

# An integrated ordered logit and latent variable model for accident injury severity and risk-taking behavior

Nicola Ortelli <sup>\*†</sup>      Matthieu de Lapparent <sup>\*</sup>      Silvia F. Varotto <sup>‡</sup>  
Michel Bierlaire <sup>†</sup>

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Transport and Mobility Laboratory  
School of Architecture, Civil and Environmental Engineering  
Ecole Polytechnique Fédérale de Lausanne  
[transp-or.epfl.ch](mailto:transp-or.epfl.ch)

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<sup>\*</sup>School of Management and Engineering Vaud, HES-SO // University of Applied Sciences and Arts Western Switzerland, {nicola.ortelli,matthieu.delapparent}@heig-vd.ch

<sup>†</sup>Transport and Mobility Laboratory, School of Architecture, Civil and Environmental Engineering, École Polytechnique Fédérale de Lausanne (EPFL), {nicola.ortelli,michel.bierlaire}@epfl.ch

<sup>‡</sup>Transport and Traffic Engineering Laboratory (LICIT-ECO7), École nationale des travaux publics de l'État (ENTPE), University Gustave Eiffel, Lyon, France, {silviafrancesca.varotto}@entpe.fr

## Abstract

This study presents a flexible model for risk-taking behavior and accident injury severity. It is specifically designed to evaluate the impact of Via Sicura, a Swiss road safety program, on the severity of accident outcomes. Our proposed model treats the risk-taking behavior of each driver as a latent variable that depends on a number of socioeconomic and contextual factors, and whose manifestation can be measured by means of behavioral indicators. The aggregated risk, a central feature of our framework, represents the combined latent risk-taking behaviors among all drivers within an accident and is successfully identified as explanatory of the severity of injuries sustained by all individuals involved. Our findings reveal that Via Sicura's repressive measures successfully deter risk-taking behavior among drivers, preventing an estimated 63 fatal, 876 major and 2'303 minor injuries over a ten-year period.

**Keywords:** accident injury severity; driving behavior; latent variable model.

# 1 Introduction

Road safety is a major concern of our modern, motorized society. According to the latest World Health Organization global status report, almost 1.2 million people die each year as a result of traffic accidents, and another 20 to 50 million suffer non-fatal injuries (World Health Organization, 2023). In addition to the pain and suffering they cause, traffic accidents also incur a heavy economic burden on victims and their families. In most countries, their consequences are estimated to exceed 3% of the annual gross domestic product.

In Switzerland, considerable efforts in favor of road safety have been carried out for the past 50 years. As a result, between 1970 and 2020 the number of fatalities on Swiss roads has dropped from 1'694 to 227. In 2013, as a further commitment to reach its ultimate target of zero fatalities or major injuries (Swiss Council for Accident Prevention, 2002), the Swiss Federal Council has initiated a road safety program called Via Sicura.

Via Sicura consists of a number of legislative measures that aim at improving road safety by ensuring that “only the drivers who have received the necessary level of instruction and possess a full driving capacity drive in safe motor vehicles and on forgiving roads” (Federal Roads Office, 2005). In addition to several preventive measures that aim at reducing accident occurrence, such as the ban on alcohol for new and professional drivers or the compulsory use of lights during the day for all motor vehicles, Via Sicura has the particularity of introducing some repressive measures too, which are believed to act as a deterrent against risk-taking behavior. In particular, a new, stricter legislation governing extreme speeding offenders and drunk drivers was introduced in January 2013, at the very beginning of the program.

The first official assessment of the program highlights its positive effect by comparing the yearly totals of major and fatal injuries between 2013 and 2015 with the ones predicted by a counterfactual model — *i.e.*, without Via Sicura — estimated on the data from 2000 to 2012 (Swiss Federal Council, 2017): according to their analysis, an average of 33 fatal injuries *per year* were prevented during the three first years of the program. Because it focuses on yearly totals, however, this approach suffers two drawbacks: (i) heterogeneity at the accident, vehicle and individual levels is ignored entirely; and (ii) the identified impact of Via Sicura is actually the combination of two distinct effects, namely on accident occurrence and on the severity of their outcomes, and those may have very different magnitudes.

To overcome these limitations, we propose a model that focuses on assessing the influence of Via Sicura on injury severity at a disaggregate level, namely through the dissuasive effect of its repressive measures on the behavior of drivers and, in turn, through the impact of the resulting change in behavior on accident outcomes. The use of a disaggregate model enables the effect of other variables to be controlled, which ultimately contributes to isolating the effect of Via Sicura.

The contributions of our research are twofold. First, we introduce a new, flexible framework for risk-taking behavior and accident injury severity modeling. Similar to the work of Lavieri et al. (2016), our framework models the risk-taking behavior of drivers as a latent variable whose value directly impacts the injury severity of all individuals involved in an accident, as well as a number of behavioral indicators used for estimation. Our framework also includes an innovative way of aggregating the risk-taking behavior of any number of drivers, meaning that our model is not limited to accidents that involve a specific number of vehicles. This is a requirement for our second contribution, which consists in using the presented framework to evaluate the efficacy of Via Sicura in a comprehensive manner. The model developed for this purpose is estimated on a dataset derived from all police reports of accidents that occurred in Switzerland between 1992 and 2022, which represent over 3.4 million accidents and 4.2 million individuals involved.

The remainder of this paper is organized as follows: Section 2 provides an overview of the existing literature on injury severity modeling and, in particular, on studies that account for the effect of driver behavior; Section 3 introduces the framework for risk-taking behavior and injury severity modeling; Section 4 presents the main characteristics of the available dataset, together with the specifics of the model developed for the assessment of the Via Sicura program; Section 5 gathers the results obtained from its estimation; finally, Section 6 summarizes the findings of this study and identifies the future steps of this research.

## 2 Literature review

While concerted efforts strive to reduce the drastic number of deaths and injuries around the world, a deep understanding of the intricacy of factors influencing traffic accident outcomes is crucial to the development of appropriate policies, laws and regulations. For this reason, accident occurrence modeling and injury severity modeling have been active fields of research for decades. Since the first accident occurrence model that included a regression component (Weber, 1970, 1971), a wide variety of studies have investigated the effect of different factors on the occurrence of accidents or on the severity of their outcomes. As concerns the latter, the existing literature deals with explaining the influence of directly observable variables on the vulnerability of individuals in different types of vehicles (de Lapparent, 2005, 2006; Xin et al., 2017), seat positions (de Lapparent, 2008; Bogue et al., 2017), on different road types (Huang et al., 2008; Qiu and Fan, 2021; Choudhary et al., 2018) or when involved in different types of accidents (Shankar and Mannering, 1996; Kockelman and Kweon, 2002).

