

# **A Preliminary Investigation of the Effectiveness of High Visibility Enforcement Programs Using Naturalistic Driving Study Data: A Grouped Random Parameters Approach**

By

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## **ABSTRACT**

This paper seeks to assess the effectiveness of high-visibility enforcement (HVE) programs in terms of reducing aggressive driving behavior. Using Strategic Highway Research Program 2 (SHRP2) Naturalistic driving study (NDS) data, behavioral reactions of drivers before, during, and after the conduct of high-visibility enforcement programs are analyzed, in order to identify the potential effect of high-visibility enforcement in driving behavior. In this context, two fundamental aspects of aggressive driving behavior (speeding and tailgating) are employed and analyzed. To simultaneously explore the intensity and the duration of these behavioral patterns, novel metrics are defined and used in the analysis. To investigate the effect of high-visibility enforcement programs, and at the same time, to control for the effect of driver-, trip-, vehicle-, and weather-specific characteristics on the extent of speeding and tailgating, univariate grouped random parameters linear regression models are estimated. In addition, likelihoods of speeding and tailgating occurrences are analyzed simultaneously, within a grouped random parameters bivariate probit modeling framework. The results of this preliminary analysis show that even though the implementation of the high-visibility enforcement has mixed effects on the extent and the likelihood of the driving behavior metrics, it demonstrates a promising potential in modifying driving behavior.

**Keywords:** High-visibility enforcement; Speeding; Tailgating; Aggressive driving behavior; Grouped random parameters.

## INTRODUCTION

Recent traffic safety research has identified aggressive driving behavior as a vital risk factor for traffic crashes and related injuries and deaths (Neuman et al., 2003; Paleti et al., 2010; Tarko et al., 2011). In fact, various aggressive behavioral patterns (for example, speeding, abrupt brake application, rushed overpass, and failure to comply with traffic signals and signs, to name a few) have been found to be directly associated with crash occurrence, and especially with the occurrence of fatal crashes. Over the last decade, the effect of aggressive driving behavior on crash occurrence is steadily increasing (Zhu et al., 2017).

In this context, a wide range of strategies, countermeasures, and approaches have been recently developed to improve roadway safety, in terms of modifying driving behavior: promoting beneficial voluntary actions; establishment of laws, regulations, and policies; and concentrated enforcement (Preusser et al., 2008; St-Aubin et al., 2013). High-visibility enforcement (HVE) programs are a representative example of the latter category of strategies. These programs typically include vigorous targeted law enforcement coupled with media campaigns to educate drivers and alert them to the enforcement activities, and have been shown to be effective in increasing seat belt use, reducing cellphone usage while driving, drunk driving and driving under the influence of drugs (Cosgrove et al., 2011; Van Houten et al., 2013; Chaudhary et al., 2012; Chaudhary et al., 2015; Zwicker et al., 2007; Johnson, 2016). Many HVE programs targeting aggressive driving behavior have been reviewed, with most of them resulting in improvements in driving behavior (Nerup et al., 2006; Thomas et al., 2008; Tarko et al., 2011; Dye, 2016). However, their long term effectiveness in reducing speeding and aggressive driving is not clearly understood (McCartt et al., 2001; Stuster, 2004; Davis et al., 2006). Typically, the evaluation of these programs has relied upon one or more of the following: the identification of the number of

crashes before and after the conduct of the program, the comparison of observed crash rates at sites at which the program was and was not conducted (control sites); roadside observational studies of driver compliance; number of citations issued before, during, and after the program; and surveys to identify any self-reported changes in driver behavior (Montella et al., 2015). These studies used a variety of statistical tools to identify factors affecting aggressive driving behavior, such as chi-square tests, *t*-tests, binary probit models, linear or logistic regression (Tarko et al., 2011; Kyasi and Abbany, 2007; Lambert-Bélanger et al., 2012). These strategies provide a parsimonious measure of the effectiveness of the high-visibility enforcement program to change aggregate driver behavior, but fall short in evaluating the long term effectiveness of the program or its effects on the disaggregate driving characteristics on different groups of drivers.

This paper seeks to provide a preliminary evaluation of the effectiveness of high-visibility enforcement programs in terms of improving significant aspects of driving behavior. To that end, the use of expanded Strategic Highway Research Program 2 (SHRP2) Naturalistic Driving Study (NDS) data enables a detailed examination of driver behavior before, during, and after the implementation of high-visibility enforcement programs. Specifically, two fundamental dimensions of aggressive driving behavior are investigated: speeding and tailgating (following too closely the lead vehicle). Combining the intensity and the duration of these behavioral patterns, as observed from the Naturalistic Driving Study data, two newly developed aggressive driving behavior metrics are presented and used for the evaluation of the high-visibility enforcement programs. In addition, through the use of advanced statistical and econometric methods, the (enforcement- and non-enforcement-related) factors affecting the extent and the likelihood of these behavioral patterns are also identified.

