay-at-home period, at a 95% confidence level (p-values 0.04). Figure 3 presents the distribution of crash severity in relation to the higher speed measures at different FRCs, respectively, for the non-stay-at-home and stay-at-home periods. Each data point in Figure 3 indicates a crash. Regardless of road functional class, the non-stay-at-home period indicates little-to-no variation in the speed measures, unless the crash involves a fatality. Additionally, the fatal crashes occurring on highways and local roads during this period had a lower average speed than the reference level. On the contrary, during the stay-at-home period, the severity of crashes tends to be higher with involvement of higher speeds, especially in cases of crashes on highways and interstates. Also, the fatal crashes on arterial and major collector roads involved a higher speed compared with the non-fatal crashes. However, no fatal crashes on local roads were found within the dataset. Based on these findings, this study intends to evaluate the probability of a crash being fatal when there are higher-than-typical speeds involved in both non-stay-at-home and stay-at-home periods.

Table 4 indicates posterior summaries for the Bayesian hierarchical binary logistic model. The results indicate that the probability of a crash being fatal on any road segment of Franklin County was 0.26% before March 15, 2020. Moreover, higher speeds do not significantly influence the probability of a crash being fatal during the non-stay-at-home period, since the 95% Bayesian confidence interval includes zero. However, the probability of a crash being fatal was 0.42% during the stay-at-home period. Besides, higher speeds appear to have a significant positive influence on the probability of a crash being fatal during this time period. As estimated by the models, the probability of a crash being fatal increases by a factor of 1.21 with a unit (1 mph) increase in speed above the reference level during the stay-at-home phase.

The results also indicate that crashes occurring on highways, interstates, and local roads have a higher probability of being fatal (0.39 and 0.35, respectively) than the crashes on principal arterial and major collector roads

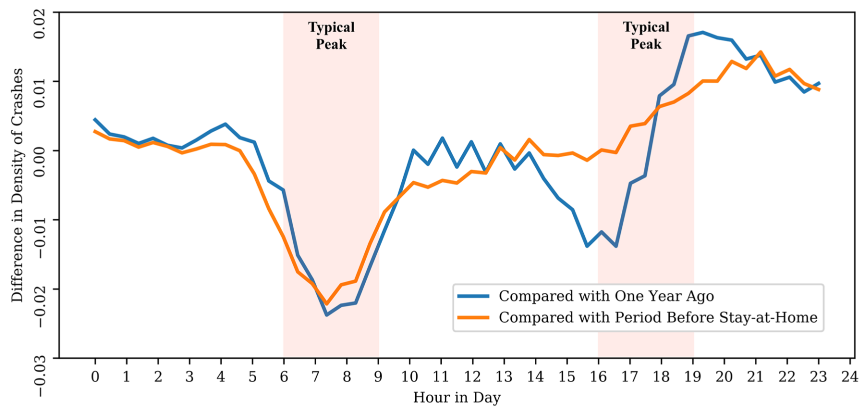

Figure 2. Difference in Kernel density estimation of crash hour between stay-at-home and non-stay-at-home periods in Franklin County, Ohio (February 1–May 8, 2020).

Table 3. Multinomial Logit Results on Severity of Crash (February 1–May 8, 2020)