These studies are valuable in that they provide insights into the complex interactions that vehicle, infrastructure, and human characteristics have on the severity of traffic accident injuries. Nevertheless, the vast majority entirely omits the yet crucial effects of driver behavior from their models, despite the clear benefits its analysis could bring to road safety. Specifically, understanding the impact of driver behavior could be helpful designing more impactful information campaigns and behavioral modification considerations (Mannering and Bhat, 2014). We see two obvious reasons for these omissions: (i) accident data generally do not include behavioral characteristics or psychological measurements; and (ii) the specification and estimation of models that enable the inclusion of attitudes and other latent constructs can be rather tedious. Hence, to the best of our knowledge, and despite an ongoing stream of research concerned with characterizing various driving behaviors (Tasca, 2000; Clapp et al., 2011; Scott-Parker and Weston, 2017; Hu et al., 2021), only three studies attempt to include such attitudinal aspects into their injury severity models. We briefly discuss these, as they are of direct relevance to the current study.

Nevarez et al. (2009) appear to be the first to account for driving behavior in their binary model of injury severity. They do so by introducing an “aggressive driving” dummy variable that is based on whether the driver was “speeding, tailgating, failed to yield right of way, changed lanes improperly, or disregarded other traffic control”. This simple approach is a certain improvement in comparison to the above-mentioned studies; however, by treating the aggressive behavior as exogenous, the model cannot provide insights into actions that seek to decrease injury severity by reducing aggressiveness in driving behavior.

In comparison, Paleti et al. (2010) include a similar dummy variable in their model, but treat it as endogenous — their “latent aggressive driving act propensity” is defined as a function of observed environmental, vehicle, accident and driver factors — and interact it with a number of explanatory variables in the injury-severity model. The framework proposed by Paleti et al. (2010) is therefore analogous to a latent segmentation scheme, the segmentation being based on the “aggressive driving propensity” binary variable.

Finally, the work of Lavieri et al. (2016) provides a valuable example of injury-severity models that accounts for driver behavior. In this case, two distinct behaviors—risky and distracted driving—are modeled as latent variables and their manifestation is measured by means of binary indicators. Not only is the use of indicators helpful in model identification and in increasing the efficiency of the estimated parameters (Walker, 2001), but it also mitigates the risks of endogeneity-related issues: in fact, the two indicators associated with the risky behavior—seatbelt usage and alcohol consumption—are known in the literature for being particularly problematic when treated as exogenous. The methodological framework proposed in Lavieri et al. (2016) constitutes a significant advancement towards the inclusion of driver behavior in accident-injury severity modeling; however, its symmetric structure is specifically designed for two-vehicle accidents and the resulting hybrid model simply cannot handle accidents involving fewer or more vehicles.

In this paper, we propose a new framework for risk-taking behavior and accident injury severity modeling. With the model of Lavieri et al. (2016) as a baseline, the main methodological novelty presented in this paper is an effective and innovative way of aggregating the risk-taking behaviors of any number of drivers. As it is demonstrated in the following sections, our proposed model is therefore able to handle accidents that involve virtually any number and type of vehicles, while maintaining a relatively straightforward modeling approach.

## 3 Modeling framework

### 3.1 Assumptions and definitions

We propose a hybrid model that allows accommodating the effect of a variety of factors on the risk-taking behavior of drivers and, in turn, the effect of said behavior on the severity of accident injuries. In this context, the risk-taking behavior is defined as the propensity to act in a way that deliberately disregards safety, while endangering other persons as well as oneself. Following the findings of Lavieri et al. (2016), our framework assumes that the risk-taking behavior of a driver not only affects the injury severity of the occupants of their own vehicle, but also that of all other individuals caught in the accident.

Let  $\mathcal{A}$  be a set of reported traffic accidents. We denote as  $\mathcal{V}(a)$  the set of vehicles involved in accident  $a \in \mathcal{A}$  and as  $\mathcal{I}(a, v)$  the set of individuals in each vehicle  $v \in \mathcal{V}(a)$ . For the sake of clarity, we define that the first occupant of a vehicle is always the driver, *i.e.*, the person that controls its direction and speed. The triplet  $(a, v, 1)$  therefore points to the driver of vehicle  $v \in \mathcal{V}(a)$ . Moreover, it is important to note that our model accommodates accidents that involve a variety of vehicle types, as well as pedestrians; the terms “driver” and “vehicle” are therefore to be understood in a broad sense, as they also refer to them.

Figure 1 presents our modeling framework. In a given accident  $a$ , the risk-taking behavior of each involved driver, denoted by  $r_{av1}^*$ , is modeled as a latent variable that depends on their socioeconomic characteristics and on some context variables. These explanatory variables include, among others, the age and gender of the driver, the presence of passengers in the vehicle, the type of road, the weather conditions, and the entry into force of Via Sicura. The manifestation of risk-taking behavior is measured by three behavioral indicators: (i) one of the presumed causes of the accident being attributable to recklessness; (ii) driving, riding or walking under the influence of alcohol, drugs or impairing medications; and (iii) not wearing a seatbelt or a helmet. The behavior of each driver is modeled independently; however, when an accident occurs, we assume that it is the conjunction of said behaviors that contributes to the severity of the injuries sustained by all involved individuals. The

aggregated risk  $r_a^*$  therefore represents the combination of the latent risks taken among all drivers, and is defined at the level of the accident. The other variables that are deemed to be explanatory of injury severity relate to the individual, to the vehicle or to the circumstances of the accident. They include, among others, the age and the gender of the individual, the use of a seatbelt, the speed limit and the number of vehicles involved.

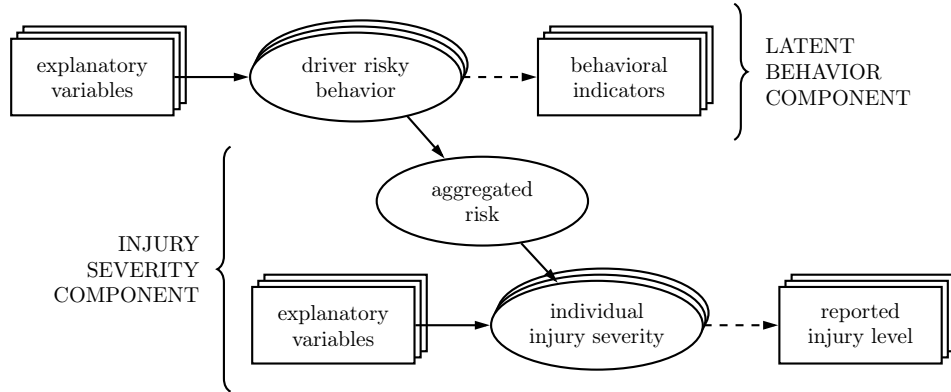


Figure 1: Structure of the integrated ordered logit and latent variable model for accident injury severity and risk-taking behavior. The observable variables are depicted as rectangles and the latent ones as ellipses. Solid arrows stand for structural equations, whereas dashed arrows represent the measurement equations between latent variables and their indicators.