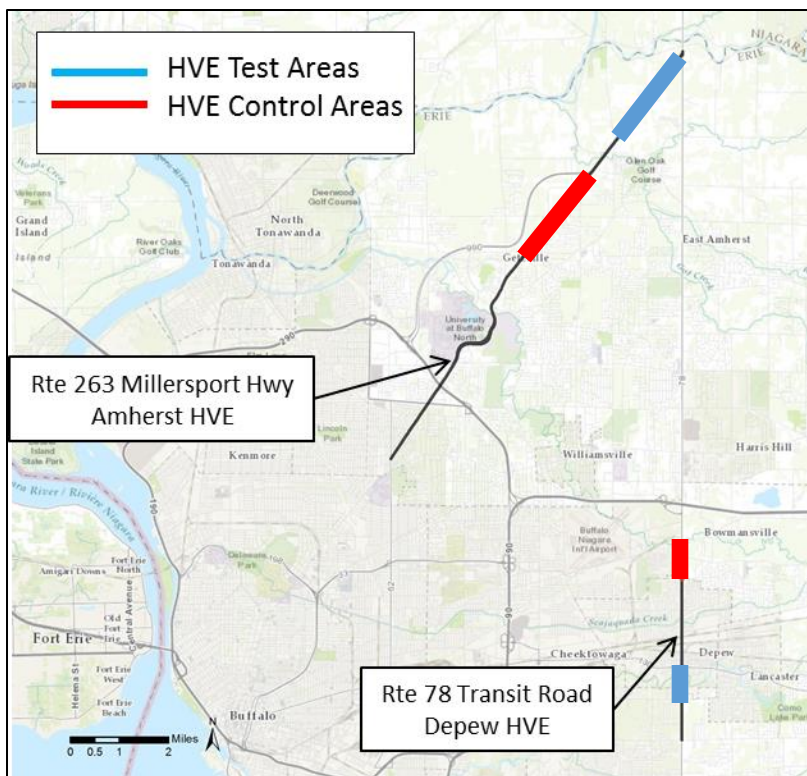
## EMPIRICAL SETTING

Due to their highly dimensional nature, the Strategic Highway Research Program 2 (SHRP2) Naturalistic Driving Study (NDS) data can provide a broad range of disaggregate driving behavior-specific characteristics, in combination with an extensive set of trip-, vehicle-, and environment-specific information (Jovanis et al., 2011; Wu and Jovanis, 2012; Mannering and Bhat, 2014). The evaluation of the effectiveness of high-visibility enforcement programs is based on sample data from two high-visibility enforcement programs that were conducted in Erie County, NY, during the collection time period of the naturalistic driving study data (i.e., from October 2010 to November 2013). It should be noted that one of the six nationwide naturalistic driving study sites was located in Erie County, NY, and consisted of 441 participants (Sarwar et al., 2017b). The first high-visibility enforcement program was conducted on a two-way (and two lanes per direction) state roadway – Millersport Highway in Amherst, NY – with speed limit of 55 miles/hour, from May through September 2012. The second high-visibility enforcement program was conducted on a short section of a two-way inter-county corridor – Transit Road in Depew, NY – with two lanes per direction, during May 2012. Due to the presence of a school zone in the segment of interest, the speed limit varied by time of the day along its length. Specifically, the speed limit changed from 30 miles/hour to 20 miles/hour when the school zone speed limit was in effect.

The high-visibility enforcement programs had both enforcement and media campaign components, which aimed at enhancing public and driver awareness for reducing speeding and aggressive driving behavior. For the enforcement, roving and fixed patrol police car locations were used throughout the implementation period. The media campaign involved public service announcements in local newspapers (*Depew Bee* and *Amherst Bee*) and radio stations broadcasted

throughout the same period. Key objectives of the high-visibility enforcement programs involved the reduction of speeding and other violations (including aggressive driving behavior), and the overall improvement of traffic safety.

To investigate and compare the driving behavior of participants – who traveled through the high-visibility enforcement locations – at non-enforcement sites, appropriate control sites were selected in the vicinity of the test sites. Basic criterion for the selection of the control sites was their similarity with the test site roadways, in terms of number of lanes, speed limits and roadway features. The locations of high-visibility enforcement and control sites selected for the analysis are illustrated in Figure 1. Upon review of the video data obtained from the control area corresponding to the Amherst test area, significant differences were observed between the roadway characteristics of the test and control area. Specifically, a traffic signal was present in the corridor of the control area. Hence, trips from this area were not used in the statistical analysis. To account for the speed limit change in the Depew enforcement area, the corresponding control area was selected to have similar characteristics, with the speed limit varying from 45 miles/hour to 35 miles/hour. It should be noted that in both enforcement and control areas the change in speed limit was 10 miles/hour and both sites were similar in terms of their geometric characteristics. The selected control site was located closely to the test site in order to increase the likelihood of identifying trips made by same drivers on both directions of the roadway segment.



**Figure 1. Locations of high-visibility enforcement (HVE) and control sites included in the analysis.**

The analysis is based on an extensive dataset consisting of a highly disaggregate set of trip-specific and behavioral data, during the traversal of the high-visibility enforcement sites, and a comprehensive set of driver- and vehicle-specific characteristics (for example, age, gender, frequency of traversals from the test or the control areas, and vehicle type, make, model and age, to name a few). The trip-specific and behavioral data were jointly obtained from forward videos and time series for each traversal. The review of each forward video provided information in terms of: environmental characteristics of the trip (time-of-the-day, lighting conditions, weather conditions); time-variant vehicle-specific characteristics (windshield condition, wipers' usage); traffic control conditions and violations (traffic control device presence and phase, location of speed limits signs, violations of traffic control devices); and vehicle interactions within the traffic

stream (lead vehicle presence, vehicle lane change). The time series data include information about the vehicle kinematics (vehicle position, speed, angular velocity, acceleration, distance from center of the lane, headway between lead and participant vehicles) and driving behavioral characteristics (use of seatbelt, brake application, steering wheel position, accelerator pedal position). Note that a significant portion of the time series data was also confirmed by the forward video review, whereas information from both sources was cross-validated and integrated on the basis of the video timestamps.

Upon the video processing and the linkage of the distinct data sources, the final dataset contains information about 437 trips (traversals through the high-visibility enforcement test and control sites) in total, performed by a random sample of 54 naturalistic driving study participants. Of the 437 traversals, 337 were conducted at the Amherst (test) site, whereas the remaining 100 traversals were conducted at the Depew (test and control) site. The selection of the traversals included in the analysis, was based upon a number of criteria such as: the time that the traversal occurred (e.g., before, during, or after the conduct of the high-visibility enforcement); number of traversals by the participant through the high-visibility enforcement sites; type of vehicle; and participant demographics (in terms of gender and age). The primary focus of the selection procedure was to proportionally represent all the different trip and driver characteristics arising from the various selection criteria. Table 1 presents descriptive statistics of key variables (those that were found to be statistically significant in the statistical analysis).