	Model 1 (stay-at-home period binary)						Model 2 (volume scale)					
	Non-incapacitating			Incapacitating/fatal			Non-incapacitating			Incapacitating/fatal		
(Base: none/possible injury)	Coef.	Sig.	OR	Coef.	Sig.	OR	Coef.	Sig.	OR	Coef.	Sig.	OR
Stay-at-home period binary	0.51	***	1.67	0.94	***	2.56	na		na	na		na
Daily traffic volume index	na		na	na		na	−0.01	***	0.99	−0.02	***	0.98
Speeding indicated	0.48	***	1.61	0.75	**	2.13	0.47	***	1.61	0.75	**	2.12
Alcohol indicated	−0.03		0.97	0.12		1.13	−0.03		0.97	0.11		1.12
Drugs indicated	0.44		1.55	1.90	***	6.67	0.46		1.59	1.93	***	6.90
Distraction indicated	0.27		1.31	0.01		1.01	0.28		1.33	0.04		1.04
Senior driver	0.17		1.18	0.76	**	2.14	0.17		1.18	0.77	**	2.16
Young driver	−0.09		0.91	0.12		1.13	−0.09		0.91	0.13		1.14
Unrestrained occupants	0.91	***	2.49	1.03	***	2.80	0.92	***	2.50	1.03	***	2.81
Type of crash (base: rear)												
Head-on	1.05	***	2.85	3.21	***	24.8	1.05	***	2.86	3.21	***	24.7
Backing	−1.16	***	0.31	1.34		3.80	−1.15	***	0.32	1.35		3.88
Sideswipe	−0.64	***	0.53	0.42		1.52	−0.64	***	0.53	0.41		1.50
Angled	0.90	***	2.45	1.75	***	5.75	0.90	***	2.45	1.74	***	5.68
Turning	−0.14		0.87	1.35		3.84	−0.14		0.87	1.32		3.76
Parked car/object	−0.34	**	0.71	1.51	***	4.52	−0.34	**	0.71	1.49	***	4.45
PedBike	3.04	***	20.81	5.93	***	376	3.03	***	20.80	5.92	***	371
Animal	−2.04	*	0.13	−10.56		0.00	−2.05	*	0.13	−10.59		0.00
Other	−0.41		0.67	2.14	*	8.48	−0.39		0.67	2.16	*	8.68
Posted speed (mph)	0.03	***	1.03	0.11	***	1.12	0.03	***	1.03	0.11	***	1.12
Number of lanes (base 1 or 2)												
Three or four	0.11		1.11	0.06		1.06	0.11		1.11	0.05		1.05
Four or more	0.38	**	1.46	−0.54		0.58	0.38	**	1.46	−0.53		0.59
Freeway/highway	−0.22		0.80	−1.57	***	0.21	−0.21		0.81	−1.56	***	0.21
Location (base: not an intersection)												
Four-way intersection	0.20	*	1.22	0.30		1.35	0.19		1.21	0.28		1.33
Other intersection	−0.31	*	0.74	−0.26		0.77	−0.31	*	0.74	−0.26		0.77
Ramp	0.07		1.08	−0.04		0.96	0.07		1.07	−0.02		0.98
Other	−1.63	**	0.20	0.18		1.20	−1.64	**	0.19	0.12		1.13
Daylight	−0.04		0.96	−0.08		0.92	−0.04		0.96	−0.08		0.92
Inclement weather	0.10		1.11	−0.09		0.92	0.09		1.09	−0.12		0.89
Peak travel time	−0.10		0.91	−0.39		0.68	−0.09		0.91	−0.40		0.67
Weekend	0.02		1.02	0.09		1.10	−0.29	**	0.75	−0.47		0.62
Contant	−3.16		0.04	−10.36		0.00	−2.31		0.10	−8.76		0.00
			Pseudo $R^2 = .1471$						Pseudo $R^2 = .1468$			

Note: Coef. = coefficient; Sig. = significance; na = not applicable; OR = odds ratio.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

