The effects of driver fatigue, gender, and distracted driving on perceived and observed aggressive driving behavior: A correlated grouped random parameters bivariate probit approach

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ABSTRACT

Previous research has shown that the determinants of perceived and observed aggressive driving behavior may differ. However, the consideration of major sources of aggressive patterns may introduce additional variations in the effect of such determinants. This study aims to provide further insights in the variations of these two behavioral components arising from driver's fatigue, gender as well as internal and external distractions (such as, rushing to destination, listening to music and solving logical problems) during the driving task. To identify how the factors determining perceived and observed aggressive behavior may vary across groups of drivers associated with such sources of aggressive driving, survey and simulation data are statistically analyzed. Separate models of perceived and observed aggressive driving behavior are estimated for fatigued and non-fatigued, distracted and non-distracted, male and female drivers. To address various aspects of unobserved heterogeneity, associated with the unobserved variations that are commonly shared among the behavioral components and participants, as well as their unobserved interactions, the correlated grouped random parameters bivariate probit modeling framework is employed. The results of the empirical analysis showed that the effect of the socio-demographic and behavioral factors on perceived and aggressive driving behavior may vary across the aforementioned groups of drivers, in terms of magnitude and directional effect. In addition, the identification of correlation among the unobserved characteristics further illustrates the complexities of the driving decision mechanism, especially when fundamental sources of aggressive driving are evident.

KEYWORDS

Aggressive driving; Driver fatigue; Driver's gender; Distracted driving; Bivariate probit; Correlated grouped random parameters

1. INTRODUCTION

Aggressive driving behavior has been considered to be one of the main concerns in transportation safety research over recent years due to its correlation with occurrence of high-severity accidents. Previous studies (AAA, 2009) have identified that aggressive driving behavior (such as tailgating, cutting someone off, and reckless or unsafe overpass) constitutes the primary contributing factor towards the occurrence of fatalities for single-vehicle and two-vehicle accidents (NSC, 2008; AAA, 2009). Despite significant advancements in traffic safety over the last few decades, aggressive driving incidents exhibit an increasing trend year-by-year (AAA, 2009). According to the National Safety Council (NSC, 2008), such increases may be attributed to the perception of driving as an individual task rather than an act involving other transportation network users, the reduced enforcement level, and the increasing congestion of the roadway networks.

Given its interrelationship with the general behavioral elements of drivers, it is difficult to identify whether aggressive driving constitutes a conscious decision of drivers or not. Specifically, a portion of drivers may self-identify themselves as non-aggressive drivers, but their actual driving patterns do involve incidents indicative of aggressive driving. According to Sarwar et al. (2017a), the emergence of advanced driver-assistance systems in modern vehicles may induce risk-compensating behavioral elements in driving task resulting, thus, in unconscious driving patterns. Likewise, the opposite may also occur – some drivers may identify their driving behavior as aggressive, while in fact they drive non-aggressively. Even though an abundance of previous studies have focused on the determinants and implications of aggressive driving behavior on traffic safety (Tasca, 2000; Philippe et al., 2009; Paleti et al., 2010; Rong et al., 2011; Calvi et al., 2012; Ouimet et al., 2013; Zhang et al., 2017; Mohamed and Bromfield, 2017; Pantangi et al., 2019) using either simulation or naturalistic driving study data, the discrepancies between the perceptual and actual patterns of driving behavior have not been thoroughly investigated.

Due to the subjective nature of human perceptions, such discrepancies are commonly encountered among the driving population. For example, according to Tarko et al. (2011), a significant portion of drivers who are cited for traffic violations may not be cognizant of perpetrating such violations. In this context, Sarwar et al. (2017a) identified that different sets of factors may affect the mechanisms of perceived and observed aggressive driving behavior. The trip-specific conditions (e.g., time of trip, relative association of trip with other activities, successive conduction of multiple trips) may affect the behavioral patterns through the induction of internal or external sources of aggressive driving, such as driving inattention or distracted driving. Considering that the factors affecting the perceived and observed aggressive driving behavior are likely to differ (Sarwar et al., 2017a), the identification of their comparative differences is further complicated when driving distractions occur. With smartphone applications, social media, and shared mobility services gaining significant popularity among drivers, distracted driving behavior is now more likely than ever to result in severe accidents. Another source of human errors during the driving task may stem from driver's fatigue, which can critically affect attention level, reaction times and maneuver-specific decisions (Mollicone et al., 2018). Another source of variations of driving behavior may arise from the gender of drivers (Ozkan and Lajunen, 2006). Interestingly, according to previous research findings (Shinar and Compton, 2004; Stephens and Sullman, 2015), male drivers are more likely – compared to female drivers – to exhibit various patterns of aggressive driving, such as cutting another vehicle, honking the horn, or exhibiting road rage. As such, the patterns of aggressive driving behavior may differ between males and females resulting, thus, in variations in the effect of their determinants.

This study aims to provide a thorough investigation of observed and perceived aggressive driving behavior, accounting for the effect of driver fatigue, gender, and the effect of distracting driving conditions. In addition to the socio-demographic, exposure and behavioral characteristics, this study focuses on the effect of external and internal distractions on driving behavior, such as: (i) the effect of different types of music (external); (ii) the effect of rushing to destination (internal); and (iii) the effect of mind-wandering (internal). Such scenarios can serve as surrogates – to some extent – to the aforementioned sources of distracted driving. Using survey and driving simulation data, the observed driving behavior is jointly modeled with the perceived (self-reported) driving behavior, for all the aforementioned cases. Given the heterogeneous nature of the simulation data, multiple methodological challenges arise from the interrelationship of both behavioral components as well as the effect of unobserved characteristics and their interactions among various groups of drivers. To address such challenges, the correlated grouped random parameters bivariate probit framework is employed for the statistical analysis.

2. DATA

To investigate perceived and observed aggressive driving behavior, data from driving simulation experiments were used. Specifically, 41 students and employees of the University at Buffalo (UB) participated in simulation experiments that took place at the Motion Simulation Laboratory at UB in 2014 and 2015. Using a six degree-of-freedom motion platform with a 2-seat sedan and surround visualization screens, the participants drove through a 4-mile route (corresponding to a 10-minute drive, approximately) that involved various roadway types and conditions (such as, local, collector and arterial roadways, school zones, work zones, segments with speed limit variations, animal-crossing areas), typical in the area of Buffalo, NY (and adjacent to the University). With regard to the traffic conditions, the simulated environment over the experimental phases primarily represented non-congested traffic conditions during morning hours, with traffic control being imposed through traffic signals and stop signs.