### 3.2 Structural equations

The latent risk-taking behavior of each driver, denoted by  $r_{av1}^*$ , is defined as a linear combination of exogenous variables that are meant to explain said behavior:

$$r_{av1}^* = \gamma \mathbf{z}'_{av1} + \eta_{av1}, \quad (1)$$

where  $\mathbf{z}_{av1}$  is a vector that contains the explanatory variables and  $\gamma$  is a vector of parameters to be estimated from the data.<sup>1</sup> In addition,  $\eta_{av1}$  is an idiosyncratic error term that captures unobserved components. It is assumed to be independently and identically Gumbel-distributed across all drivers, as well as uncorrelated with observable factors:

$$\eta_{av1} \stackrel{\text{iid}}{\sim} \text{Gumbel}(0, \mu). \quad (2)$$

The manifestation of risk-taking behavior is measured using a number of behavioral indicators, which, irrespective of their nature in the data, rely on the same number of latent continuous variables. Let  $I_{av1p}^*$  be one such underlying continuous variable; its value depends on the driver's risk-taking behavior  $r_{av1}^*$ , as well as on a vector of variables  $\mathbf{s}_{av1p}$  that are deemed to be explanatory of the behavioral indicator:

$$I_{av1p}^* = \theta_p \mathbf{s}'_{av1p} + \lambda_p r_{av1}^* + \nu_{av1p}, \quad (3)$$

where  $\theta_p$  and  $\lambda_p$  are parameters to be estimated from the data and  $\nu_{av1p}$  are idiosyncratic terms that account for unobserved variables.<sup>2</sup> The error terms are assumed to be independently and identically distributed across all observations, as well as uncorrelated with

<sup>1</sup>For the sake of compactness in notation, the intercept term is included in the vector of parameters  $\gamma$ .

<sup>2</sup>For the sake of compactness in notation, the intercept term is included in the vector of parameters  $\theta_p$ .

observable factors. They follow a logistic distribution with scale parameter  $\delta_p > 0$ :

$$\nu_{av1p} \stackrel{\text{iid}}{\sim} \text{Logistic}(0, \delta_p). \quad (4)$$

As already stated, individual injury severity is influenced by the latent risk-taking behavior of all drivers involved in the accident. The challenge here is to formulate an appropriate synthetic variable that aggregates all these latent behaviors into a single value that reflects the overall level of risk in the accident. In the context of this study, we define the aggregated risk  $r_a^*$  as the maximum risk-taking behavior among all involved drivers:

$$r_a^* = \max_{v \in \mathcal{V}(a)} (r_{av1}^*) \quad (5)$$

Given that the risk-taking behaviors of all drivers follow the same Gumbel distribution, the aggregated risk  $r_a^*$  is also Gumbel-distributed:

$$r_a^* \stackrel{\text{iid}}{\sim} \text{Gumbel} \left( \mu \sum_{v \in \mathcal{V}(a)} \exp \left( \frac{\gamma \mathbf{z}'_{av1}}{\mu} \right), \mu \right), \quad (6)$$

where  $\mu$  is the same scale parameter as in (2).

Finally, the latent injury severity associated with individual  $i \in \mathcal{I}(a, v)$  is denoted by  $U_{avi}$  and defined as:

$$U_{avi} = \beta \mathbf{x}'_{avi} + \alpha r_a^* + \varepsilon_{avi}, \quad (7)$$

where  $\mathbf{x}_{avi}$  is a vector containing the observable variables that are deemed to be explanatory of individual levels of injury,  $\beta$  and  $\alpha$  are vectors of parameters to be estimated from the data,<sup>3</sup> and  $\varepsilon_{avi}$  is an idiosyncratic error term that accounts for unobserved variables. It is assumed to be independently and identically distributed across all observations, as well as uncorrelated with observable factors:

$$\varepsilon_{avi} \stackrel{\text{iid}}{\sim} \text{Logistic}(0, \sigma). \quad (8)$$

## 4 Case study

### 4.1 Data description

The data under consideration are derived from police reports of traffic accidents that occurred in Switzerland between 1992 and 2022.<sup>4</sup> In total, the dataset contains information about 2.03 million accidents, 3.40 million involved vehicles—including pedestrians—and 4.22 million occupants of said vehicles; however, due to missing values in important explanatory variables, approximately one in ten observations cannot be exploited.<sup>5</sup>

Figure 2 shows the proportion of observations retained for model estimation. Different samples are used for each component: the latent behavior component is estimated using only the observations associated to drivers, whereas the injury severity component is estimated using the observations of all individuals involved in “complete accidents”, *i.e.*, accidents for

<sup>3</sup>For the sake of compactness in notation, the intercept term is included in the vector of parameters  $\beta$ .

<sup>4</sup>Verkehrsunfall Jahresdatensatz (DWH-VU), Federal Roads Office.

<sup>5</sup>We identify two reasons behind these missing values: (i) the number of collected variables increased through the years, as the official report template was updated in 2011 and in 2018; and (ii) the level of detail and completeness of the reports seems to be dependent on the severity of the accidents, which means that the share of severe accidents is slightly higher in the selected samples than in the original dataset.

which not a single value is missing. That represents 1.61 million accidents, or 79.4% of the accidents in the original dataset. The observations relative to drivers involved in “incomplete accidents” are still used to estimate the latent behavior component, so as to make the most out of the available data and improve the overall quality of the model. Table 7 in the Appendix presents an overview of the two samples used for estimation as well as of the original dataset, for comparative purposes.

The variables that we consider to be explanatory of the risk-taking behavior and of injury severity are described in Table 1 and Table 2, respectively. The original dataset distinguishes between 54 distinct vehicle types. For the sake of simplicity, we group those into six categories that we define based on the maximum speed each vehicle type can reach and the level of protection it offers to its occupants: (i) pedestrians; (ii) slow modes — *i.e.*, skateboards, scooters, bicycles and slow e-bikes; (iii) fast e-bikes and mopeds; (iv) motorcycles — including quad bikes; (v) cars and vans; and (vi) heavy vehicles — *i.e.*, trucks, coaches, lorry units and tractors. In total, these six categories gather 92.4% of the observations, and missing values account for another 5.0%. The remaining 2.6% are vehicles that do not clearly fit in any of these categories and are therefore dropped from the data.

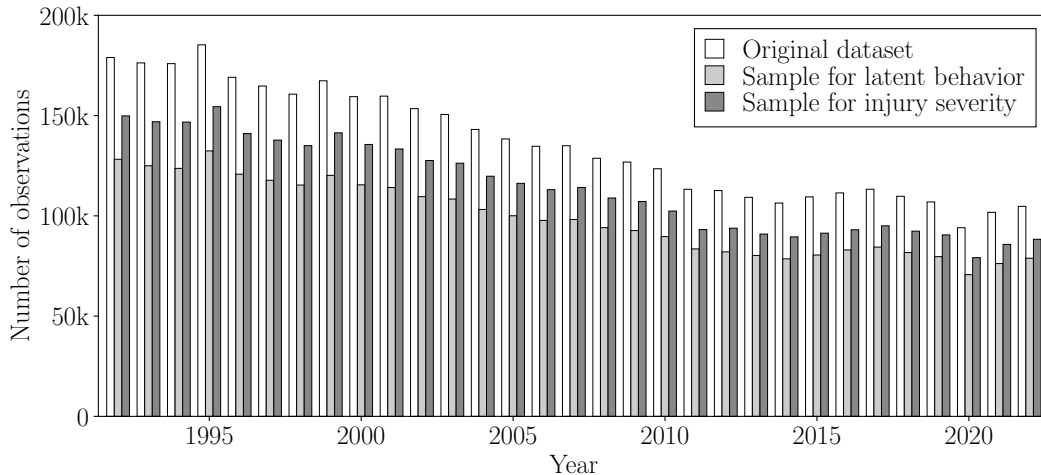


Figure 2: Number of observations per year in the original dataset and amounts retained from each year for the estimation of the latent behavior and injury severity components.