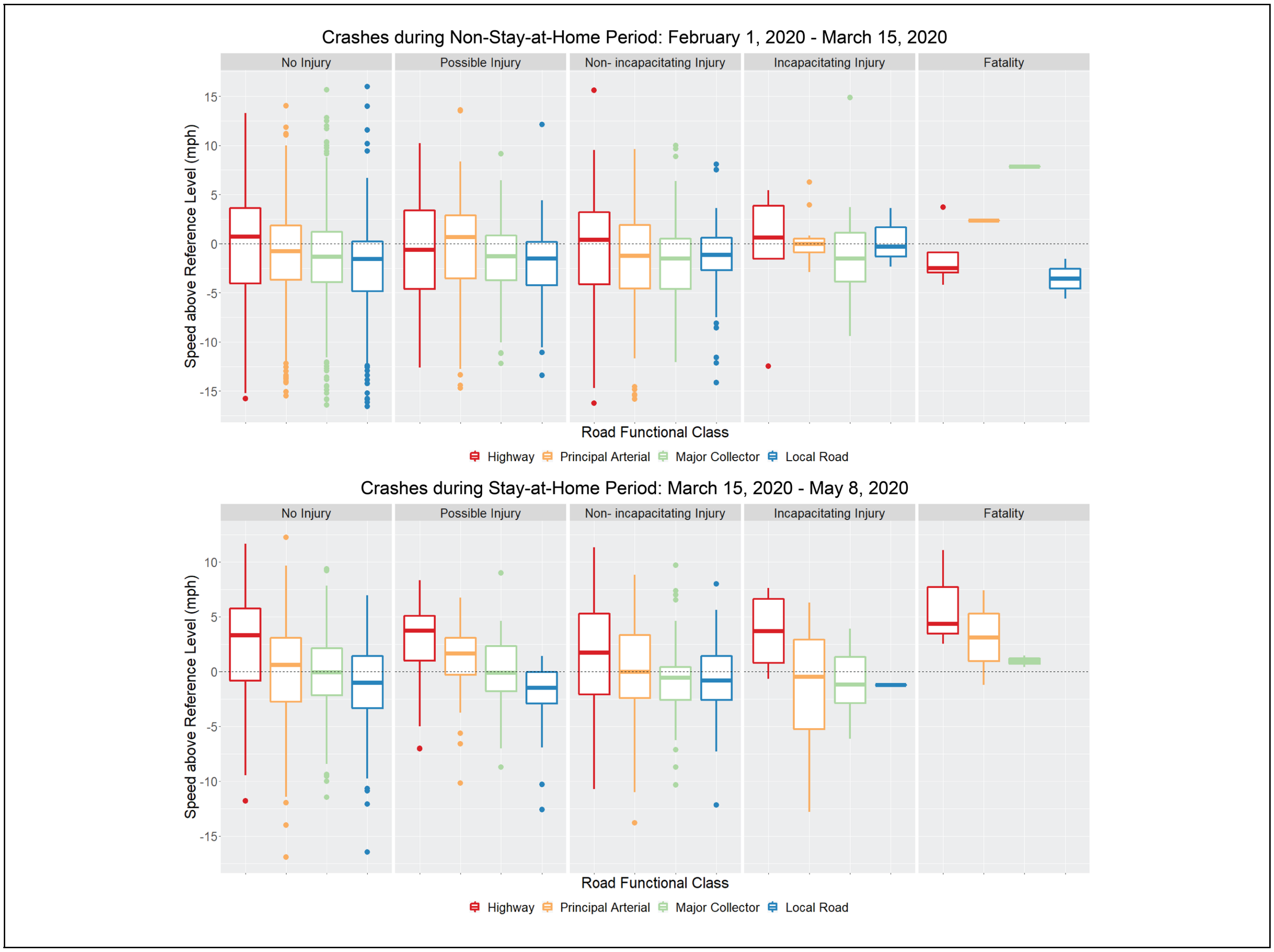

Figure 3. Relationship between crash severity and speed.

(0.19 and 0.18, respectively) during the non-stay-at-home period. Later in the stay-at-home period, all road classes experienced around 0.5% probability of a crash being fatal except the local roads (0.20% probability).

The ICC values of the hierarchical models for both non-stay-at-home and stay-at-home periods are 28.32% and 31.85%, respectively. These results suggest that 28.32% and 31.85% of the overall model variances of the non-stay-at-home and stay-at-home period, respectively, can be explained by the group-level or FRC variances. These ICC values justify the appropriateness of using hierarchical models for this particular analysis. A comparison of models using leave-one-out cross-validation information criterion (LOOIC) estimates supported this decision.

Figure 4 indicates the predicted probability of a crash being fatal with increased speed based on the hierarchical model of crashes (Table 4). As shown in Figure 4, the increase in the probability of a crash being fatal is very low with increased speed above reference level during the non-stay-at-home period. In contrast, the probability starts to rise for all classes when the average daily speed of a segment is higher than its reference speed during the stay-at-home period. According to the model, the probabilities of crashes being fatal are 3%, 4.4%, 4.5%, and 4%, respectively, for local roads, major roads, arterial roads, and highways when the average daily road speed is 10 mph higher than its reference speed. The probabilities further increase to 9.4%, 13.7%, 13.5%, and 12.2%, respectively, for the previously mentioned FRCs with the increase of average road speed 15 mph higher than its reference speed.