**Table 1. Descriptive statistics of key variables**

<b>Variable</b>	<b>Mean</b>	<b>Std. Dev.</b>	<b>Minimum</b>	<b>Maximum</b>
Tailgating metric <sup>1</sup>	-14.959	26.440	-141.417	0
Speed metric	0.112	0.092	0	0.545
Speeding indicator (1 if speeding was observed throughout the traversal, 0 otherwise)	0.953	--	0	1
Tailgating indicator (1 if tailgating was observed throughout the traversal, 0 otherwise)	0.651	--	0	1
High-visibility enforcement site indicator (1 if the traversal occurred in the test – high-visibility enforcement – site, 0 otherwise)	0.887	--	0	1
High-visibility enforcement / Day of the week interaction indicator (1 if the traversal occurred on a Wednesday at the test – high-visibility enforcement – site and during the high-visibility enforcement implementation period, 0 otherwise)	0.135	--	0	1
High-visibility enforcement implementation indicator (1 if the traversal occurred during the high-visibility enforcement implementation period, 0 otherwise)	0.070	--	0	1
Vehicle type indicator (1 if the vehicle was a sedan or SUV, 0 otherwise)	0.809	--	0	1
Vehicle age indicator (1 if the vehicle was less than 8 years old, 0 otherwise)	0.641	--	0	1
Vehicle age indicator (1 if vehicle was less than 3 years old, 0 otherwise)	0.442	--	0	1
Vehicle make indicator (1 if the vehicle's make was US-based – Chevrolet, Ford, Mercury, Pontiac, Saturn, or Dodge, 0 otherwise)	0.404	--	0	1
Driver's age indicator (1 if the driver was 60 years old or older, 0 otherwise)	0.208	--	0	1
Driver's gender and age interaction indicator (1 if the driver was male and younger than 30 years old, 0 otherwise)	0.087	--	0	1
Driver's gender and age indicator (1 if the driver was female and over 40 years old, 0 otherwise)	0.191	--	0	1
Average speed on the traversal (km/hr)	78.843	23.888	22.105	100
Speeding indicator (1 if the average traversal speed exceeds the speed limit, 0 otherwise)	0.633	--	0	1
Square root of the average traversal speed	8.751	1.510	4.702	10

<sup>1</sup> Tailgating and speeding metrics have been defined in the subsequent Methodology section.

Variable	Mean	Std. Dev.	Minimum	Maximum
Traversal frequency indicator (1 if the driver traversed the same site more than 5 times, 0 otherwise)	0.721	--	0	1
Time of day indicator (1 if the traversal occurred during the day, 0 otherwise) [speeding metrics model]	0.608	--	0	1
Time of day indicator (1 if the traversal occurred during the day, 0 otherwise) [tailgating occurrence model]	0.642	--	0	1
Time of day indicator (1 if traversal occurred during the dawn, dusk, or night, 0 otherwise)	0.358	--	0	1
Weather indicator (1 if the weather was clear during the traversal, 0 otherwise)	0.702	--	0	1

## METHODOLOGICAL APPROACH

To evaluate the effectiveness of high-visibility enforcement programs in terms of modifying the driving behavior, two primary dimensions of aggressive driving behavior are investigated: speeding and tailgating. In order to analyze such behavioral aspects in terms of intensity and duration, novel metrics – which are independent of trip- or roadway-specific conditions – are defined and used for the driving behavior analysis.

Speeding can be typically defined as exceeding the posted speed limit (Bagdade et al., 2012); however, this – by itself – cannot capture the magnitude of speeding. To that end, a quantitative measure that jointly accounts for the intensity of speeding during the traversal (i.e., number of miles per hour above the speed limit during the traversal) and the duration of speeding (i.e., length of time during the traversal that speeding was observed) is developed. Specifically, the proposed speeding metric is calculated as:

$$Speeding\ Metric_{m,j} = \frac{\left[ \sum_{k=1}^n A_k \right]}{L_j} \quad (1)$$

where,  $A_k$  is the area between the vehicle network speed and the speed limit whenever the vehicle speed is greater than the posted speed limit,  $n$  is the number of instances during the traversal,  $j$ , when the vehicle speed is greater than the posted speed limit, and  $L_j$  is the length of traversal,  $j$ . This formulation of the speeding metric allows for comparison of the speeding behavior over time, as well as over different roadway segments of varying speed limits and lengths. An illustration of the calculation of the speeding metric is provided in Figure 2, which shows an 85 second long traversal through a section of one of the high-visibility enforcement test sites of interest. The black circles indicate the vehicle network speed reported at 10 Hz in the naturalistic driving study time series data. As noted in the figure, the roadway traversed during the trip had three changes in the posted speed limits (i.e., 30 mi/h, 20 mi/h, and 30 mi/h). Four areas are shown where the observed vehicle speed exceeded the posted speed limit. For the traversal illustrated in Figure 2, the previously defined speeding metric is calculated using Equation 1, which for simplicity is equal to:

$$\text{Speeding Metric} = (A_1 + A_2 + A_3 + A_4) / L, \quad (2)$$

where,  $A_1$ ,  $A_2$ ,  $A_3$ , and  $A_4$  are the areas of speeding given the speed limit (illustrated with the red dashed line), and  $L$  is the total length of the traversal.

With respect to the second measure of driving behavior, tailgating generally occurs when a vehicle follows too closely the lead vehicle. Herein, tailgating is defined to occur when a vehicle follows a lead vehicle with a headway less than two seconds, which is a commonly acceptable distance for safe driving (Wang and Song, 2011). The initial step in the calculation of tailgating was to determine the presence of a lead vehicle, which was accomplished through the review of the forward view videos. Once the presence of a lead vehicle was identified through the video review, the time series data were reviewed to confirm the presence or absence of a lead vehicle.

Apart from the presence of a lead vehicle, the calculation of the tailgating metric was based on the driver's vehicle speed and the lead vehicle headway. These sets of information were obtained through two different methods: the vehicle network, or the Global Positioning System (GPS) within the Next Generation Acquisition System (NextGen). The selection of the appropriate source of information was highly associated with the make, model year, and model of the vehicle and the type of the on-board equipment. Using the processed data from the on-vehicle radar (an association algorithm was applied to the raw radar data to allow tracking of individual targets), the lead vehicle headway was calculated by dividing the radar reported distance from the driver's vehicle to the lead vehicle by the driver's vehicle velocity. The comparison of the latter with the pre-specified threshold of two seconds was used to determine whether the driver was tailgating.

In order to identify possible tailgating incidents in free-flowing traffic conditions, conditional statements were used to find those cases where the driver was traveling at 90 percent of the posted speed limit or above, and a lead vehicle was present. To that end, the tailgating behavior was evaluated only for time intervals where both conditions were satisfied. For this purpose, radar data provided in the form of time-series were utilized to determine the speed of the traversals, and to confirm presence of lead vehicles, which was also observed during the review of the traversal videos. The time series data were recorded at a 10 Hz frequency, however, in very few occasions, speed measurements were not available for each data point millisecond. In these cases, linear interpolation was employed to obtain the speed values. To better illustrate the calculation procedure of the tailgating metric, Figure 2 shows a graphical representation of the headway profile as a function of the traversal duration. In the Figure, the X-axis represents the duration of the traversal (in microseconds), and the Y-axis the difference between the headway from the leading vehicle and the 2-second headway threshold (in seconds). Based on the previous

definition, the tailgating metric is calculated as the total curve area below the X-axis (note that the point zero on the Y-axis represents the 2-second headway threshold). This area captures the extent of tailgating, simultaneously in terms of intensity (how close the participant is following the leading vehicle) and duration (how long tailgating occurred).