## 4.2 Measurement equations

Three binary indicators of risk-taking behavior are identified in the available data: (i) one of the presumed causes of the accident being attributable to recklessness; (ii) driving, riding or walking under the influence of alcohol, drugs or impairing medications; and (iii) not wearing a seatbelt or a helmet. In our model, each of them is defined as

$$I_{av1p} = \begin{cases} 0 & \text{if } I_{av1p}^* \leq \kappa_{p1}, \\ 1 & \text{otherwise,} \end{cases} \quad (9)$$

where  $I_{av1p}^*$  is the underlying continuous variable of indicator  $I_{av1p}$ , as defined in (3), and  $\kappa_{p1}$  is the associated threshold parameter, to be estimated from the data. For the sake of compactness in notation, let  $\Theta_p = (\theta'_p, \lambda_p, \delta_p, \kappa_{p1})'$  be the vector of unknown parameters. Conditional on  $r_{av1}^*$ , the probability that the discrete indicator  $I_{av1p}$  takes value  $\ell \in \{0, 1\}$



Table 1: Description of the explanatory variables of the risk-taking behavior.

Variable	Type	Description
Age	cont.	<i>Age of the driver in years.</i>
Gender	bin.	<i>1 if female and 0 otherwise.</i>
Learner driver	bin.	<i>1 if the vehicle requires a license and the driver only holds a learner or probationary one, and 0 otherwise.</i>
Passenger	bin.	<i>1 if one or more passengers in the vehicle, 0 otherwise.</i>
Child passenger	bin.	<i>1 if one or more passengers are less than 13 years old, 0 otherwise.</i>
Adverse weather	bin.	<i>1 if it was raining, snowing or hailing at the time and place of the accident, and 0 otherwise.</i>
Late night	bin.	<i>1 if the accident occurred between 22 PM and 5 AM, 0 otherwise.</i>
Location	cat.	<i>Location of the accident — urban, rural or highway — encoded using dummy variables.</i>
Via Sicura	bin.	<i>1 for all accidents that occurred in 2013 or later, and 0 otherwise.</i>
Collection year	cont.	<i>Year of collection of the observation, from 0 for 1992 to 30 for 2022.</i>

is computed as

$$\Pr(I_{av1p} = \ell \mid \mathbf{s}_{av1p}, r_{av1}^*; \Theta_p) = F\left(\frac{\kappa_{p\ell+1} - \boldsymbol{\theta}_p \mathbf{s}'_{av1p} - \lambda_p r_{av1}^*}{\delta_p}\right) - F\left(\frac{\kappa_{p\ell} - \boldsymbol{\theta}_p \mathbf{s}'_{av1p} - \lambda_p r_{av1}^*}{\delta_p}\right), \quad (10)$$

where  $F$  is the cumulative distribution function of the logistic distribution and, by convention,  $\kappa_{p0} \equiv -\infty$  and  $\kappa_{p2} \equiv +\infty$ .

For the sake of illustration, Figure 3 shows the distribution of values of the indicators through the years. The indicator related to substance abuse shows a sudden increase in negative values in 2011, which is explained by the introduction of a new official accident report template. Prior to that, the results of breathalyzers and blood tests had to be reported only if positive. The few missing values in the indicator related to seatbelt or helmet usage correspond to pedestrians, for whom said indicator is not defined; their risk-taking behavior is therefore measured using only the two other indicators. Figure 4 illustrates the distribution of values of the indicators for each vehicle category, missing values excluded. It is worth noting that the ratio between positive and negative values varies greatly across indicators, but also from one vehicle category to another.

Finally, the severity of the injuries suffered by each individual is reported on the following four-level scale: 0—none, 1—minor, 2—major, and 3—fatal. In our model, these outcomes are generated by their corresponding latent injury severity  $U_{avi}$ , as follows:

$$y_{avi} = \begin{cases} 0 & \text{if } U_{avi} \leq \tau_1, \\ 1 & \text{if } \tau_1 < U_{avi} \leq \tau_2, \\ 2 & \text{if } \tau_2 < U_{avi} \leq \tau_3, \\ 3 & \text{if } \tau_3 < U_{avi}, \end{cases} \quad (11)$$

where  $\tau_1$ ,  $\tau_2$  and  $\tau_3$  are threshold parameters to be estimated from the data. Fatal injuries are those that result in death within 30 days after the accident, whereas major injuries are defined as those that require a hospitalization of more than one day. Before 2015, however, major injuries also included injuries that “preclude all normal home activities for at least 24 hours”. This change is taken into account by defining two different parameters for threshold

Table 2: Description of the explanatory variables of injury severity.

Variable	Type	Description
Age	cont.	Age of the individual in years.
Gender	bin.	1 if female and 0 otherwise.
Vehicle category	cat.	We distinguish six: (i) pedestrians, (ii) slow modes, (iii) e-bikes & mopeds, (iv) motorcycles, (v) cars & vans, and (vi) heavy vehicles.
Seatbelt	bin.	1 if the individual is wearing a seatbelt and 0 otherwise.
While driving	bin.	1 if the accident occurred while driving, and 0 if while parking.
Single vehicle	bin.	1 if a single vehicle was involved in the accident, and 0 otherwise.
Speed limit	cont.	Speed limit at the site of the accident. In Switzerland, it ranges from 20 km/h in some city center areas to 120 km/h on highways.
Aggregated risk	cont.	Defined as the maximum risk-taking behavior among all drivers involved in the accident.

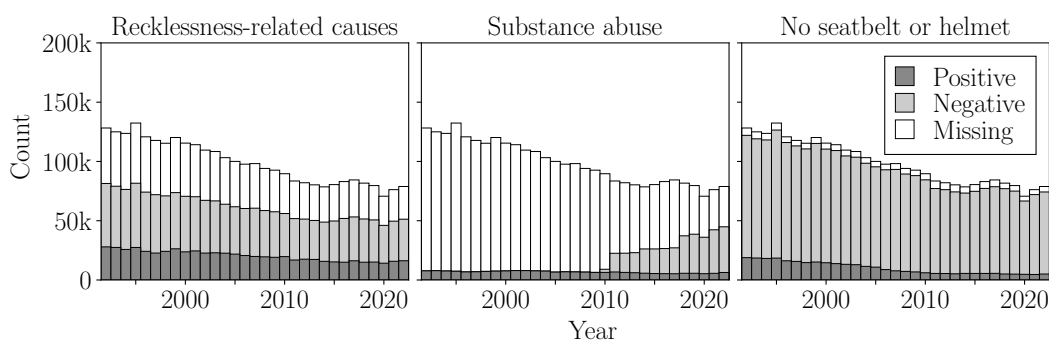


Figure 3: Evolution of the values of the indicators over time.