Conclusions

Under a period of stay-at-home policy during which traffic volumes declined by more than 60%, the total number of crashes in Franklin County dropped from an average of 92 per day to just 24 per day. However, among the remaining crashes, the percentage that were

Table 4. Posterior Summaries of Bayesian Hierarchical Model

	Non-stay-at-home period				Stay-at-home period			
	Coef.	2.5 BCI	97.5 BCI	Mean prob. for intercepts/ OR for coefficients	Coef.	2.5 BCI	97.5 BCI	Mean probability for intercepts/ OR for coefficients
Population-level estimates								
Intercept	−5.95	−8.06	−4.34	0.26*	−5.47	−7.96	−3.61	0.42*
Speeding	0.04	−0.10	0.18	1.04	0.19	0.01	0.39	1.21*
Group-level intercepts								
Highway and Interstate	−5.54	−9.19	−1.65	0.39*	−5.27	−9.66	−0.98	0.51*
Other principal arterial	−6.28	−10.86	−2.96	0.19*	−5.26	−9.65	−0.93	0.52*
Minor arterial/ major collector	−6.34	−10.86	−3.10	0.18*	−5.27	−9.61	−0.98	0.51*
Minor collector/local road	−5.66	−9.51	−1.72	0.35*	−6.22	−13.68	−2.61	0.20*
SD in group-level intercept	1.14	0.03	4.57	na	1.24	0.03	6.33	na
ICC (%)			28.32				31.85	

Note: Coef. = coefficient; BCI = Bayesian credible interval; ICC = intra-class correlation coefficient; na = not applicable; na = not applicable; OR = odds ratio; SD = standard deviation.

*Indicates significance of estimates at 95% confidence interval.

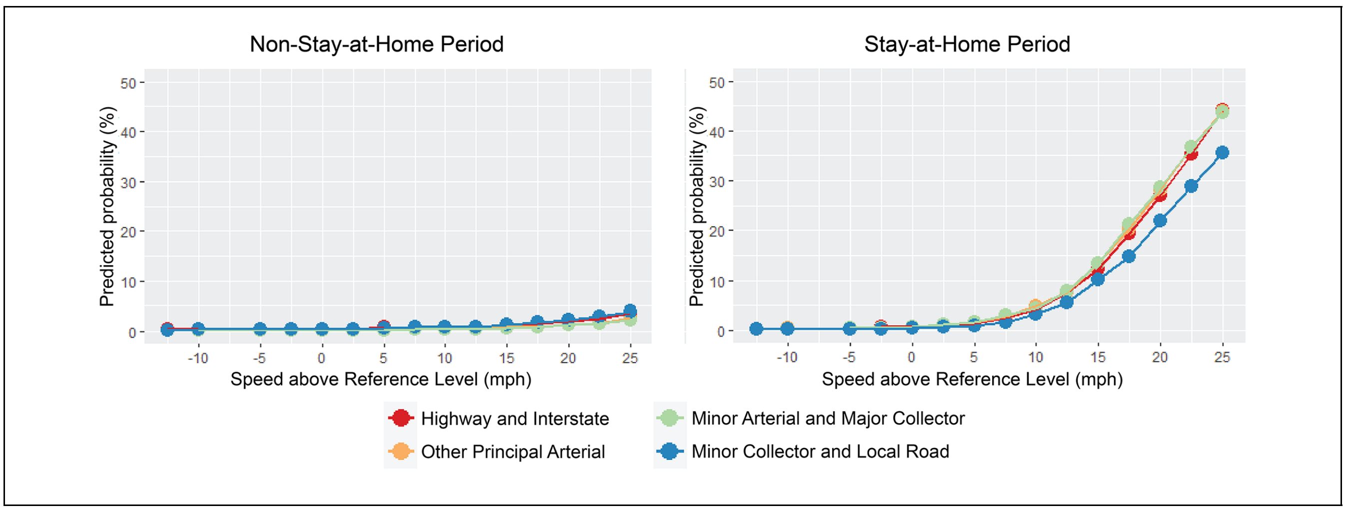

Figure 4. Predicted probability of a crash being fatal for different functional road classes (FRCs).

incapacitating or fatal increased. The analysis of crash type and time of crash showed that crashes were less likely to occur during the morning peak period, and that fewer crashes involved multiple vehicles or were rear collisions. The multinomial logistic modeling of the relationship of decreased traffic volumes indicates that severe crash outcomes were more likely under stay-at-home guidelines because of that period's decreased volumes. The hierarchical binary logistic modeling of the relationship of increased road speeds and the likelihood of crashes being fatal showed that fatal crashes were related to higher-than-normal speeds under the stay-at-home policy but not before, especially on highways and arterial roads. Additionally, a higher percentage of crashes were designated by police reports as being caused by speeding behavior, and to involve alcohol or drugs.