Before the conduction of the simulation experiment, the participants completed a survey (Sarwar et al., 2017a), where they were asked about their socio-demographic attributes (e.g., age, gender, income level, education level, ethnicity/race, household traits), driving experience, exposure and mobility patterns (number of years they legally drive, driving and overall trip frequency, driving reactions against various traffic scenarios, accident and traffic violations history), and personal habits and behavioral patterns (caffeine or alcohol consumption patterns, music listening patterns). Prior to the start of the experiment, the participants attended a short training session in order to learn the basic functions of the driving simulator. With regard to the structure of the experiment, various phases/scenarios were implemented in an effort to capture behavioral variations across various (internal and external) distracted driving cases. The experimental phases involved a baseline driving scenario (i.e., driving to the destination under normal conditions) and various distracting scenarios, in which mind wandering and distracting stimuli were induced (namely, rushing to the destination, listening various types of music, solving logical problems).

Each scenario included multiple, yet successive driving sessions, with separate or combined sources of distraction being interchangeably induced. For the sessions involving rushing to the destination, participants were motivated to drive as quickly as possible, but non-aggressively, through the imposition of penalties for committed traffic violations or aggressive driving incidents, and prize awards for the participant with the lowest travel time. It should be noted that 15-minute breaks were applied between the experimental phases. Before and after each phase, participants were questioned about their simulation-related emotional state, in terms of stress, fatigue, desire for music and they also provided feedback about their perceived driving performance (i.e., if they drove aggressively or non-aggressively) in the previous experimental phase.

During the experimental phases, the aggressive driving incidents of the participants were identified by appropriately trained moderators, who monitored the entire experimental process. Such incidents include: tailgating (following a lead vehicle too closely); speeding (exceeding posted speed limit by 5 miles per hour or more); overtaking and passing another vehicle without maintaining safety margins; not obeying traffic regulations (e.g., violating stop/yield signs, traffic signals, other traffic violations); performing unsafe turns or lane changes (not using turn signals); hard or abrupt braking, and cutting in front of another vehicle.

Since each participant conducted multiple simulation sessions, the dataset consists of 189 observations, with each observation reflecting a specific simulation session. Due to the abundance of possible independent variables, Table 1 provides the descriptive statistics of the key variables that were identified as determinants of aggressive driving behavior. Further details on the experimental process and stages are provided in the study of Sarwar et al. (2017a), in which the same dataset was used.

Table 1. Descriptive statistics of key variables

Variable description	Mean (or %)	Minimum	Maximum
Socio-demographic characteristics			
Education indicator (1 if the participant has a post-graduate degree, 0 otherwise) [DISTRACTED PARTICIPANTS]	30.91%	0	1
Education indicator (1 if the participant has a post-graduate degree, 0 otherwise) [FATIGUED PARTICIPANTS]	18.75%	0	1
Education indicator (1 if the participant has a college or a post-graduate degree, 0 otherwise) [NON-DISTRACTED PARTICIPANTS]	84.21%	0	1
Education indicator (1 if the participant has a post-graduate degree, 0 otherwise) [MALE PARTICIPANTS]	37.60%	0	1
Education indicator (1 if the participant has a college or a post-graduate degree, 0 otherwise) [FEMALE PARTICIPANTS]	49.63%	0	1
Ethnicity indicator (1 if the participant is Asian, 0 otherwise) [NON-DISTRACTED PARTICIPANTS]	33.64%	0	1
Ethnicity indicator (1 if the participant is Asian, 0 otherwise) [NON-FATIGUED PARTICIPANTS]	32.26%	0	1
Income indicator (1 if the participant's income is lower than $20,000, 0 otherwise) [NON-DISTRACTED PARTICIPANTS]	21.79%	0	1
Income indicator (1 if the participant's income is greater than $75,000, 0 otherwise) [DISTRACTED PARTICIPANTS]	22.73%	0	1
Hometown indicator (1 if the participant grew up in an urban area, 0 otherwise) [DISTRACTED PARTICIPANTS]	60.00%	0	1
Hometown indicator (1 if the participant grew up in a suburban or rural area, 0 otherwise) [FATIGUED PARTICIPANTS]	39.06%	0	1
Hometown indicator (1 if the participant grew up in a rural area, 0 otherwise) [FEMALE PARTICIPANTS]	39.58%	0	1
Hometown indicator (1 if the participant grew up in an urban area, 0 otherwise) [FEMALE PARTICIPANTS]	50.40%	0	1
Marital status indicator (1 if the participant is single, 0 otherwise) [DISTRACTED PARTICIPANTS]	73.64%	0	1
Marital status indicator (1 if the participant is single, 0 otherwise) [NON-DISTRACTED PARTICIPANTS]	70.51%	0	1
Marital status indicator (1 if the participant is married, 0 otherwise) [MALE PARTICIPANTS]	25.60%	0	1
Hometown and permanent household indicator (1 if the respondent grew up in a suburban area and lives in a household considered as permanent home, 0 otherwise) [MALE PARTICIPANTS]	10.40%	0	1
Driving experience and behavioral characteristics			
Driving experience indicator (1 if the participant was a licensed driver for 6 years or more, 0 otherwise) [NON-DISTRACTED PARTICIPANTS]	44.87%	0	1

Variable description	Mean (or %)	Minimum	Maximum
Driving experience indicator (1 if the participant was a licensed driver for 4 years or more, 0 otherwise) [DISTRACTED PARTICIPANTS]	54.55%	0	1
Driving experience indicator (1 if the participant was a licensed driver for 6 years or more, 0 otherwise) [MALE PARTICIPANTS]	54.40%	0	1
Speeding indicator (1 if the participant was not pulled over for speeding over the last five years, 0 otherwise) [FEMALE PARTICIPANTS]	36.84%	0	1
Traffic violation indicator (1 if the participant has been pulled over more than once for traffic violations over the last 5 years, 0 otherwise) [FATIGUED PARTICIPANTS]	14.06%	0	1
Simulation scenario indicator (1 if rushing to destination while listening to music, 0 otherwise) [MALE PARTICIPANTS]	16.80%	0	1
Willingness to drive indicator (1 if the participant considers another mode, such as flying, if the destination is more than 12hours by driving or depending on situation, 0 otherwise) [FATIGUED PARTICIPANTS]	12.50%	0	1
Willingness to drive indicator (1 if the participant considers another mode, such as flying, if the destination is more than 12hours by driving or depending on situation, 0 otherwise) [NON-FATIGUED PARTICIPANTS]	20.16%	0	1
Traffic signal behavior indicator (1 if, in the change of a traffic signal from green to yellow, the participant either accelerates and crosses the signal or behaves depending on the vicinity of the signal or on what other drivers do, 0 otherwise) [FATIGUED PARTICIPANTS]	82.81%	0	1
Traffic signal behavior indicator (1 if, in the change of a traffic signal from green to yellow, the participant either accelerates and crosses the signal or behaves depending on the vicinity of the signal or on what other drivers do, 0 otherwise) [NON-FATIGUED PARTICIPANTS]	94.35%	0	1
Accident history indicator (1 if the participant has not been involved in any non-severe accident during lifetime, 0 otherwise) [DISTRACTED PARTICIPANTS]	41.82%	0	1
Accident history indicator (1 if the participant has not been involved in any severe or non-severe accident during lifetime, 0 otherwise) [NON-FATIGUED PARTICIPANTS]	54.69%	0	1
Accident history indicator (1 if the participant has not been involved in any severe or non-severe accident during lifetime, 0 otherwise) [FATIGUED PARTICIPANTS]	63.71%	0	1