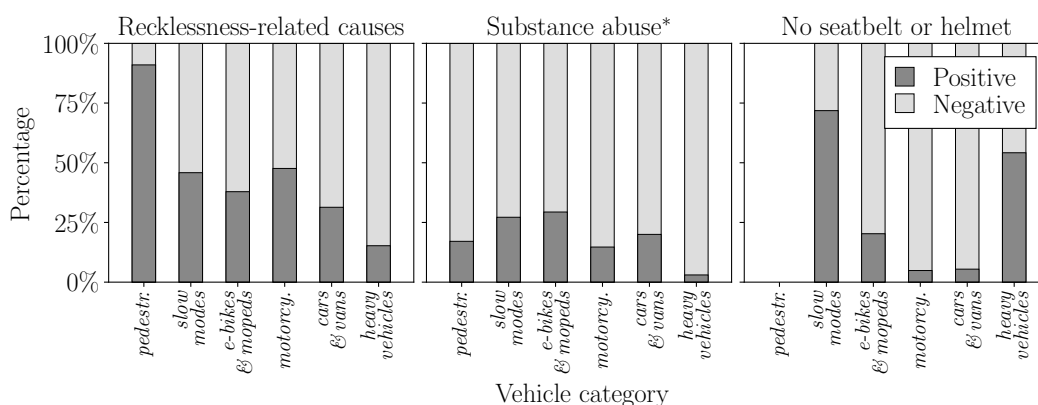


Figure 4: Distribution of the values of the indicators for each vehicle category, missing values excluded. The indicator related to substance abuse only reports the values from 2011 onward to account for the change of accident report template.

$\tau_2$ : the first is used for accidents that occurred between 1992 and 2014, and the second for those between 2015 and 2022.

For the sake of compactness in notation, let  $\mathbf{B} = (\boldsymbol{\beta}', \alpha, \sigma, \tau_1, \tau_2, \tau_3)'$  be the vector of unknown parameters. For all  $a \in \mathcal{A}$ ,  $v \in \mathcal{V}(a)$  and  $i \in \mathcal{I}(a, v)$ , the probability—conditional on  $r_a^*$ —that the reported level of injury  $y_{avi}$  is equal to  $k \in \{0, 1, 2, 3\}$  is defined as

$$\Pr(y_{avi} = k \mid \mathbf{x}_{avi}, r_a^*; \mathbf{B}) = F\left(\frac{\tau_{k+1} - \boldsymbol{\beta}\mathbf{x}'_{avi} - \alpha r_a^*}{\sigma}\right) - F\left(\frac{\tau_k - \boldsymbol{\beta}\mathbf{x}'_{avi} - \alpha r_a^*}{\sigma}\right), \quad (12)$$

where  $\tau_0 \equiv -\infty$  and  $\tau_K \equiv +\infty$ .

## 5 Identification and estimation

The two components of the model are estimated sequentially, for the sake of reducing the overall computational cost. The sequential approach also allows aggregating the individual driving behaviors between the two steps, rather than within an otherwise single but complex simultaneous-estimation process. The observations from 2012 and 2013 are set aside for out-of-sample validation, as those are the years immediately preceding and following the entry into force of the Via Sicura road safety program. We use the Biogeme package for Python (Bierlaire, 2023) for both estimations. The estimation reports of both components are given in Table 4.

### 5.1 Latent behavior component

The latent behavior component is estimated first. The contribution of each driver to the likelihood function is given by:

$$\int_{\mathbb{R}} \prod_{p=1}^3 \Pr(I_{av1p} = \ell_{av1p} \mid \mathbf{s}_{av1p}, r_{av1}^*; \boldsymbol{\Theta}_p) g(\eta_{av1} \mid \mu) d\eta_{av1}, \quad (13)$$

where  $g$  is the probability density function of  $\eta_{av1}$ , conditional on  $\mu$ , and  $\ell_{av1p}$  is the observed value of the  $p$ -th indicator for the driver of vehicle  $v \in \mathcal{V}(a)$ . Up to some additional normalization constraints, the derived log likelihood function is tractable using Monte-Carlo integration methods and the asymptotic properties of the estimator therefore rely on standard simulation-based inference results. The estimation results of the latent behavior component are reported in Table 3.

Following the observation that the values of the indicators seem to depend on the type of vehicle—see Figure 4—a distinct set of measurement equations is defined for each vehicle category. In addition to the latent behavior and the intercept term, we assume that the value of the indicator related to the use of a seatbelt or helmet also depends on whether the vehicle was legally required to be equipped with a seatbelt at the time of the accident.<sup>6</sup> The measurement equation of the indicator related to recklessness also includes an additional term, which accounts for poor weather conditions. We add this term because the cause “speed not suited to weather conditions”, which we associate with recklessness, is systematically identified whenever the weather is adverse at the time and place of the accident. Finally, the measurement equation of the indicator related to substance abuse includes a binary variable that accounts for the change of accident report template.

<sup>6</sup>In Switzerland, trucks, coaches, lorry units and quad bikes were not required to be fitted with seatbelts until 2006, and the obligation to fit seatbelts on tractors was introduced in 2017.

Table 3: Estimation results of the latent behavior component.

Parameter	Value	<i>t</i> -test
<b>Recklessness-related causes</b>		
<i>θ</i> -intercept, pedestrians	2.90	44.8
<i>θ</i> -intercept, slow modes	0.264	4.01
<i>θ</i> -intercept, e-bikes & mopeds	-0.337	-3.65
<i>θ</i> -intercept, motorcycles	0.498	3.12
<i>θ</i> -intercept, cars & vans	-0.680	-2.98
<i>θ</i> -intercept, heavy vehicles	-2.01	-11.1
<i>θ</i> -poor weather	1.53	86.4
<i>λ</i> -risk-taking behavior, pedestrians	0.381	18.3
<i>λ</i> -risk-taking behavior, slow modes	0.559	16.1
<i>λ</i> -risk-taking behavior, e-bikes & mopeds	0.588	13.9
<i>λ</i> -risk-taking behavior, motorcycles	0.829	59.4
<i>λ</i> -risk-taking behavior, cars & vans	1.12	94.9
<i>λ</i> -risk-taking behavior, heavy vehicles	0.866	37.3
<b>Substance abuse</b>		
<i>θ</i> -intercept, pedestrians	-0.591	-0.657
<i>θ</i> -intercept, slow modes	1.98	1.46
<i>θ</i> -intercept, e-bikes & mopeds	-0.407	-0.423
<i>θ</i> -intercept, motorcycles	-3.31	-8.41
<i>θ</i> -intercept, cars & vans	-3.94	-4.98
<i>θ</i> -intercept, heavy vehicles	-5.13	-16.2
<i>θ</i> -old template	28.6	19.0
<i>λ</i> -risk-taking behavior, pedestrians	4.37	8.02
<i>λ</i> -risk-taking behavior, slow modes	6.17	21.9
<i>λ</i> -risk-taking behavior, e-bikes & mopeds	4.50	20.9
<i>λ</i> -risk-taking behavior, motorcycles	3.27	7.12
<i>λ</i> -risk-taking behavior, cars & vans	4.04	20.8
<i>λ</i> -risk-taking behavior, heavy vehicles	1.18	13.3
<b>No seatbelt or helmet</b>		
<i>θ</i> -intercept, pedestrians	0	—
<i>θ</i> -intercept, slow modes	1.52	16.6
<i>θ</i> -intercept, e-bikes & mopeds	-1.22	-37.3
<i>θ</i> -intercept, motorcycles	-2.84	-88.8
<i>θ</i> -intercept, cars & vans	-2.74	-118
<i>θ</i> -intercept, heavy vehicles	-1.99	-107
<i>θ</i> -no protection needed	4.03	219
<i>λ</i> -risk-taking behavior, pedestrians	0	—
<i>λ</i> -risk-taking behavior, slow modes	0.336	16.6
<i>λ</i> -risk-taking behavior, e-bikes & mopeds	0.165	16.1
<i>λ</i> -risk-taking behavior, motorcycles	0.143	15.9
<i>λ</i> -risk-taking behavior, cars & vans	0.113	45.2
<i>λ</i> -risk-taking behavior, heavy vehicles	0.0368	4.27