Combined, these analyses suggest that the overall effect of stay-at-home policies on crash severity through speed was threefold. Firstly, there are fewer individuals that are spending time on the roads caught in traffic congestion, resulting in fewer of the types of collisions that occur in close quarters and at lower speeds, which tend to have lower severity. Secondly, with road users free from congestion, they travel at higher speeds, which are associated with more-severe crashes. Thirdly, drivers engage in riskier behavior by more frequently engaging in speeding, and driving under the influence. Some of this speeding behavior may be extreme, as evidenced by this analysis, as well as a reported rise in the number of speeding tickets issued over 100 mph under the stay-at-home period (*36*). Under stay-at-home policies, this increased risk of a crash being more severe is disproportionately borne by lower-income "essential workers" who do not have options to conduct work from home.

There are several important limitations to these analyses. Firstly, the data for traffic volumes and speeds were not detailed to reflect their exact values at the time and point of each crash. For traffic volumes, the authors only had access to volumes on a major highway summarized by day, which were used to create an index of relative volume changes over time. Similarly, for speeding data, the only thing calculated was average daily speeds for the road segment of each crash. Also, the real-time speed data was missing for a few segments because of the mismatch in the road network defined by ODOT and INRIX. Therefore, the Bayesian hierarchical model was limited to the crash points that had average daily speeds available. Besides, the differences observed in the effects of explanatory variables between the pre- and post-stay-at-home period models can be an outcome of chance. This modeling approach is limited in evaluating the statistical significance of the changes in influence of variables over time. However, this level of detail was adequate in fulfilling the model purpose. Additionally, the choice of a multinomial logistic regression model does not take advantage of the ordinal level of measurement of severity, but, again, given the comparison across periods, this is considered to be adequate. Finally, both the models are based on the premise that a neat division exists between the period in which people were traveling and that in which they were "staying home." This is unlikely, as some individuals would be more or less cautious, resulting in blurring of that boundary, which would have some effect on the results.

Discussion

The usefulness of the findings is in considering how transportation professionals and policymakers can be prepared for two types of future scenarios involving reduced volume on roads, the first of which is additional temporary shocks to local travel demand. These may again be in response to a pandemic, but could also result from natural disasters, environmental conditions, or economic conditions, possibly relating to climate change. In such cases, certain purposes of travel might again be considered essential, including work trips by the same essential workers who, under COVID-19, tended to be lower income. In any event, this would almost certainly include the travel of first responders. This paper demonstrated that, under these reduced volume conditions, higher speeds are responsible for more-severe crashes on roads, including at time periods in which roads would previously have been congested. A simple policy response in such a case would be to use existing variable message signs to warn users against speeding and reckless driving in light of the increased risk of more-severe crashes on major roads. Although, one likely challenge to this approach is that these signs may be in use for messaging related to the crisis that precipitated the reduced demand. A step further could entail the temporary closure of selected lanes on highways and arterials roads as a traffic-calming measure. Finally, the strain that individuals experience in such a time may be linked to reckless driving and driving under the influence, as evidenced by this analysis. In light of this paper, future research might investigate these relationships and their effects on safety more deeply from the onset of a similar situation.

The second future scenario to consider is the possibility that social distancing practices, such as working more from home, dining more at home, and shopping less frequently, might become more prevalent in the long term. The notion of urban recalibration describes a mode of planning that bases decisions on wellbeing—including safety—rather than a goal of increasing mobility—a previous paradigm that promoted road-oriented development (*37*). The current road network of the Columbus metropolitan area was developed to accommodate a level of demand for automobility forecast based on measurements of current travel in relation to planned development. However, in a "new normal" scenario in which social distancing practices continue to reduce travel demand in a lasting way, this network would be overspecified, providing more capacity than is warranted. While resulting increased speeds will improve mobility, this comes at a cost of safety. In the pandemic response, these risks were borne more by lower-income essential workers who have less control over work trips, such as the option to work from home. This challenge of higher-than-needed road capacity is one that is also recently faced by shrinking cities such as Detroit (*38*). Shefer argued that, because of the higher risk of lower volume and higher speed conditions, a "socially optimal level of congestion" may exist (*39*). The findings of this study support this idea, and point to a potential need to recalibrate some road networks if travel demand were to remain lowered in the long run. Policies such as complete streets, road diets, and making shared spaces can recalibrate the capacity of roads while supporting other planning goals (*37*). The long-term effects of COVID-19 on travel patterns are as yet unknown; however analyzing the short-term effects of stay-at-home policies has shown that lower volumes create higher speeds, which can produce risks of more severe crashes for road users.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: J. Stiles, A. Kar, J. Lee, H. Miller; data collection: J. Stiles, A. Kar, J. Lee; analysis and interpretation of results: J. Stiles, A. Kar, J. Lee, H. Miller; draft manuscript

preparation: J. Stiles, A. Kar, J. Lee, H. Miller. All authors reviewed the results and approved the final version of the manuscript.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