3. METHODOLOGICAL APPROACH

Past research (Sarwar et al., 2017a; Harbeck et al., 2017) has shown that the determinants of observed and perceived aggressive driving behavior may differ, due to possible discrepancies between the perceptual and actual driving performance. To identify how the determinants of these behavioral components may vary under the effect of driver fatigue, gender, and driving distractions (i.e., rushing to the destination, listening to music, and logical problem solving), bivariate probit models of observed and perceived aggressive driving behavior are estimated. The bivariate probit context enables the simultaneous modeling of these behavioral components, by accounting for their possible interrelationship. The latter may imply the presence of commonly shared unobserved variations among the dependent variables (Sarwar et al., 2017a; Sarwar et al., 2017b; Pantangi et al., 2019; Fountas and Anastasopoulos, 2018), which cannot be effectively addressed by univariate models.

Specifically, the dependent variable representing the perceived aggressive driving behavior is derived from the question "How aggressively do you think you drove the simulator?", which was included in the self-reporting survey following the completion of each experimental phase. Participants' responses in such questions indicate the self-reported aggressive or non-aggressive driving behavior. Regarding the observed aggressive behavior, we followed the method described in Sarwar et al. (2017a). Specifically, the weighted frequency of observed aggressive incidents per trip (as previously listed) was calculated on the basis of pre-determined weighting factors and taking into account the trip duration. The classification of the aggressive incidents, in terms of their accident risk, as well as the determination of the scaling factors were based on guidelines provided by the AAA Foundation for Traffic Safety (AAA, 2009) and the AASHTO's Highway Safety Manual (2009) as well as on crash modification factors included in the Crash Modification Factors Clearinghouse (FHWA, 2009). In addition, a trip-specific aggressive driving norm was defined on the basis of the aggregate weighted number of all observed aggressive incidents and each trip duration. The difference between the weighted number of aggressive incidents and the aggressive driving norm shows how much the trip-specific observed aggressive driving patterns exceed the typical aggressive driving norm; the median of this excess was used as the criterion for determining the binary outcome variable that reflects the observed aggressive driving behavior[1].

With both dependent variables having two discrete outcomes, the binary probit approach is coupled with the bivariate probit framework. Thus, the model structure can be expressed as (Washington et al., 2011; Russo et al., 2014; Sarwar et al., 2017a; Pantangi et al., 2019):

$$\begin{aligned} Z_{i,1} &= \boldsymbol{\beta}_{i,1}\mathbf{X}_{i,1} + \varepsilon_{i,1}, \quad z_{i,1} = 1 \text{ if } Z_{i,1} > 0, \text{ and } z_{i,1} = 0 \text{ otherwise} \\ Z_{i,2} &= \boldsymbol{\beta}_{i,2}\mathbf{X}_{i,2} + \varepsilon_{i,2}, \quad z_{i,2} = 1 \text{ if } Y_{i,2} > 0, \text{ and } z_{i,2} = 0 \text{ otherwise} \end{aligned} \tag{1}$$

where, **X** is a vector of independent variables affecting perceived and observed aggressive driving behavior relating to session *i*, **β** is the vector of coefficients corresponding to **X**, *z* denote the binary outcomes (zero or one) of both dependent variables, $Z_{i,1}$ and $Z_{i,2}$, are latent variables, and ε denotes a standard normally distributed random error term. Due to the possible presence of common unobserved variations, the error terms are considered to be correlated, with the structure of the cross-equation error term correlation being defined as (Sarwar et al., 2017a; Greene, 2017):

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

where, ρ is the correlation coefficient of the error terms and all other terms are as previously defined. With the addition of the cross-equation error term correlation, the bivariate model and the relevant log-likelihood function can be expressed as (Greene, 2017):

[1] For further details on the specification of the variable reflecting the observed driving behavior, see the study of Sarwar et al. (2017a).

$$\Phi\left(Z_1, Z_2, \rho\right) = \frac{\exp\left[-0.5(Z_1^2 + Z_2^2 - 2\rho Z_1 Z_2)/(1-\rho^2)\right]}{\left[2\pi\sqrt{(1-\rho^2)}\right]}, \tag{3}$$

$$\begin{aligned}\sum_{i=1}^{N}[&z_{i,1}z_{i,2}\ln\Phi(\boldsymbol{\beta}_{i,1}\mathbf{X}_{i,1},\boldsymbol{\beta}_{i,2}\mathbf{X}_{i,2},\rho)+(1-z_{i,1})z_{i,2}\ln\Phi(-\boldsymbol{\beta}_{i,1}\mathbf{X}_{i,1},\boldsymbol{\beta}_{i,2}\mathbf{X}_{i,2},-\rho)\\ &+(1-z_{i,2})z_{i,1}\ln\Phi(\boldsymbol{\beta}_{i,1}\mathbf{X}_{i,1},-\boldsymbol{\beta}_{i,2}\mathbf{X}_{i,2},-\rho)+(1-z_{i,1})(1-z_{i,2})\ln\Phi(-\boldsymbol{\beta}_{i,1}\mathbf{X}_{i,1},-\boldsymbol{\beta}_{i,2}\mathbf{X}_{i,2},\rho)]\end{aligned} \tag{4}$$

with Φ(.) representing the cumulative function of the bivariate normal distribution.

A significant misspecification issue of the conventional bivariate models arises from the effect of unobserved characteristics that may vary across the observational units in a systematic manner (i.e., unobserved heterogeneity). To address this issue, random parameters are incorporated in the estimation framework; such a modeling approach can capture the effect of unobserved factors, by identifying systematic fluctuations in the effect of the identified determinants (Mannering et al., 2016; Savolainen, 2016; Anastasopoulos, 2016; Fountas and Anastasopoulos, 2017; Behnood and Mannering, 2017; Bhat et al., 2017; Fountas et al., 2018b; Cai et al., 2018; Han et al., 2018). Previous research (Mannering et al., 2016; Yu et al., 2015; Fountas et al., 2018a; Fountas et al., 2018c; Balusu et al., 2018) has shown that the sources of unobserved variations may not be mutually independent. For example, the unobserved effects associated with aggressive driving may stem from participant-specific behavioral patterns, or common perceptions regarding the operational conditions of the simulation. As such, the effect of unobserved characteristics on perceived and observed driving behavior may also be correlated. However, the independent effect of the unobserved factors and the uncorrelated nature of their interactions constitute inherent assumptions of the conventional random parameters' structure. Herein, to overcome this restriction, the random parameters are assumed to be correlated. To account, at the same time, for panel effects stemming from multiple simulation sessions conducted by the same participant, correlated grouped random parameters are estimated. Specifically, the latter are defined as (Fountas et al., 2018a; Fountas et al., 2018c):