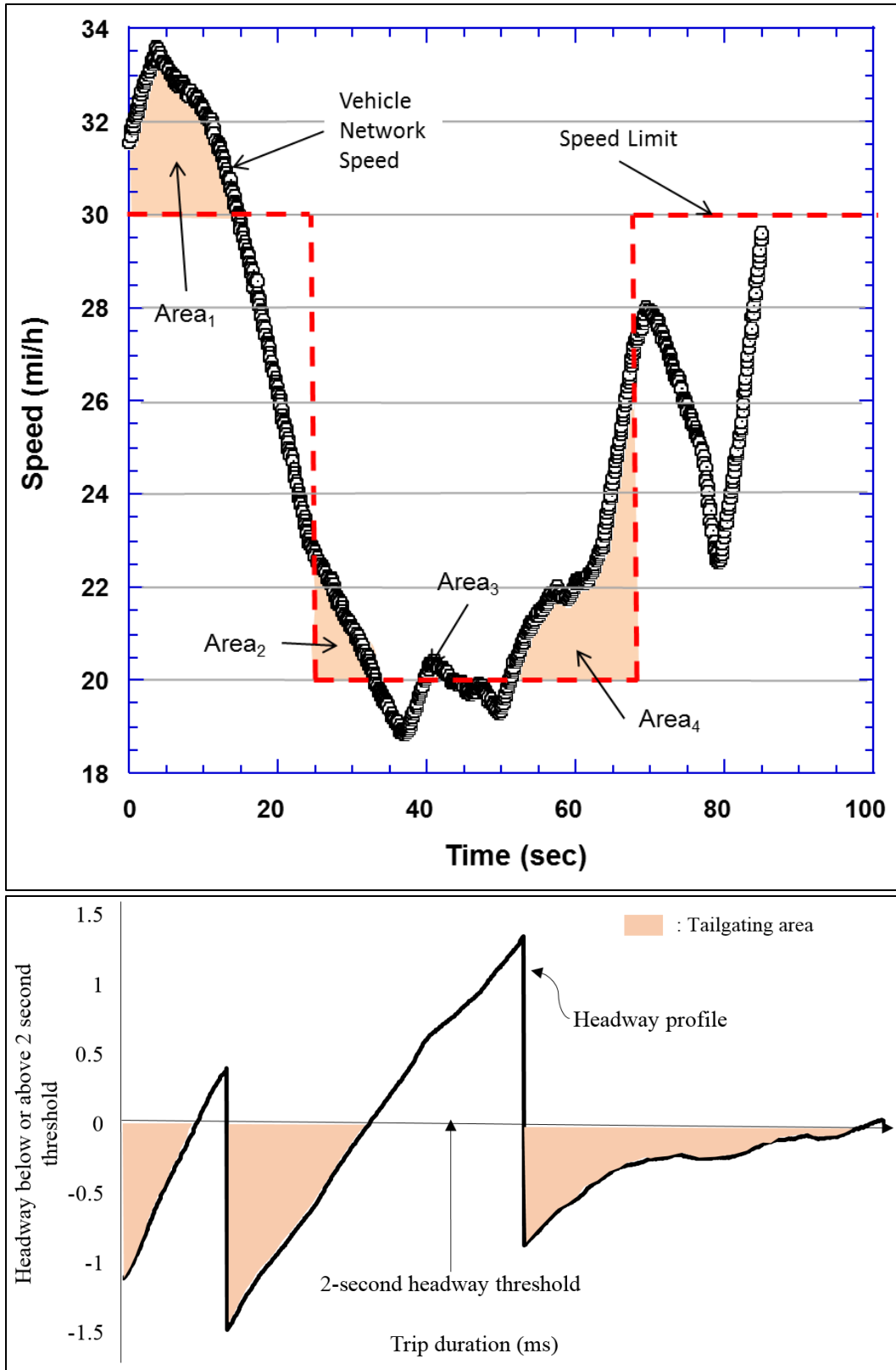


Figure 2. Graphical representation of speeding (top) and tailgating (bottom) metric definitions.

To identify the effect of high-visibility enforcement on critical aspects of driving behavior, and at the same time, to control for driver- and vehicle-specific factors as well as for roadway, weather, and other environmental characteristics, statistical models of speeding and tailgating are developed. To statistically model the extent of speeding and tailgating metrics (as defined above) over time (prior to, during, and after the conduct of the high-visibility enforcement), a linear regression framework is employed (note that non-linear models were also estimated, but the presented models were statistically superior, in terms of statistical fit). The linear regression model is defined as (Washington et al., 2011; Pierowicz et al., 2016; Nahidi et al., 2017):

$$y_i = \alpha + \beta_i X_i + \varepsilon_i \quad (3)$$

where,  $y$  is the dependent variable (i.e., the speeding or tailgating metric), which is a function of a constant term  $\alpha$  and a coefficient  $\beta$  times the value of independent variables  $X$  (e.g., high-visibility enforcement implementation, roadway/roadside and weather conditions, and driver/vehicle/trip characteristics) for driver  $i$  ( $i = 1, 2, \dots, n$ ), plus an error term  $\varepsilon$ .

To account for the effect of unobserved heterogeneity (i.e., unobserved factors varying systematically across the observations), a random parameters modeling approach is employed (Anastasopoulos and Mannering, 2009; Anastasopoulos and Mannering, 2011; Venkataraman et al., 2014; Mannering et al., 2016; Anastasopoulos and Mannering, 2016; Fountas and Anastasopoulos, 2017; Bogue et al., 2017; Alarifi et al., 2017; Seraneeprakarn et al., 2017; Behnood and Mannering, 2017; Xin et al., 2017; Bhat et al., 2017; Sarwar et al., 2018; Guo et al., 2018). Because there were traversals performed by the same driver, it is very likely that similar unobserved characteristics are commonly encountered among the driver-specific traversals (Wu et al., 2014). Thus, to account for unobserved heterogeneity varying across driver-specific subsamples of the traversal population (i.e., panel effects), grouped random parameters are estimated.