ORCID iDs

Jonathan Stiles https://orcid.org/0000-0001-7613-1814
Harvey J. Miller https://orcid.org/0000-0001-5480-3421

References

1. Ohio Department of Health. *Director's Stay at Home Order*. 2020. https://drive.google.com/file/d/1P_GpxP8LHlMu3mqymKQA99jMSDN0z7qt/view.
2. Lee, J., A. Porr, and H. J. Miller. Evidence of Increased Vehicle Speeding in Ohio's Major Cities During the COVID-19 Pandemic. *Transportation Findings*, 2020. https://doi.org/10.32866/001c.12988.
3. Belmont, D. M., and T. W. Forbes. Effect of Average Speed and Volume on Motor-Vehicle Accidents on Two-Lane Tangents. *Highway Research Board Proceedings*, Vol. 32, 1953, pp. 383–395.
4. Hall, J. W., E. W. Rutman, and J. D. Brogan. Highway Safety Challenges on Low-Volume Rural Roads. *Proc., Institute of Transportation Engineers Annual Meeting*, Seattle, WA, 2003.
5. Polus, A., and M. Cohen. A New, Non-Canonical Poisson Regression Model for the Prediction of Crashes on Low-Volume Rural Roads. *IATSS Research*, Vol. 35, No. 2, 2012, pp. 98–103.
6. American Association of State Highway and Transportation Officials. *Guidelines for Geometric Design of Low-Volume Roads*. AASHTO, Washington, D.C., 2019.
7. Gwynn, D. W. Relationship of Accident Rates and Accident Involvements with Hourly Volumes. *Traffic Quarterly*, Vol. 21, No. 3, 1967, pp. 407–418.
8. Retallack, A. E., and B. Ostendorf. Current Understanding of the Effects of Congestion on Traffic Accidents. *International Journal of Environmental Research and Public Health* Vol. 16, No. 18, 2019, p. 3400.
9. Chang, G. L., and H. Xiang. *The Relationship Between Congestion Levels and Accidents*. No. MD-03-SP 208B46. Maryland Department of Transportation, Baltimore, MD, 2003.
10. Quddus, M. A., C. Wang, and S. G. Ison. Road Traffic Congestion and Crash Severity: Econometric Analysis Using Ordered Response Models. *Journal of Transportation Engineering*, Vol. 136, No. 5, 2010, pp. 424–435.
11. Golob, T. F., and W. W. Recker. A Method for Relating Type of Crash to Traffic Flow Characteristics on Urban Freeways. *Transportation Research Part A: Policy and Practice*, Vol. 38, No. 1, 2004, pp. 53–80.
12. Noland, R. B., and M. A. Quddus. Congestion and Safety: A Spatial Analysis of London. *Transportation Research Part A: Policy and Practice*, Vol. 39, No. 7–9, 2005, pp. 737–754.
13. Abdel-Aty, M. Analysis of Driver Injury Severity Levels at Multiple Locations Using Ordered Probit Models. *Journal of Safety Research*, Vol. 34, No. 5, 2003, pp. 597–603.
14. Van Schagen, I., and L. Aarts. Driving Speed and the Risk of Road Crashes. *Accident Analysis & Prevention*, Vol. 38, No. 2, 2006, pp. 215–224.
15. Shinar, D., E. Schechtman, and R. Compton. Self-Reports of Safe Driving Behaviors in Relationship to Sex, Age, Education and Income in The US Adult Driving Population. *Accident Analysis & Prevention*, Vol. 33, No. 1, 2001, pp. 111–116.
16. De Pelsmacker, P., and W. Janssens. The Effect of Norms, Attitudes and Habits on Speeding Behavior: Scale Development and Model Building and Estimation. *Accident Analysis & Prevention*, Vol. 39, No. 1, 2007, pp. 6–15.
17. Tarko, A. P. Modeling Drivers' Speed Selection as a Trade-Off Behavior. *Accident Analysis & Prevention*, Vol. 41, No. 3, 2009, pp. 608–616.
18. Ellison, A. B., and S. P. Greaves. Speeding in Urban Environments: Are the Time Savings Worth the Risk? *Accident Analysis & Prevention*, Vol. 85, 2015, pp. 239–247.
19. Renski, H., A. J. Khattak, and F. M. Council. Effect of Speed Limit Increases on Crash Injury Severity: Analysis of Single-Vehicle Crashes on North Carolina Interstate Highways. *Transportation Research Record: Journal of Transportation Research Board*, 1999. 1665: 100–108.
20. Lave, C. A. Speeding, Coordination, and the 55 mph Limit. *The American Economic Review*, Vol. 75, No. 5, 1985, pp. 1159–1164.
21. Perry, C. A. The Neighbourhood Unit. In *The Regional Survey of New York and Its Environs. Neighbourhood and Community Planning*, Routledge, London, 2001.
22. Weiner, E. *Urban Transportation Planning in the United States: History, Policy, and Practice*. Springer, New York, NY, 2016.
23. Meyer, M. D., and E. J. Miller. *Urban Transportation Planning: A Decision-Oriented Approach*. McGraw-Hill, New York, NY, 1984.
24. Ewing, R., and E. Dumbaugh. The Built Environment and Traffic Safety: A Review of Empirical Evidence. *Journal of Planning Literature*, Vol. 23, No. 4, 2009, pp. 347–367.
25. Dumbaugh, E., and R. Rae. Safe Urban Form: Revisiting the Relationship between Community Design and Traffic Safety. *Journal of the American Planning Association*, Vol. 75, No. 3, 2009, pp. 309–329.
26. INRIX. 2020. *INRIX Traffic Data Glossary*. http://docs.inrix.com/reference/glossary.
27. Wang, X., and M. Abdel-Aty. Analysis of Left-Turn Crash Injury Severity by Conflicting Pattern Using Partial Proportional Odds Models. *Accident Analysis & Prevention*, Vol. 40, No. 5, 2008, pp. 1674–1682.