$$\boldsymbol{\beta}_n = \boldsymbol{\beta} + \Gamma \nu_n \tag{5}$$

where, $\boldsymbol{\beta}_n$ denotes the participant-specific vector including the explanatory parameters of perceived and observed aggressive driving, $\boldsymbol{\beta}$ is the mean value of the aforementioned vector, Γ denotes an unconstrained formulation of the Choleksy matrix with non-zero off-diagonal elements (Greene, 2017), and v_n denotes a standard normally distributed random term. Due to the unconfined consideration of the Γ matrix, the covariance matrix (C) of the correlated grouped random parameters also allows non-zero values for both diagonal and off-diagonal elements (as opposed to the conventional random parameters models where zero values are *a priori* used for the off-diagonal elements – see also Paleti et al., 2013; Bhat et al., 2013) and can be defined as (Greene, 2017; Fountas et al., 2018a; Fountas et al., 2018c)[2]:

$$C = \Gamma\Gamma' \tag{6}$$

The standard deviations of the correlated random parameters are based on the diagonal and off-diagonal elements of the covariance matrix (Fountas et al., 2018a), whereas the corresponding *t*-statistics are computed using the post-estimation computational procedure described in Fountas et al. (2018a; 2018c).

Thus, the bivariate probit framework with correlated grouped random parameters is expected to capture two separate layers of unobserved heterogeneity correlation, due to: (i) similar or same unobserved variations captured by the error terms of model components (Sarwar et al., 2017b; Fountas and Anastasopoulos, 2018); and (ii) unobserved heterogeneity interactions captured by the correlated grouped random parameters.

To quantify the relative magnitude of the effect of each independent variable on both behavioral components, pseudo-elasticities are calculated. The latter provide the change in the probability of each behavior component, due to a shift from "0" to "1" in the values of independent variables and can be expressed as (Sarwar et al., 2017a; Greene, 2017):

[2] In line with the estimation procedure of the bivariate probit model (see also Greene, 2017; Sarwar et al., 2017; Pantangi et al., 2019), the Γ matrix, and the covariance matrix (C) of random parameters include elements from both components of the bivariate probit model (i.e., perceived and observed aggressive driving behavior).

$$E = \Phi\left(\frac{\beta_j X_{j,1}}{\sigma}\middle| X_i = 1\right) - \Phi\left(\frac{\beta_j X_{j,1}}{\sigma}\middle| X_i = 0\right) \quad (7)$$

For the estimation of the bivariate models, the simulated maximum likelihood estimation technique (Bhat, 2003; Washington et al., 2011) was combined with the Halton sequence approach (Halton, 1960), in an effort to obtain stable and robust model specifications.

4. ANALYSIS AND RESULTS

To identify whether different sets of factors affect perceived and observed aggressive driving behavior under driver fatigue, a likelihood ratio test was conducted. The likelihood ratio test is defined as (Washington et al., 2011):

$$X^2 = -2[LL(\boldsymbol{\beta}_T) - LL(\boldsymbol{\beta}_F) - LL(\boldsymbol{\beta}_{NF})] \quad (8)$$

where $LL(\boldsymbol{\beta}_T)$ is the log-likelihood at convergence for the model corresponding to all simulation experiments, whereas $LL(\boldsymbol{\beta}_F)$ and $LL(\boldsymbol{\beta}_{NF})$ denote the log-likelihood at convergence for the models using data from simulation experiments where participants self-reported fatigue and did not self-report fatigue, respectively. The level of driver fatigue was identified through the survey that was filled out before and after each experimental scenario. Specifically, the driving behavior of participants who self-reported as somewhat tired, tired or extremely tired before the conduction of one or more experimental scenarios was considered as being under the effect of fatigue. For the computation of the test statistic, which is chi-squared distributed, the model estimated by Sarwar et al. (2017a) was used. The results of the test indicated that the parameters of the specific model are not transferable among fatigued and non-fatigued drivers, warranting, thus, the estimation of separate models for these two sub-groups of participants.

Table 2 presents the estimation results as well as the pseudo-elasticities of the correlated grouped random parameters bivariate probit models for fatigued and non-fatigued drivers. Focusing on the socio-demographic characteristics, participants with self-reported fatigue, whose hometowns are located in suburban or rural areas, exhibit heterogeneous driving patterns. Specifically, the vast majority of these participants (81.9%) are less likely to drive aggressively. This group may consist of drivers familiar with traffic control-, roadway- or lighting infrastructure-related limitations, which are typically met in suburban or rural networks. Such drivers may have developed a high degree of driving alertness, which may determine their driving performance, even when fatigue patterns are evident.

Pertaining to the effect of education level on perceived aggressive driving behavior, fatigued participants who hold a post-graduate degree are less likely (by -3.8%, as shown by the pseudo-elasticities) to perceive their driving patterns as aggressive. A similar trend is observed for Asian participants who did not self-report any level of fatigue during the experimental phases. The majority of these participants (75.29%) are less likely to perceive that they drove aggressively, whereas the remaining 24.71% of these participants are more likely to correctly perceive their driving behavior. This variable may be capturing unobserved characteristics associated either with their habitual driving patterns or their perceptual mechanism about the incident types that are indicative of aggressive driving.

The accident history is found to affect the driving behavior of both fatigued and non-fatigued participants. Specifically, non-involvement in severe or non-severe accidents decreases (by -3.8%, as shown by the pseudo-elasticities) the probability of non-fatigued participants to drive aggressively and increases the probability (by 1.6%) of the same participants to perceive their behavior as aggressive. In contrast, fatigued participants are less likely (by -4%) to perceive their aggressive driving. This finding illustrates how the driver fatigue may distort the perceptual mechanism relating to driving performance. Furthermore, the behavioral habits in the vicinity of a traffic signal are found to have variable effect across the perceptions of fatigued and non-fatigued drivers. Particularly, the majority of participants who did not self-report fatigue (60.72%) are more likely to correctly perceive their aggressive driving, while the same trend is also observed for the vast majority of participants (83.94%) with self-reported fatigue. Their willingness to self-report aggressive driving habits in the presence of a traffic signal may imply possible self-awareness, especially when they indulge in aggressive driving incidents. In contrast, participants, who have been pulled over multiple times over the last five years for traffic violations and drive under the effect of fatigue, are less likely (by -6.4%) to perceive that they drove aggressively. The propensity of such participants towards traffic violations possibly unmasks their habitual aggressive patterns as well as habitual discrepancies between their perceived and actual driving patterns.