Under this modeling structure, one separate parameter estimate ( $\beta$ ) is estimated for each driver; thus, all the driver-specific traversals are represented by the same parameter estimates. In this context, the effect of the parameters are allowed to vary across the drivers, as (Wu et al., 2013; Sarwar et al., 2017a; Fountas et al., 2018a):

$$\beta_i = \beta + u_i \quad (4)$$

where,  $\beta_i$  is the driver-specific vector of random parameter,  $\beta$  denotes the vector with the mean values of the random parameters, and  $u_i$  is a randomly distributed error term for each driver  $i$  (with mean equal to 0 and variance equal to  $\sigma^2$ ). Note that the driver-specific grouped random parameters are pre-assumed to follow a continuous distribution. For the density function of this distribution, a wide variety of the most popular parametric density functions can be used (such as, normal, log-normal, triangular, uniform and Weibull). In line with previous studies (Venkataraman et al., 2013; Russo et al., 2014; Anastasopoulos et al., 2016; Behnood and Mannering, 2016; Anastasopoulos et al., 2017; Fountas et al., 2018a; Fountas et al., 2018c), herein, the normal distribution was found to provide the best statistical fit and was thus used in the model specifications.

To analyze the likelihood of occurrence of speeding and tailgating, a binary discrete outcome framework is employed. Specifically, using the definition criteria of these metrics, the binary dependent variables were 1 if speeding or tailgating occurred during the traversal, respectively, and 0 otherwise. Since speeding and tailgating constitute two distinct, but interrelated aspects of the aggressive driving behavior of the same driver (Sarwar et al., 2017a), they may share the same or similar unobserved characteristics. Therefore, it is likely for the error terms – associated with the two dependent variables – to be correlated (Chiou et al., 2014; Fountas and Anastasopoulos, 2018). To account for the cross-equation (contemporaneous) error term



correlation, speeding and tailgating are modeled simultaneously, by employing a bivariate probit formulation. The bivariate binary probit model can be defined as (Anastasopoulos et al., 2012; Greene, 2016; Sarwar et al., 2017a):

$$\begin{aligned} Z_{i,1} &= \mathbf{X}_{i,1}\boldsymbol{\beta}_{i,1} + \varepsilon_{i,1} & y_{i,1} &= 1 \text{ if } Z_{i,1} > 0, = 0 \text{ otherwise} \\ Z_{i,2} &= \mathbf{X}_{i,2}\boldsymbol{\beta}_{i,2} + \varepsilon_{i,2} & y_{i,2} &= 1 \text{ if } Z_{i,2} > 0, = 0 \text{ otherwise} \end{aligned} \quad (5)$$

with the cross-equation correlated error terms:

$$\begin{pmatrix} \varepsilon_{i,1} \\ \varepsilon_{i,2} \end{pmatrix} \sim N \left[ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right] \quad (6)$$

where,  $y_{i,1}$  and  $y_{i,2}$  are binary outcomes for speeding and tailgating, respectively, for traversal  $i$ ,  $\mathbf{X}$ s denote vectors of explanatory variables affecting speeding and tailgating,  $\boldsymbol{\beta}$  is the vector of coefficients corresponding to  $\mathbf{X}$ ,  $\varepsilon$  is a random error term, and  $\rho$  is the cross-equation error correlation coefficient. In this probit model formulation, the error terms are assumed to be normally distributed with mean equal to zero and variance equal to one. Equations 7 and 8 present the bivariate probit model and its corresponding log-likelihood function, respectively (Greene, 2012):

$$\Phi(Z_1, Z_2, \rho) = \frac{\exp\left[-0.5\left(Z_1^2 + Z_2^2 - 2\rho Z_1 Z_2\right) / \left(1 - \rho^2\right)\right]}{\left[2\pi\sqrt{1 - \rho^2}\right]} \quad \text{and} \quad (7)$$

$$\sum_{i=1}^N \left[ \begin{aligned} & y_{i,1} y_{i,2} \ln \Phi(\boldsymbol{\beta}_{i,1} \mathbf{X}_{i,1}, \boldsymbol{\beta}_{i,2} \mathbf{X}_{i,2}, \rho) + (1 - y_{i,1}) y_{i,2} \ln \Phi(-\boldsymbol{\beta}_{i,1} \mathbf{X}_{i,1}, \boldsymbol{\beta}_{i,2} \mathbf{X}_{i,2}, -\rho) + \\ & y_{i,1} (1 - y_{i,2}) \ln \Phi(\boldsymbol{\beta}_{i,1} \mathbf{X}_{i,1}, -\boldsymbol{\beta}_{i,2} \mathbf{X}_{i,2}, -\rho) + (1 - y_{i,1}) (1 - y_{i,2}) \ln \Phi(-\boldsymbol{\beta}_{i,1} \mathbf{X}_{i,1}, -\boldsymbol{\beta}_{i,2} \mathbf{X}_{i,2}, \rho) \end{aligned} \right] \quad (8)$$

where,  $\Phi(\cdot)$  is the cumulative distribution function corresponding to the bivariate probit model, and all other terms as previously defined.

To simultaneously account for unobserved heterogeneity and panel effects, grouped random parameters are also introduced in the estimation of the bivariate probit model. Similar to

the grouped random parameters linear regression models, a separate parameter estimate ( $\beta$ ) is estimated for each driver. Note that the bivariate model is estimated only for those pairs of  $y_{i,1}$  and  $y_{i,2}$  with available information.

For the estimation of the random parameter models, simulated maximum likelihood estimation techniques are adopted. To increase the efficiency of the complex numerical integrations required within the simulation procedure, Halton draws are used (Halton, 1960; Train, 2003). The relevant econometric literature (Train, 2003; Bhat, 2003) recommends a minimum of 200 Halton draws for obtaining stable random parameters; however, in this study, 1000 Halton draws were found to provide parameter stability, and were thus used in model estimation.

To assess the magnitude of the effect of the explanatory variables on the probability of speeding and tailgating, pseudo-elasticities are computed (Ulfarsson et al., 2010). The pseudo-elasticities measure the effect of a change from “0” to “1” for an indicator variable, on the probability of the dependent variables.