continued

Table 3— continued: Estimation results of the latent behavior component.

Parameter	Value	<i>t</i> -test
<b>Risk-taking behavior</b>		
$\gamma$ -age, 0-18	-0.108	-10.8
$\gamma$ -age, 18-35	-0.0245	-32.2
$\gamma$ -age, 35-65	-0.0105	-21.8
$\gamma$ -age, 65-100	0.00296	2.31
$\gamma$ -age, with passenger, 0-18	0.0275	27.8
$\gamma$ -age, with passenger, 18-35	-0.0278	-16.8
$\gamma$ -age, with passenger, 35-65	-0.00877	-7.58
$\gamma$ -age, with passenger, 65-100	0.00134	0.448
$\gamma$ -age, female driver, 0-18	-0.0488	-43.0
$\gamma$ -age, female driver, 18-35	0.0195	13.0
$\gamma$ -age, female driver, 35-65	0.00316	3.32
$\gamma$ -age, female driver, 65-100	0.00619	2.41
$\gamma$ -age, female driver, with passenger, 0-18	-0.0188	-9.56
$\gamma$ -age, female driver, with passenger, 18-35	0.0219	6.70
$\gamma$ -age, female driver, with passenger, 35-65	-0.00174	-0.701
$\gamma$ -age, female driver, with passenger, 65-100	-0.00342	-0.443
$\gamma$ -learner driver	-0.239	-16.9
$\gamma$ -child passenger	-0.254	-13.3
$\gamma$ -adverse weather	-0.227	-14.3
$\gamma$ -late night	2.09	88.5
$\gamma$ -urban	0	—
$\gamma$ -rural	1.16	76.6
$\gamma$ -highway	1.21	76.2
$\gamma$ -year	0.0175	14.1
$\gamma$ -year, squared	-0.000874	-16.2
$\gamma$ -via sicura	-0.240	-14.9
$\mu$	1.50	79.7

Table 4: Estimation reports of the latent behavior and injury severity components.

	Latent behavior	Injury severity
Number of estimated parameters	63	22
Sample size	2'903'409	3'355'668
Initial log likelihood, normalized	-0.693	-0.870
Final log likelihood, normalized	-0.347	-0.480
Out-of-sample log likelihood, normalized	-0.349	-0.489

The effect of age on the risk-taking behavior is modeled as a piecewise-linear function with, as breakpoints, the values 18, 35 and 65; it is also segmented based on the gender of the driver and the presence of passengers in the vehicle. For ease of interpretation, Figure 5 illustrates the obtained results. Those indicate that substantial differences in behavior exist between males and females under 40, whereas older drivers of both genders tend to have a more similar behavior. Up to that age, males are shown to take significantly more risks, and the presence of passengers further increases such behavior. After 35, the risk-taking behavior is shown to slowly decrease for both genders, even though a slight difference between males and females persists. Interestingly, 40 also coincides with the age at which the effect of passengers reverses and starts reducing the risk-taking behavior of drivers. The high level of risk-taking behavior associated with children is due to an extremely low rate of seatbelt or helmet usage: only 21.2% of drivers under 13 are wearing either, against 89.3% in the whole sample.

All other parameters in the structural equation of the risk-taking behavior are statistically significant and have the expected signs. In particular, learner drivers, child passengers and adverse weather are associated with a reduction in risk-taking behavior, whereas the late night variable is shown to increase the risk-taking behavior of drivers. Drivers also seem to take more risks on highways and rural roads than in urban areas. The year of collection is used to capture the evolution of risk-taking behavior among drivers in Switzerland, including the effect of all other efforts made by the Swiss government to promote safe behavior in the past 30 years — awareness-raising campaigns, safety education programs, driver training courses, and so on; this effect is modeled as a second-degree power series of the year of collection, and both parameters seem to be significant. Finally, the variable accounting for the dissuasive effect of Via Sicura is shown to reduce the risk-taking behavior of drivers; its impact is similar in magnitude to the one associated with learner drivers.

The effect of Via Sicura is also visible in the top half of Figure 6, which exhibits the distribution of risk-taking behavior among drivers for each year of data, as obtained via Monte-Carlo integration. The bottom half of the figure shows the distribution of the *aggregated risk* for each year of data, that is, the maximum risk-taking behavior among the drivers involved in each accident, as defined in (6). From 2013 onward, Figure 6 also shows the counterfactual distribution of risk-taking behavior without the effect of Via Sicura, *i.e.*, as if the measures of the road safety program were never implemented.

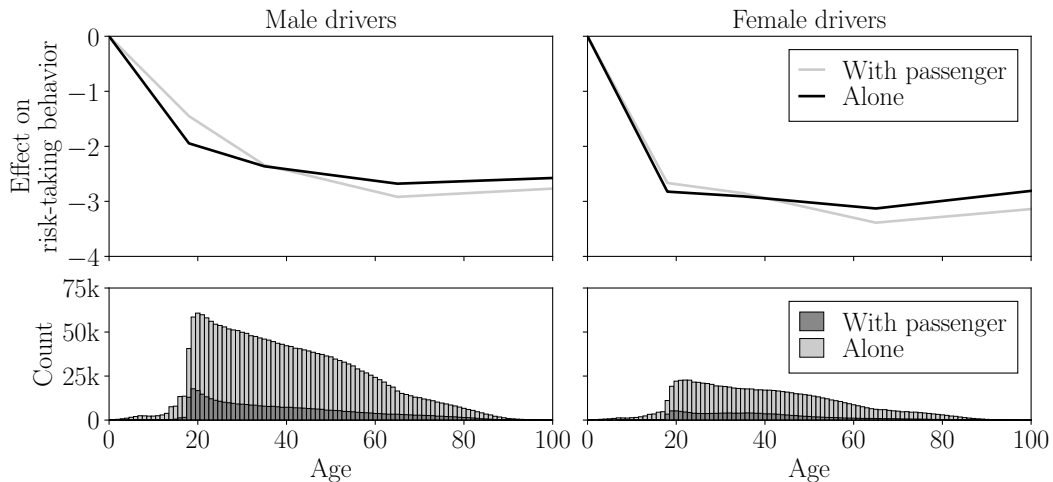


Figure 5: Age distribution and effect on risk-taking behavior for each segment of drivers.