Finally, we focus on the correlation coefficients corresponding to random parameters. The positive correlation (i.e., the coefficient is 0.72) between the unobserved characteristics captured by the Asian ethnicity indicator and the variable reflecting the behavior in the vicinity of a traffic signal indicates their homogeneous effect on perceived aggressive driving behavior of non-fatigued drivers. On the contrary, the unobserved heterogeneity interactions (i.e., interactions of unobserved characteristics) associated with participants who grew up in suburban or rural areas and participants who exhibit aggressive patterns in the vicinity of traffic signals have a non-uniform effect (the coefficient is – 0.75) on observed and perceived driving behavior under the effect of driver fatigue. Each of these two variables affects different model components (see Table 2), thus their unobserved heterogeneity interaction has a simultaneous impact on perceived and observed driving behavior. That means when this unobserved interaction is associated with a higher likelihood of observed aggressive driving behavior, it may simultaneously be associated with lower likelihood of perceived aggressive behavior, and vice versa. This finding possibly captures the driving performance-specific variations that are induced due to the presence of driver fatigue.

Table 2. Estimation results and pseudo-elasticities of the bivariate probit models for non-fatigued and fatigued participants.

	Non-fatigued participants						**Fatigued participants**					
	Observed aggressive driving behavior			*Perceived aggressive driving behavior*			*Observed aggressive driving behavior*			*Perceived aggressive driving behavior*		
	Coeff.	*t*-stat	Pseudo-elasticity	Coeff.	*t*-stat	Pseudo-elasticity	Coeff.	*t*-stat	Pseudo-elasticity	Coeff.	*t*-stat	Pseudo-elasticity
Constant	-0.463	-2.88	–	–	–	–	-0.869	-4.66		3.895	2.48	
Socio-demographic characteristics												
Education indicator (1 if the participant has a post-graduate degree, 0 otherwise)	–	–	–	–	–	–	–	–	–	-1.245	-4.51	-0.038
Ethnicity indicator (1 if the participant is Asian, 0 otherwise)	–	–	–	-7.568	-4.49	-0.020	–	–	–	–	–	–
Standard deviation of parameter density function	–	–	–	*11.069*	*15.33*		–	–	–	–	–	–
Hometown indicator (1 if the participant grew up in a suburban or rural area, 0 otherwise)	–	–	–	–	–	–	-0.741	-1.84	-0.110	–	–	–
Standard deviation of parameter density function	–	–	–	–	–	–	*0.813*	*20.42*	–	–	–	–
Driving experience and behavioral characteristics												
Traffic violation indicator (1 if the participant has been pulled over at least once over the last five years for traffic violations, 0 otherwise)	–	–	–	–	–	–	–	–	–	–	–	–
Accident history indicator (1 if the participant has not been involved in any severe or non-severe accident during lifetime, 0 otherwise)	-0.584	-2.45	-0.038	1.353	2.82	0.016	–	–	–	-1.582	-4.25	-0.040
Willingness to drive indicator (1 if the participant considers another mode, such as flying, if the destination is more than 12hours by driving or depending on situation, 0 otherwise)	–	–	–	-1.840	-4.51	-0.005	–	–	–	2.945	3.82	0.062

	Non-fatigued participants						Fatigued participants					
	Observed aggressive driving behavior			*Perceived aggressive driving behavior*			*Observed aggressive driving behavior*			*Perceived aggressive driving behavior*		
	Coeff.	*t*-stat	Pseudo-elasticity	Coeff.	*t*-stat	Pseudo-elasticity	Coeff.	*t*-stat	Pseudo-elasticity	Coeff.	*t*-stat	Pseudo-elasticity
Traffic signal behavior indicator (1 if, in the change of a traffic signal from green to yellow, the participant either accelerates and crosses the signal or behaves depending on the vicinity of the signal or on what other drivers do, 0 otherwise)	–	–	–	0.878	2.34	0.004	–	–	–	1.990	3.28	0.031
Standard deviation of parameter density function	–	–	–	*3.229*	*4.50*		–	–	–	*2.006*	*4.52*	
Traffic violation indicator (1 if the participant has been pulled over more than once for traffic violations over the last 5 years, 0 otherwise)	–	–	–	–	–	–	–	–	–	-2.369	-3.45	-0.064
Cross-equation correlation (*t*-stat in parentheses)	0.999 (1379.36)						0.999 (7397.46)					
Number of observations	124						65					
Number of participants	30						22					
Number of Halton draws	1,200						1,500					
Restricted Log-Likelihood	-140.280						-73.225					
Log-likelihood at convergence	-110.320						-54.466					
McFadden Pseudo-R^2	0.214						0.256					
Distributional effect of random parameters across the participants												
	Below zero			**Above zero**			**Below zero**			**Above zero**		
Ethnicity indicator (1 if the participant is Asian, 0 otherwise) [PADB]	75.29%			24.71%			–			–		

	Below zero	**Above zero**	**Below zero**	**Above zero**
Hometown indicator (1 if the participant grew up in an suburban or rural area, 0 otherwise) [OADB]	–	–	81.90%	18.10%
Traffic signal behavior indicator (1 if in the change of a traffic signal from green to yellow, the participant either accelerates and crosses the signal or behaves depending to the vicinity of the signal or on what other drivers do, 0 otherwise) [PADB]	39.28%	60.72%	16.06%	83.94%

Diagonal and off-diagonal elements of the Γ matrix [t-stats in brackets], and correlation coefficients (in parentheses) for the correlated random parameters

	Ethnicity indicator (1 if the participant is Asian, 0 otherwise) [PADB]	Traffic signal behavior indicator [PADB]		Hometown indicator (1 if the participant grew up in an urban area, 0 otherwise) [OADB]	Traffic signal behavior indicator [PADB]
Ethnicity indicator (1 if the participant is Asian, 0 otherwise) [PADB]	7.743 [4.16] (1.000)	–	Hometown indicator (1 if the participant grew up in an suburban or rural area, 0 otherwise) [OADB]	0.541 [2.90] (1.000)	–
Traffic signal behavior indicator [PADB]	7.910 [3.53] (0.715)	3.229 [4.50] (1.000)	Traffic signal behavior indicator [PADB]	-0.607 [-1.90] (-0.746)	2.006 [4.52] (1.000)

[OADB]: Observed aggressive driving behavior
[PADB]: Perceived aggressive driving behavior

Similar to the analysis of driver fatigue, a likelihood ratio test was also conducted to identify whether separate models of perceived and observed aggressive driving behavior are warranted for distracting and normal driving conditions. Specifically, distracting driving conditions were evident in the experimental sessions where the participants were asked to drive while rushing to their destination, listening to various types of music, solving logical questions or under the combination of such distractions. The results of the specific likelihood ratio test also showed that different sets of factors affect the driving behavior of distracted and non-distracted drivers; thus, separate models were estimated for these two groups of participants.