## **MODEL ESTIMATION RESULTS**

Table 2 presents the estimation results of the grouped random parameters linear regression models for speeding and tailgating metrics along with the distributional effect of the random parameters – in terms of positive or negative effect – on speeding and tailgating metrics. Table 3 presents the estimation results of the grouped random parameter bivariate probit model of speeding and tailgating occurrence along with the distributional effect of the random parameters – in terms of positive or negative effect – on speeding and tailgating occurrence probabilities. For the grouped random parameter bivariate probit model, the average (across the drivers) pseudo-elasticities of the explanatory variables are also provided. For the bivariate model, positive

coefficients indicate higher likelihood of speeding or tailgating during the specific traversal, whereas for the linear regression models positive coefficients are associated with greater values of the speeding and tailgating metrics. All explanatory variables included in the models result in statistically significant parameters at 0.90 level of confidence.

Table 2 shows that a number of driver-, vehicle-, and trip-specific characteristics affect the extent and the duration of speeding (speeding metric). Specifically, the variable representing traversals that occurred on an area where the high-visibility enforcement program was implemented (test area) results in a statistically significant random parameter; for the majority of the drivers (66.48%, as shown in Table 2), traversals conducted on a high-visibility enforcement site are associated with an increase in the extent and the duration of the speeding, whereas for the remaining 33.52% of the drivers, these traversals are associated with a reduction in the extent and the duration of speeding. This finding is an indication that high-visibility enforcement programs are likely to reduce speeding on some occasions. The mixed effect of this variable warrants further investigation, and can be attributed to unobserved heterogeneity related to the presence of low speed limits (especially, for the majority of segments in Depew area, the speed limit was 35mi/h) or to the frequent presence of near free-flow traffic conditions (especially, for the majority of traversals in Amherst area).

Traversals that occurred during the day are found to have variable effect across the drivers, with the majority of these traversals (55.68%, as shown in Table 2) being associated with lower extent and duration of speeding (while the remaining 44.32% are associated with an increase in speeding, as shown in Table 2). It should be noted that police presence during high-visibility enforcement was significant, particularly during the daytime, leading, thus, to increased driver's

alertness and compliance with the traffic regulations – this finding is in line with past research (Tarko et al., 2011).

**Table 2. Estimation results for the grouped random parameters linear regression models**

<b>Dependent Variable: Speeding</b>	<b>Coeff.</b>	<b>t-stat</b>
Constant	0.117	8.290
High-visibility enforcement site indicator (1 if the traversal occurred in the test – high-visibility enforcement – site, 0 otherwise)	0.020	2.340
<i>Standard deviation of parameter density function</i>	<i>0.047</i>	<i>55.200</i>
Vehicle type indicator (1 if the vehicle was a sedan or SUV, 0 otherwise)	0.027	3.340
Vehicle age indicator (1 if the vehicle was less than 8 years old, 0 otherwise)	-0.067	-7.900
Vehicle make indicator (1 if the vehicle’s make was US-based – Chevrolet, Ford, Mercury, Pontiac, Saturn, or Dodge, 0 otherwise)	0.016	2.080
Driver’s age indicator (1 if the driver was 60 years old or older, 0 otherwise)	-0.047	-4.950
Time of day indicator (1 if the traversal occurred during the day, 0 otherwise)	-0.001	-0.090
<i>Standard deviation of parameter density function</i>	<i>0.007</i>	<i>4.780</i>
Variance parameter, $\sigma$	0.063	90.630
Number of drivers / Number of observations	54 / 423	
$LL(\beta)$	-2396.140	
$LL(0)$	-2514.202	
$R^2$ / Adjusted $R^2$	0.455 / 0.443	
<b>Dependent Variable: Tailgating</b>	<b>Coeff.</b>	<b>t-stat</b>
Constant	229.718	1.760
High-visibility enforcement and day of the week interaction indicator (1 if the traversal occurred on a Wednesday at the test – high-visibility enforcement – site and during the high-visibility enforcement implementation period, 0 otherwise)	10.708	2.010
<i>Standard deviation of parameter density function</i>	<i>16.404</i>	<i>3.160</i>
Driver’s gender and age interaction indicator (1 if the driver was male and younger than 30 years old, 0 otherwise)	15.246	2.090
Average speed on the traversal	4.155	1.870
Square root of the average traversal speed	-62.323	-1.790
Variance parameter, $\sigma$	23.418	41.350
Number of drivers / Number of observations	39 / 226	
$LL(\beta)$	-1037.809	
$LL(0)$	-1060.637	
$R^2$ / Adjusted $R^2$	0.224 / 0.203	
<b>Aggregate distributional effect of the random parameters across the observations</b>		
	<b>Above zero</b>	<b>Below zero</b>
<b>Dependent Variable: Speeding</b>		
High-visibility enforcement site indicator (1 if the traversal occurred in the test – high-visibility enforcement – site, 0 otherwise)	66.48%	33.52%
Time of day indicator (1 if the traversal occurred during the day, 0 otherwise)	44.32%	55.68%
<b>Dependent Variable: Tailgating</b>		
High-visibility enforcement / Day of the week interaction indicator (1 if the traversal occurred on a Wednesday at the test – high-visibility enforcement – site and during the high-visibility enforcement implementation period, 0 otherwise)	74.30%	25.70%

Turning to the fixed parameters, driving SUVs or sedans increases the extent and duration of speeding; vehicles manufactured by US-based companies (Chevrolet, Ford, Mercury, Pontiac, Saturn, and Dodge) are found to increase speeding; old drivers (older than 60 years old) are intuitively associated with lower extent and duration of speeding; and traversals made with relatively new vehicles (less than 8 years old) are found to reduce speeding. These findings are accounting for driver- and vehicle-specific characteristics, and may be capturing heterogeneity stemming from the demographic characteristics of the drivers and their driving habits.