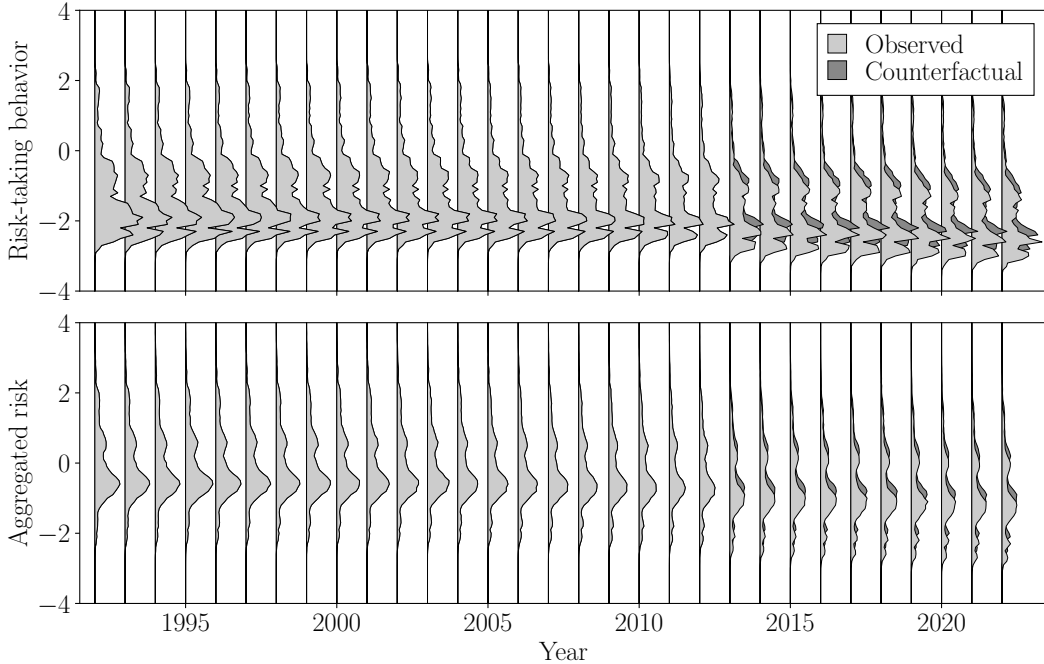


Figure 6: Distribution of driver risk-taking behavior and resulting aggregated risks for each year of data. The counterfactual distributions refer to ignoring the effect of Via Sicura, as if the measures of the road safety program were never implemented.

## 5.2 Injury severity component

In the second component of the model, the individual contribution to the likelihood function is given as

$$\int_{\mathbb{R}} \Pr(y_{avi} = k \mid \mathbf{x}_{avi}, r_a^*; \mathbf{B}) g(r_a^* \mid \mu) dr_a^*. \quad (14)$$

Again, we resort to simulated maximum likelihood estimation based on Monte-Carlo integration techniques. The deterministic part of the aggregated risk  $r_a^*$  is computed prior to the estimation process by injecting into (6) the values of  $r_{av1}^*$  and  $\omega$  obtained in the previous step. Table 5 gathers the estimation results of the injury severity component. It is worth pointing out that the difference between the two estimated values of the threshold  $\tau_2$  — until 2014 and since 2015 — is statistically significant.

Age is again modeled as a piecewise-linear function with the values 18, 35 and 65 as break-points and segmented based on the gender of the individual. Figure 7 illustrates its effect for male and female individuals, together with the age distribution for each gender. All other parameters are statistically significant and have the expected signs: the parameters associated with the vehicle categories coincide with the level of protection each vehicle provides to its occupants, wearing a seatbelt is associated with a decrease in injury severity and so are accidents that occurred while parking, whereas single-vehicle accidents and higher speed limits increase the chances of sustaining injuries.<sup>7</sup> These two last variables are taken into account only for accidents that occurred while driving; their effect is set to zero for accidents that occurred while parking.

<sup>7</sup>The speed limit is included as a proxy of the actual driving speed, which unfortunately is not available.

Table 5: Estimation results of the injury severity component.

Parameter	Value	<i>t</i> -test
<b>Individual injury severity</b>		
$\alpha$ -aggregated risk	0.136	76
$\beta$ -age, 0-18	0.0223	29.9
$\beta$ -age, 18-35	0.000874	2.05
$\beta$ -age, 35-65	0.00563	20.2
$\beta$ -age, 65-100	0.019	26.9
$\beta$ -age, female, 0-18	0.0395	94.9
$\beta$ -age, female, 18-35	0.0000581	0.0868
$\beta$ -age, female, 35-65	-0.00227	-5.20
$\beta$ -age, female, 65-100	-0.00696	-6.47
$\beta$ -pedestrians	0.635	49.9
$\beta$ -slow modes	0.238	18.3
$\beta$ -e-bikes & mopeds	-0.0654	-4.23
$\beta$ -motorcycles	-0.0692	-5.03
$\beta$ -cars & vans	-2.12	-161
$\beta$ -heavy vehicles	-3.89	-203
$\beta$ -seatbelt	-1.34	-215
$\beta$ -while parking	-1.34	-82.9
$\beta$ -while driving, single-vehicle accident	0.559	138
$\beta$ -while driving, speed limit	0.00963	141
<b>Reported injury level</b>		
$\tau_1$	0	—
$\tau_2$ -until 2014	2.38	631
$\tau_2$ -since 2015	2.65	405
$\tau_3$	5.37	513

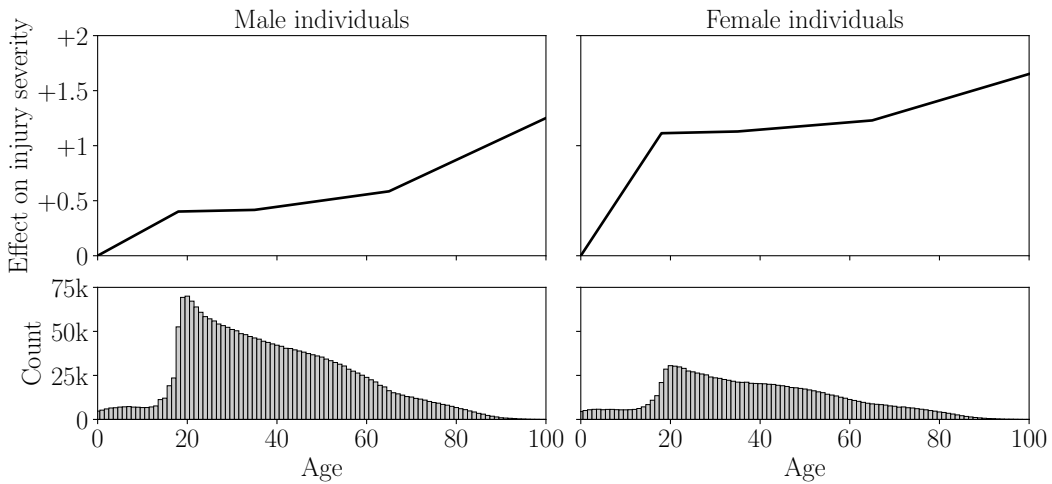


Figure 7: Age distribution and effect on injury severity for male and female individuals.