Table 3 presents the estimation results as well as the pseudo-elasticities of the bivariate correlated grouped random parameters models of perceived and observed aggressive driving behavior under normal and distracting driving conditions. Starting with the effect of education level, participants with a post-graduate degree are less likely (by -23.2%) to drive aggressively under distracting conditions, while the vast majority of non-distracted participants with a college or post-graduate degree (95.3%) are also less likely to drive aggressively. This finding is in line with previous studies (Tasca, 2000; Sarwar et al., 2017a) and likely reflects that the awareness of well-educated drivers about the components and consequences of aggressive driving results in greater driving caution, regardless of the prevailing behavioral state during the driving task. Similarly, Asian participants who drove under the effect of distracting conditions are less likely to drive aggressively, with the corresponding probability being reduced by -15.3% (as shown by the pseudo-elasticities). The opposite effect is observed for participants whose hometowns are located in urban areas; almost all these participants (99.9%) are found to exhibit aggressive driving patterns during the simulation experiments. Traffic congestion, environment characteristics and driving comfort constraints constitute some of the typical sources of stimuli for drivers in urban areas, which – along with the induced distractions – act as contributing factors towards aggressive behavioral patterns. Similarly, participants who are free of non-severe accidents in their driving lifetime are more likely (by 26.1%) to exhibit aggressive driving behavior, possibly due to their elevated level of driving self-efficacy.

With regards to the determinants of perceived aggressive driving behavior, low-income participants (i.e., those with an annual household income less than $20,000) are less likely (by -0.5%) to perceive that they drove aggressively under normal driving conditions. Under distracting conditions, a similar effect is observed for the high-income participants (i.e., those with annual household income greater than $75,000). This finding is expected, since driving distractions are typically accompanied by driving inattention and restricted consciousness, which may considerably affect perceptual driving patterns. In contrast, the inconsistent perceptions of low-income participants under normal conditions may reflect their perceptual patterns, given the minimal or non-existent effect of external stimuli in such cases. Regarding the effect of marital status, the variable representing single participants is found to have a varying effect across the participants as well as across distracting and normal driving conditions. Specifically, the majority of single participants, who drove under distracting conditions (59.1%), are more likely to perceive their behavior as aggressive; whereas, approximately half of the single participants (51.1%), who drove under normal conditions, are less likely to perceive their behavior as aggressive. This finding may be detecting the alerting effect of external distractions on the perceptual mechanism of single drivers; the induction of distracting stimuli may enhance the acknowledgment of aggressive behavioral patterns. Regarding the effect of driving experience, Table 3 shows the inverse correlation between driving experience and the perception that one’s driving behavior is non-aggressive, under both distracting and normal conditions. This intuitive result may capture the risk-taking behavior of such participants, possibly arising from high driving confidence (Cestac et al., 2011).

Table 3. Estimation results and pseudo-elasticities of the bivariate probit models for distracted and non-distracted participants.

	Distracted participants						**Non-Distracted participants**					
	Observed aggressive driving behavior			*Perceived aggressive driving behavior*			*Observed aggressive driving behavior*			*Perceived aggressive driving behavior*		
	Coeff.	*t*-stat	Pseudo-elasticities	Coeff.	*t*-stat	Pseudo-elasticities	Coeff.	*t*-stat	Pseudo-elasticities	Coeff.	*t*-stat	Pseudo-elasticities
Constant	-0.896	-3.56	–-	1.856	5.21	–-	-1.359	-1.97	–-	3.895	2.48	–-
Socio-demographic characteristics												
Education indicator (1 if the participant has a post-graduate degree, 0 otherwise)	-0.909	-3.75	-0.232	–-	–-	–-	–-	–-	–-	–-	–-	–-
Education indicator (1 if the participant has a college or a post-graduate degree, 0 otherwise)	–-	–-	–-	–-	–-	–-	-1.745	-1.72	-0.111	–-	–-	–-
Standard deviation of parameter density function	–-	–-	–-	–-	–-	–-	*1.043*	*2.06*				
Ethnicity indicator (1 if the participant is Asian, 0 otherwise)	-0.602	-2.70	-0.153	–-	–-	–-	–-	–-	–-	–-	–-	–-
Income indicator (1 if the participant's income is lower than $20,000, 0 otherwise)	–-	–-	–-	–-	–-	–-	–-	–-	–-	-3.047	-2.00	-0.005
Income indicator (1 if the participant's income is greater than $75,000, 0 otherwise)	–-	–-	–-	-0.528	-2.4	-0.02	–-	–-	–-	–-	–-	–-
Hometown indicator (1 if the participant grew up in an urban area, 0 otherwise)	0.953	4.18	0.228	–-	–-	–-	–-	–-	–-	–-	–-	–-
Standard deviation of parameter density function	*0.306*	*2.39*	–-	–-	–-	–-	–-	–-	–-	–-	–-	–-
Marital status indicator (1 if the participant is single, 0 otherwise)	–-	–-	–-	0.227	0.79	0.009	–-	–-	–-	-0.195	-0.36	-0.001

	Distracted participants						Non-Distracted participants					
	Observed aggressive driving behavior			*Perceived aggressive driving behavior*			*Observed aggressive driving behavior*			*Perceived aggressive driving behavior*		
	Coeff.	*t*-stat	Pseudo-elasticities	Coeff.	*t*-stat	Pseudo-elasticities	Coeff.	*t*-stat	Pseudo-elasticities	Coeff.	*t*-stat	Pseudo-elasticities
Standard deviation of parameter density function	––	––	––	*0.986*	*6.22*		––	––	––	*7.09*	*4.99*	
Driving experience and behavioral characteristics												
Driving experience indicator (1 if the participant was a licensed driver for 6 years or more, 0 otherwise)	––	––	––	––	––	––	––	––	––	-4.599	-2.91	-0.006
Driving experience indicator (1 if the participant was a licensed driver for 4 years or more, 0 otherwise)	––	––	––	-1.334	-5.01	-0.018	––	––	––	––	––	––
Accident history indicator (1 if the participant has not been involved in any non-severe accident during lifetime, 0 otherwise)	0.877	3.60	0.261	––	––	––	––	––	––	––	––	––
Cross-equation correlation, ρ (*t*-stat in parentheses)	0.999 (10304.54)						-0.999 (-13.38)					
Number of observations	125						78					
Number of participants	26						39					
Number of Halton draws	1,200						1,400					
Restricted Log-Likelihood	-129.230						-62.724					
Log-likelihood at convergence	-99.811						-37.908					
McFadden Pseudo-R^2	0.228						0.396					

Distributional effect of correlated random parameters				
	Below zero	**Above zero**	**Below zero**	**Above zero**
Education indicator (1 if the participant has a college or a post-graduate degree, 0 otherwise) [OADB]	-–	-–	95.30%	4.70%
Hometown indicator (1 if the participant grew up in an urban area, 0 otherwise) [OADB]	0.10%	99.9%	-–	-–
Marital status indicator (1 if the participant is single, 0 otherwise) [PADB]	40.9%	59.1%	51.10%	48.90%