28. Tay, R., J. Choi, L. Kattan, and A. Khan. A Multinomial Logit Model of Pedestrian–Vehicle Crash Severity. *International Journal of Sustainable Transportation*, Vol. 5, No. 4, 2011, pp. 233–249.
29. Nalborczyk, L., C. Batailler, H. Lœvenbruck, A. Vilain, and P. C. Bürkner. An Introduction to Bayesian Multilevel Models Using Brms: A Case Study of Gender Effects on Vowel Variability in Standard Indonesian. *Journal of Speech, Language, and Hearing Research*, Vol. 62, No. 5, 2019, pp. 1225–1242.
30. Bürkner, P. C. Advanced Bayesian Multilevel Modeling with The R Package brms. *arXiv Preprint arXiv*:1705.11123, 2017.
31. Huang, H., H. C. Chin, and M. M. Haque. Severity of Driver Injury and Vehicle Damage in Traffic Crashes at Intersections: A Bayesian Hierarchical Analysis. *Accident Analysis & Prevention*, Vol. 40, No. 1, 2008, pp. 45–54.
32. Bürkner, P.-C., and M. P.-C. Buerkner. *Package 'brms.'* 2016. https://cran.r-project.org/web/packages/brms/index.html
33. Kim, D. G., Y. Lee, S. Washington, and K. Choi. Modeling Crash Outcome Probabilities at Rural Intersections: Application of Hierarchical Binomial Logistic Models. *Accident Analysis & Prevention*, Vol. 39, No. 1, 2007, pp. 125–134.
34. Gelman, A., and J. Hill. *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge University Press, 2006.
35. Vehtari, A., A. Gelman, and J. Gabry. Practical Bayesian Model Evaluation Using Leave-One-Out Cross-Validation and WAIC. *Statistics and Computing*, Vol. 27, No. 5, 2017, pp. 1413–1432.
36. Kenney, J. Ohio's Pandemic Shutdown Led to Big Rise in Speeding Tickets Over 100 MPH. *WOSU Public Media*, 2020.
37. Cervero, R., E. Guerra, and S. Al. *Beyond Mobility: Planning Cities for People and Places*. Island Press, 2017.
38. Gallagher, J. *Reimagining Detroit: Opportunities for Redefining an American City*. Wayne State University Press, 2010.
39. Shefer, D. Congestion, Air Pollution, and Road Fatalities in Urban Areas. *Accident Analysis & Prevention*, Vol. 26, No. 4, 1994, pp. 501–509.