Turning to the estimation results of the tailgating metrics model, the interaction between the high-visibility enforcement and the weekday driving conditions has mixed effect across the driving population. Table 2 shows that the variable representing traversals that occurred in a high-visibility enforcement area during a typical weekday (Wednesday) results in a statistically significant random parameter. This variable increases the extent and duration of tailgating for the majority of the drivers (74.30%, as shown in Table 2), while it reduces it for the remaining 25.70%. This finding may be capturing the predominant role of traffic conditions and unobserved trip-specific characteristics (e.g., trip origin-destination, purpose, frequency of the specific trip), especially during a typical mid-week day. In addition, the tailgating metric is found to increase amongst young (less than 30 years old) male drivers, which is in line with previous findings relating to the propensity of young male drivers in aggressive driving behavior (Lambert-Bélanger, 2012; Hassan and Abdel-Aty, 2013). Furthermore, the average traversal speed is found to have a non-linear effect on the tailgating metric. The non-linear effect is captured by the combination of the average traversal speed and the square root of the average traversal speed, where the first increases tailgating and the second reduces it.<sup>2</sup>

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<sup>2</sup> Note that to account for possible endogeneity between the speed-related variables and the tailgating metric, an instrumental variable approach was employed: the speed-related variables were regressed against all exogenous

Moving to the results of the bivariate probit model, Table 3 shows that the cross-equation error correlation ( $\rho$ ) is statistically significant. This implies the presence of significant correlation among the unobserved factors captured in the error terms of the speeding and tailgating occurrence variables, and supports the use of the bivariate modeling framework (Sarwar and Anastasopoulos, 2017). Specifically, the results show that traversals that occurred during the high-visibility enforcement period at the test areas (i.e., in areas where the high-visibility enforcement programs were implemented) decrease the probability of speeding occurrence (by 7.5%, as indicated by the pseudo-elasticity). This suggests the potential of high-visibility enforcement programs to improve driving behavior, in terms of reducing speeding. In addition, frequent travelers (i.e., drivers that traversed the same location more than 5 times during the study period), and older than 40 years old female drivers are also less likely to speed (the speeding occurrence probability decreases by 6.9% and 12.6%, respectively, as indicated by the pseudo-elasticities). These results are likely capturing habitual effects formed by the frequent traversals on the high-visibility enforcement site, and are supported by previous research (Anastasopoulos, 2016). Traversals that occurred during dawn, dusk, or at night are also found to decrease the probability of speeding occurrence (by 6.2%, as indicated by the pseudo-elasticity). This is intuitive considering that drivers may need to compensate for restrictive lighting conditions, and thus adjust their driving behavior. Finally, the vehicle type (sedan or SUV) is found to have mixed effects on the speeding occurrence probability, with the vast majority of drivers (84.52 %, as shown in Table 3) having higher probability to speed (the opposite is observed for the remaining 15.48% of drivers, as shown in Table 3). This finding may be capturing vehicle- or driver-specific heterogeneity.

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variables and their instruments were used as independent variables in the tailgating model (Washington et al., 2011; Sarwar and Anastasopoulos, 2016; Sarwar et al., 2017c).

**Table 3. Model estimation results and pseudo-elasticities of the grouped random parameters bivariate probit model of speeding and tailgating**

Variables	<i>Speeding</i>		<i>Tailgating</i>		<i>Pseudo-elasticities</i>
	Coeff.	t-stat	Coeff.	t-stat	
Constant	7.774	2.020	--	--	
High-visibility enforcement site indicator (1 if the traversal occurred in the test – high-visibility enforcement – site, 0 otherwise)	-3.396	-1.890	--	--	-7.50%
Vehicle type indicator (1 if the vehicle was a sedan or SUV, 0 otherwise)	4.836	2.190	--	--	13.60%
<i>Standard deviation of parameter density function</i>	4.760	2.610	--	--	
Vehicle age indicator (1 if vehicle was less than 3 years old, 0 otherwise)	--	--	-0.636	-2.430	-20.70%
Driver's gender and age indicator (1 if the driver was female and over 40 years old, 0 otherwise)	-4.615	-2.240	--	--	-12.60%
Driver's age indicator (1 if the driver was 60 years old or older, 0 otherwise)	--	--	-0.630	-2.470	-21.80%
Speeding indicator (1 if the average traversal speed exceeds the speed limit, 0 otherwise)	--	--	0.476	1.660	16.10%
Traversal frequency indicator (1 if the driver traversed the same site more than 5 times, 0 otherwise)	-3.761	-1.910	--	--	-6.90%
Time of day indicator (1 if the traversal occurred during the day, 0 otherwise)	--	--	0.598	2.000	20.10%
Time of day indicator (1 if traversal occurred during the dawn, dusk, or night, 0 otherwise)	-3.509	-1.890	--	--	-6.20%
Weather indicator (1 if the weather was clear during the traversal, 0 otherwise)	--	--	0.347	1.350	7.20%
<i>Standard deviation of parameter density function</i>	--	--	0.366	3.080	--
Cross equation correlation, $\rho$	0.999		177.150		
Number of drivers / Number of observations			38 / 215		
$LL(\beta)$			-139.018		
$LL(0)$			-179.490		
$R^2$ / Adjusted $R^2$			0.225 / 0.147		
<b>Aggregate distributional effect of the random parameters across the observations</b>					
			<b>Above zero</b>	<b>Below zero</b>	
Vehicle type indicator (1 if the vehicle was a sedan or SUV, 0 otherwise)			84.52%	15.48%	
Weather indicator (1 if the weather was clear during the traversal, 0 otherwise)			82.85%	17.15%	



Table 3 also shows that a set of driver-, trip- and weather-specific characteristics affect the likelihood of tailgating occurrence. Interestingly, favorable weather conditions during the traversal (i.e., clear weather conditions) have variable effects on the tailgating occurrence probability. The variable results in a normally distributed random parameter, with the majority of drivers (82.85%, as shown in Table 3) being associated with higher probability of tailgating, and the minority (17.15%, as shown in Table 3) with a lower probability of tailgating. This may be attributed to a higher level of driving confidence – due to the more favorable weather conditions – that in turn is likely to result in aggressive driving behavior (in terms of tailgating). The tailgating occurrence (1 if tailgating occurs, 0 otherwise) probability is also increasing for traversals that occurred during the daytime (by 20.1%, as indicated by the pseudo-elasticity), likely due to the favorable lighting conditions that may encourage risk-taking driving behavior. Similarly, tailgating is more likely to occur if the average traversal speed is greater than the posted speed limit; for these cases the corresponding probability increases by 16.1% (as indicated by the pseudo-elasticity). On the contrary, the variables representing older drivers (60 years old or older) and new vehicles (less than 3 years old) are both found to decrease the probability of tailgating occurrence (by 21.8% and 20.7%, respectively), which is in line with the earlier findings of the speeding metric model.