Diagonal and off-diagonal elements of the Γ matrix [t-stats in brackets], and correlation coefficients (in parentheses) for the correlated random parameters					
	Hometown indicator (1 if the participant grew up in an urban area, 0 otherwise) [OADB]	Marital status indicator (1 if the participant is single, 0 otherwise) [PADB]		Education indicator (1 if the participant has a college or a post-graduate degree, 0 otherwise) [OADB]	Marital status indicator (1 if the participant is single, 0 otherwise) [PADB]
Hometown indicator (1 if the participant grew up in an urban area, 0 otherwise) [OADB]	0.306 [2.39] (1.000)	–	Education indicator (1 if the participant has a college or a post-graduate degree, 0 otherwise) [OADB]	1.043 [2.06] (1.000)	–
Marital status indicator (1 if the participant is single, 0 otherwise) [PADB]	0.986 [5.15] (0.999)	0.024 [4.69] (1.000)	Marital status indicator (1 if the participant is single, 0 otherwise) [PADB]	5.177 [2.88] (0.683)	4.844 [2.92] (1.000)

[OADB]: Observed aggressive driving behavior
[PADB]: Perceived aggressive driving behavior

Focusing on the random parameters of the model reflecting normal driving conditions, the positive correlation (i.e., the coefficient is 0.68) between the unobserved factors captured by the single driver indicator and the higher education indicator illustrates their uniform effect on perceived and observed driving behavior. In other words, the combined effect of such unobserved characteristics either increases or decreases the likelihood of a participant to drive aggressively - and to perceive such behavior as being aggressive. Similarly, the positive correlation (i.e., the coefficient is 0.99) between the random parameters (urban area indicator and single driver indicator) of the model reflecting distracting conditions also implies the homogeneity of the unobserved heterogeneity interactions on observed and perceived aggressive driving.

To investigate the effect of gender on the determinants of perceived and observed aggressive driving behavior, another likelihood ratio test was conducted using the experimental data for male and female drivers. The test results showed that the variations in the driving behavior mechanism between male and female drivers are statistically evident; thus, separate models were estimated for these two groups of participants.

Table 4 presents the estimation results as well as the pseudo-elasticities of the bivariate correlated grouped random parameters models of perceived and observed aggressive driving behavior for male and female participants. Starting with the socio-demographic determinants, female participants with a college or post-graduate degree are associated with a reduced probability of driving aggressively. A similar trend is observed for the vast majority (98.4%) of male participants with a post-graduate degree. Such findings are consistent with the previous model specifications, but also with earlier studies (NSC, 2008; Sarwar et al., 2017a). The hometown location is found to affect the driving behavior of female participants, with the variable reflecting urban hometown location increasing the probability of aggressive driving for almost all female participants (99.1%). As previously discussed, this variable possibly captures unobserved variations associated with the effect of the prevailing traffic and environment conditions of urban settings on the behavioral mechanism of female participants. Furthermore, the behavior of male participants is found to be prone to the impact of external distractions, since the session involving concurrent “rushing to destination” and “listening to music” increases their probability to drive aggressively. Considering that male drivers have a tendency towards aggressive driving (Shinar and Compton, 2004; Cestac et al., 2011), the induced distractions are intuitively anticipated to enhance such tendency and result in aggressive behavioral patterns.

Focusing on the socio-demographic determinants of perceived driving behavior, female participants whose hometowns are located in rural areas are less likely (by -11.8%) to perceive their behavior as aggressive. In contrast, male participants whose hometowns are located in suburban areas and currently live in their permanent residence are more likely (by 2.6%) to perceive their behavior as aggressive. This finding possibly captures the behavioral patterns of drivers who are familiar with the roadway network they typically use and can easily identify the sources and circumstances potentially resulting in aggressive driving behavior. In similar manner, Table 4 shows that single male participants are associated with a higher probability to correctly perceive their driving behavior; note that the association of single marital status and perceived driving behavior is consistent across distracted, non-distracted and male drivers. Regarding the effect of traffic violations history, 69.32% of female participants who were not pulled over for speeding over the last 5 years are more likely to perceive that they drove aggressively. Given that female drivers may be associated with a lower probability of traffic violations and less risk-taking behavior (Abay and Mannering, 2016), the overall consistency between perceived and observed behavioral patterns may also be attributed to their greater level of cognitive alertness and self-consciousness during the driving task. Driving experience is found to have a variable effect across the male participants, with the vast majority of them (81.83%) being less likely to perceive their behavior as aggressive. The latter may constitute an additional indication of the effect of driving confidence on the perceptual mechanisms of male drivers (Cestac et al., 2011).

Table 4. Estimation results and pseudo-elasticities of the bivariate probit models for male and female participants.

	Male participants						Female participants					
	Observed aggressive driving behavior			*Perceived aggressive driving behavior*			*Observed aggressive driving behavior*			*Perceived aggressive driving behavior*		
	Coeff.	*t*-stat	Pseudo-elasticity	Coeff.	*t*-stat	Pseudo-elasticity	Coeff.	*t*-stat	Pseudo-elasticity	Coeff.	*t*-stat	Pseudo-elasticity
Constant	-0.794	-3.44	–	1.103	6.60	–	-0.910	-1.93	–	0.471	1.68	–
Education indicator (1 if the participant has a post-graduate degree, 0 otherwise)	-0.826	-4.70	-0.131	–	–	–	–	–	–	–	–	–
Standard deviation of parameter density function	*0.386*	*34.88*	–	–	–	–	–	–	–	–	–	–
Education indicator (1 if the participant has a college or a post-graduate degree, 0 otherwise)	–	–	–	–	–	–	-1.261	-2.59	-0.074	–	–	–
Hometown indicator (1 if the participant grew up in a rural area, 0 otherwise)	–	–	–	–	–	–	–	–		-4.411	-2.07	-0.118
Hometown indicator (1 if the participant grew up in an urban area, 0 otherwise)	–	–	–	–	–	–	1.578	2.79	0.149	–	–	–
Standard deviation of parameter density function	–	–	–	–	–	–	*0.671*	*2.28*	–	–	–	–
Hometown and permanent household indicator (1 if the respondent grew up in a suburban area and lives in a household considered as permanent home, 0 otherwise)	–	–	–	1.536	3.43	0.026	–	–	–	–	–	–
Marital status indicator (1 if the participant is married, 0 otherwise)	–	–	–	0.974	2.41	0.027	–	–	–	–	–	–