## **MODEL EVALUATION**

To further evaluate the models, a number of forecasting accuracy measures are computed and counter-imposed against their fixed parameters modeling counterparts: the mean absolute deviation (MAD); the sum squared error (SSE); the mean squared error (MSE); the root mean square error (RMSE); and the standard deviation of errors (SDE). For the linear regression models, the prediction error is calculated as the difference between the observed and predicted metric

values; whereas, for the bivariate probit model, it is calculated as the difference between the observed outcome (speeding/tailgating occurrence or not) and the model-predicted probability of the observed outcome (Sarwar and Anastasopoulos, 2016; Fountas and Anastasopoulos, 2017). Lower values of the aforementioned accuracy measures indicate better prediction performance (Anastasopoulos, 2016; Amoh-Gyimah et al., 2017; Fountas et al., 2018b).

Table 4 provides the mathematical formulations of the accuracy measures, along with a comprehensive overview of the results for the competitive models. The Table shows that the grouped random parameter models consistently outperform their fixed parameters counterparts, since they yield significantly lower prediction error. It should be finally noted that the fixed parameters modeling counterparts resulted in statistically inferior model specifications (in terms of explanatory power and statistical fit), thus, their detailed estimation results are omitted.

**Table 4. Forecasting accuracy measures**

<b>Fixed Vs. Grouped Random Parameters Linear Regression Models</b>					
		<i>Speeding metric</i>		<i>Tailgating metric</i>	
		Grouped random parameters model	Fixed parameters model	Grouped random parameters model	Fixed parameters model
<b>MAD</b>	$\frac{\sum_{i=1}^n  \varepsilon_i }{n}$	0.049	0.056	15.798	16.58455
<b>SSE</b>	$\sum_{i=1}^n \varepsilon_i^2$	1.964	2.387	122386.2	133370.6
<b>MSE</b>	$\frac{\sum_{i=1}^n \varepsilon_i^2}{n}$	0.005	0.006	541.532	590.136
<b>RMSE</b>	$\sqrt{\frac{\sum_{i=1}^n \varepsilon_i^2}{n}}$	0.068	0.075	23.271	24.293
<b>SDE</b>	$\sqrt{\frac{\sum_{i=1}^n \varepsilon_i^2}{n-1}}$	0.068	0.075	23.322	24.347
<b>Fixed Vs. Grouped Random Parameters Bivariate Probit Models</b>					
		<i>Speeding metric</i>		<i>Tailgating metric</i>	
		Grouped random parameters model	Fixed parameters model	Grouped random parameters model	Fixed parameters model
<b>MAD</b>	$\frac{\sum_{i=1}^n  \varepsilon_i }{n}$	0.022	0.067	0.382	0.404
<b>SSE</b>	$\sum_{i=1}^n \varepsilon_i^2$	2.108	7.336	40.033	43.437
<b>MSE</b>	$\frac{\sum_{i=1}^n \varepsilon_i^2}{n}$	0.010	0.034	0.186	0.202
<b>RMSE</b>	$\sqrt{\frac{\sum_{i=1}^n \varepsilon_i^2}{n}}$	0.099	0.185	0.432	0.449
<b>SDE</b>	$\sqrt{\frac{\sum_{i=1}^n \varepsilon_i^2}{n-1}}$	0.099	0.185	0.433	0.451

Mean absolute deviation: MAD; Sum squared error: SSE; Mean squared error: MSE; Root mean square error: RMSE; Standard deviation of errors: SDE.

## SUMMARY AND CONCLUSIONS

This paper provides a preliminary analysis of the effectiveness of high-visibility enforcement programs (HVEs) in terms of modifying driving behavior. To accomplish this, Strategic Highway Research Program 2 (SHRP2) Naturalistic Driving Study (NDS) data were used, in an effort to capture highly disaggregate behavioral characteristics of the drivers before, during, and after high-visibility enforcement. To that end, traversals from two locations in Erie County, NY – where high-visibility enforcement programs were implemented – were analyzed.

To analyze the effect of high-visibility enforcement on driving behavioral patterns, aggressive driving behavior was investigated in terms of speeding and tailgating. In order to account for the highly dimensional nature of the speeding and tailgating events, two novel – to the authors' knowledge – metrics were developed and used in the analysis. These metrics simultaneously quantify – in measurable and effectively comparable area units – the intensity and the duration of the speeding and tailgating incidents.

In this context, statistical models of speeding and tailgating metrics were estimated, to evaluate the driving behavior under the effect of high-visibility enforcement programs. To examine the extent and the duration of speeding and tailgating, grouped random parameters linear regression models were estimated; while, to simultaneously examine the likelihood of speeding and tailgating occurrence, a grouped random parameters bivariate probit model was estimated. The employed modeling frameworks account for significant misspecification issues arising from the nature of the dataset, namely, for unobserved heterogeneity, panel effects, and cross-equation error correlation (the latter is addressed only within the bivariate modeling scheme).

A number of trip-, driver-, weather-, and vehicle-specific characteristics were found to significantly affect the dependent variables. Among those, the high-visibility enforcement was found to play a dominant role in all models. Specifically, the linear regression models showed that the high-visibility enforcement has mixed effects on the extent and the duration of speeding and tailgating. Whereas, the bivariate probit model demonstrated that the high-visibility enforcement program decreases the likelihood of speeding behavior.

The use of the proposed aggressive driving behavior metrics may impose some restrictions in the assessment of the effectiveness of the high-visibility enforcement programs. For example, trips with significant speeding over a short period of time may yield similar speeding metric values with trips observing marginal speeding over a long period of time. Such aggregate consideration may also affect the stability of the parameter estimates over time (Mannering, 2018), especially within a before-after analysis. Simultaneous equation methods can also be used to concurrently account for the extent and duration of speeding and tailgating, by addressing any potential underlying cross-equation error correlation. However, the present empirical study should be viewed as a preliminary step towards evaluating the potential of high-visibility enforcement programs, as a tool to modify driving behavior and habits, and in turn improve traffic safety. Despite minor computational challenges (in terms of model convergence and parameter stability), the proposed evaluation method can be generalized for the investigation of the effectiveness of similar safety countermeasures (e.g., red light enforcement, speed limit enforcement, and enforcement with automatic number plate recognition systems, to name a few).

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