	Male participants						Female participants					
	Observed aggressive driving behavior			*Perceived aggressive driving behavior*			*Observed aggressive driving behavior*			*Perceived aggressive driving behavior*		
	Coeff.	*t*-stat	Pseudo-elasticity	Coeff.	*t*-stat	Pseudo-elasticity	Coeff.	*t*-stat	Pseudo-elasticity	Coeff.	*t*-stat	Pseudo-elasticity
Driving experience and behavioral characteristics												
Speeding indicator (1 if the participant was not pulled over for speeding over the last five years, 0 otherwise)	–	–	–	–	–	–	–	–	–	2.165	1.92	0.129
Standard deviation of parameter density function	–	–	–	–	–	–	–	–	–	*4.287*	*7.39*	–
Simulation scenario indicator (1 if rushing to destination while listening to music, 0 otherwise)	0.646	2.63	0.124	–	–	–	–	–	–	–	–	–
Driving experience indicator (1 if the participant was a licensed driver for 6 years or more, 0 otherwise)	–	–	–	-1.326	-5.52	-0.026	–	–	–	–	–	–
Standard deviation of parameter density function	–	–	–	*1.459*	*12.67*	–	–	–	–	–	–	–
Cross-equation correlation, ρ (*t*-stat in parentheses)	0.999 (522.30)						0.999 (32.43)					
Number of observations	125						63					
Number of participants	26						14					
Number of Halton draws	1,500						1,500					
Restricted Log-Likelihood	-130.165						-75.799					
Log-likelihood at convergence	-98.311						-51.815					
McFadden Pseudo-R^2	0.245						0.316					
Distributional effect of random parameters across the participants												
	Below zero			**Above zero**			**Below zero**			**Above zero**		
Education indicator (1 if the participant has a post-graduate degree, 0 otherwise) [OADB]	98.38%			1.62%			–			–		

	Below zero	Above zero	Below zero	Above zero
Hometown indicator (1 if the participant grew up in an urban area, 0 otherwise) [OADB]	–	–	0.93%	99.07%
Speeding indicator (1 if the participant was not pulled over for speeding over the last five years, 0 otherwise) [PADB]	–	–	30.68%	69.32%
Driving experience indicator (1 if the participant was a licensed driver for 6 years or more, 0 otherwise) [PADB]	81.83%	18.17%	–	–
Diagonal and off-diagonal elements of the Γ matrix [t-stats in brackets], and correlation coefficients (in parentheses) for the correlated random parameters				

	Education indicator (1 if the participant has a post-graduate degree, 0 otherwise) [OADB]	Driving experience indicator (1 if the participant was a licensed driver for 6 years or more, 0 otherwise) [PADB]		Hometown indicator (1 if the participant grew up in an urban area, 0 otherwise) [OADB]	Speeding indicator (1 if the participant was not pulled over for speeding over the last five years, 0 otherwise) [PADB]
Education indicator (1 if the participant has a post-graduate degree, 0 otherwise) [OADB]	0.386 [2.35] (1.000)	–	Hometown indicator (1 if the participant grew up in an urban area, 0 otherwise) [OADB]	0.671 [2.28] (1.000)	–
Driving experience indicator (1 if the participant was a licensed driver for 6 years or more, 0 otherwise) [PADB]	-0.913 [-5.51] (-0.626)	1.137 [5.60] (1.000)	Speeding indicator (1 if the participant was not pulled over for speeding over the last five years, 0 otherwise) [PADB]	-3.977 [-2.32] (-0.928)	1.599 [2.43] (1.000)

[OADB]: Observed aggressive driving behavior
[PADB]: Perceived aggressive driving behavior

Focusing on the random parameters included in the model of male drivers, the negative correlation (i.e., the coefficient is -0.63) between the unobserved characteristics captured by the post-graduate education indicator and the driving experience indicator illustrates their heterogeneous effect on both behavioral components. As such, the participant-specific variations arising from the educational and driving background have a counter-acting impact on the likelihood of a male participant to drive aggressively and to perceive his behavior as aggressive. Similarly, the unobserved heterogeneity interactions (i.e., interactions of the unobserved factors) associated with the urban hometown indicator and the speeding violation indicator also have a mixed effect (i.e., the correlation coefficient is -0.93) on the observed and perceived aggressive driving behavior of female participants.

As a final point, the coefficient reflecting the cross-equation error term correlation is found to be statistically significant in all model specifications providing further statistical evidence on the appropriateness of the bivariate modeling framework. Unlike the other model specifications, the cross-equation error correlation of the non-distracted driving model is found to be negative. Thus, the unobserved characteristics that increase the likelihood of non-distracted drivers to drive aggressively may decrease the likelihood to correctly perceive their driving patterns. Given the non-distracted emotional state of drivers, such unobserved variations may stem from their habitual aggressive patterns as well as their limited awareness or incorrect impression of the driving incidents that constitute aggressive driving.

5. SUMMARY AND CONCLUSION

Previous research has shown that the driver-specific mechanisms determining the observed and perceived aggressive driving behavior may differ, due to variations in socio-demographic profiles, driving habits and perceptual patterns. This study aims to shed more light on the effect on these variations in cases when major sources of aggressive driving are present during the driving task, such as driver fatigue and external or internal distractions. Apart from the temporary or situational sources of aggressive driving, the driving patterns are also systematically affected by habitual trends that are inherent in the behavioral profile of male or female drivers. To that end, the systematic effect of gender on behavioral patterns of drivers is also investigated. Using driving simulation and survey data, statistical models of perceived and observed driving behavior that account for the effect of self-reported fatigue, driving distractions (rushing to destination; listening to music, and solving logical problems) and gender were estimated. To statistically accommodate the effect of multiple layers of unobserved heterogeneity arising from the nature of the simulation data (i.e., systematic unobserved variations among the driving behavior components, panel effects, unobserved factors varying systematically across drivers and interactive effect of such unobserved factors), the correlated grouped random parameters bivariate probit framework is employed.

The estimation results showed that various socio-demographic (post-graduate education level of drivers; non-urban location of hometown) and behavioral (traffic violations over the last five years) characteristics affect perceived and observed driving behavior, primarily under the effect of driver fatigue. In cases when the determinants are common between fatigued and non-fatigued drivers, the magnitude of their effect considerably differs. When driving distractions are present, the socio-demographic background of drivers (education level; ethnicity; income level; hometown location) is more influential in determining driving behavior, with some determinants having an inverse correlation across the distracted and non-distracted drivers. For example, the majority of non-distracted single drivers are more likely to perceive their behavior as aggressive, as opposed to distracted drivers, who are overall less likely to perceive that they drove aggressively. With regard to the effect of gender, a higher education level generally decreases the likelihood of male and female drivers to drive aggressively, whereas male drivers with significant driving experience are expected to overestimate their driving performance. The combined effect of gender and driving distraction is evident in the driving patterns of male drivers, especially when they “rush to destination” and “listen to music” simultaneously.

Despite the possibility of data-specific variations and underlying sample bias, this study suggests a simulation-based statistical framework for the identification of the determinants of perceived and observed driving behavior, with special focus on the major contributing sources of aggressive driving. The use of the specific framework in datasets with simulation or naturalistic driving study data can further enhance the empirical insights with regard to the mechanisms of perceived and aggressive driving behavior. Such insights can form the basis of targeted educational or training programs that will focus on the elimination of distinct causes of aggressive driving behavior.

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