The effect of wearing a helmet is not considered in our model because its effect could not be correctly identified for any of the relevant vehicle categories. Our explanation for this unexpected result is that a helmet reduces the chances of major and fatal injuries, but is not as effective in preventing minor injuries. In fact, the available data shows a higher rate of minor injuries for cyclists and motorcyclists that wear a helmet than for those who do not. This effect could be captured by replacing the threshold parameters with functions of relevant exogenous variables as in Eluru et al. (2008), but we leave this for future work.

Finally, using a simple iterative procedure, we calibrate the threshold parameters of the injury severity component such that the model replicates the observed shares of the four levels of severity. We then simulate the *counterfactual* shares between 2013 and 2022, that is, without including the effect of Via Sicura in the latent behavior component. The results in Table 6 indicate a difference of 63 fatal, 876 major and 2'303 minor injuries over the ten-year period. While those can be attributed to the dissuasive effect of Via Sicura, they should not be directly compared with the 33 fatal injuries per year mentioned in the official evaluation because our approach only accounts for the effect of the road safety program on the severity of injuries, and not on the occurrence of the accidents that cause them.

Table 6: Observed and counterfactual shares of the levels of severity between 2013 and 2022.

Level of injury	Observed shares		Counterfactual	
None	702'739	78.4 %	699'497	78.1 %
Minor	156'362	17.5 %	158'665	17.7 %
Major	34'898	3.9 %	35'774	4.0 %
Fatal	1'926	0.2 %	1'989	0.2 %

## 6 Conclusion

This paper proposes a flexible framework for risk-taking behavior and accident injury severity modeling, for the purpose of evaluating the effect of the Via Sicura road safety program on accident outcomes. Recognizing the importance of driver behavior in determining accident injury severity, the main novelty of our framework is the introduction of the aggregated risk, defined as the maximum risk-taking behavior among all drivers involved in an accident. This definition implies that our framework can accommodate accidents involving any number of vehicles, which is central to the comprehensive assessment of public policies.

Our proposed model is shown to successfully capture the dissuasive effect that the repressive measures have on the behavior of drivers and, in turn, the impact of this change in behavior on the severity of accident outcomes. According to our model, by acting as a deterrent against risk-taking behavior, the repressive measures of Via Sicura would have successfully prevented 63 fatal injuries, 876 major injuries and 2'303 minor injuries over ten years, had the same number and types of accidents occurred without the program. Since it is plausible that more accidents would have happened without Via Sicura, these numbers should be understood as lower bound estimates.

Intended future work focuses on replacing the ordered logit formulation of the injury severity component by a generalized ordered logit (Eluru et al., 2008), which allows for a more realistic modeling of variables that are known to impact specific levels of injury differently, such as the use of a helmet for cyclists and motorcyclists. Compared to the current approach, the generalized ordered logit formulation defines the threshold values of the injury severity scale

as functions of relevant exogenous variables; all thresholds may then vary across accidents, vehicles and individuals, so as to better capture heterogeneity in the data. Another natural advancement of this work could consist in including other behaviors that drivers may adopt, such as distracted or careless driving as in Lavieri et al. (2016), to further improve the realism of our model and to account for additional unobserved heterogeneity among drivers. Finally, further investigation could focus on alternative ways of aggregating the risk-taking behavior of drivers. While the maximum was chosen for its simplicity, relevance and interpretability, developing and comparing other candidates could deserve a paper in its own rights.

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## Appendix

See Table 7.

Table 7: Descriptive statistics of the original dataset and the samples. The variables available in the dataset are organized into three hierarchical levels. At the highest level, the variables describe the context of the accident, which is common to all involved individuals. The intermediate level gathers the attributes of the vehicles and of their drivers; these are therefore shared by all their occupants. Finally, the lowest level refers to the individual characteristics of the occupants of each vehicle.

	Original dataset		Sample for latent behavior component		Sample for injury severity component	
Accidents:	2'031'162	100.0 %	1'809'150	100.0 %	1'612'272	100.0 %
Location:						
<i>urban</i>	1'353'266	66.6 %	1'149'654	63.5 %	1'009'080	62.6 %
<i>rural</i>	420'257	20.7 %	405'877	22.4 %	368'753	22.9 %
<i>highway</i>	257'639	12.7 %	253'619	14.0 %	234'439	14.5 %
Vehicles involved:						
1	823'187	40.5 %	612'725	33.9 %	565'599	35.1 %
2	1'076'823	53.0 %	1'065'371	58.9 %	929'146	57.6 %
3	106'334	5.2 %	106'252	5.9 %	95'555	5.9 %
4+	24'818	1.2 %	24'802	1.4 %	21'972	1.4 %
Vehicles:	3'404'730	100.0 %	3'065'704	100.0 %	2'806'155	100.0 %
Vehicle category:						
<i>pedestrians</i>	84'638	2.5 %	83'879	2.7 %	72'340	2.6 %
<i>soft modes</i>	136'613	4.0 %	133'876	4.4 %	122'781	4.4 %
<i>e-bikes &amp; mopeds</i>	41'184	1.2 %	40'161	1.3 %	37'362	1.3 %
<i>motorcycles</i>	171'716	5.0 %	169'571	5.5 %	154'107	5.5 %
<i>cars &amp; vans</i>	2'577'401	75.7 %	2'509'508	81.9 %	2'301'289	82.0 %
<i>heavy vehicles</i>	135'087	4.0 %	128'709	4.2 %	118'276	4.2 %
<i>other/unknown</i>	258'252	7.6 %	0	0.0 %	0	0.0 %
Occupants:						
1	2'832'858	83.2 %	2'502'439	81.6 %	2'289'401	81.6 %
2	414'251	12.2 %	408'379	13.3 %	375'688	13.4 %
3+	157'621	4.6 %	154'886	5.1 %	141'066	5.0 %
Individuals:	4'224'308	100.0 %	3'065'705	100.0 %	3'540'412	100.0 %
Gender:						
<i>male</i>	2'644'447	62.6 %	2'206'132	72.0 %	2'359'508	66.6 %
<i>female</i>	1'299'163	30.8 %	859'573	28.0 %	1'180'904	33.4 %
<i>unknown</i>	280'698	6.6 %	0	0.0 %	0	0.0 %
Age:						
0-18	392'819	9.3 %	148'974	4.9 %	349'620	9.9 %
19-35	1'541'767	36.5 %	1'240'197	40.5 %	1'393'073	39.3 %
36-65	1'642'686	38.9 %	1'394'862	45.5 %	1'476'088	41.7 %
66+	352'845	8.4 %	281'672	9.2 %	321'631	9.1 %
<i>unknown</i>	294'191	7.0 %	0	0.0 %	0	0.0 %
Level of injury:						
<i>none</i>	3'422'664	81.0 %	2'417'489	78.9 %	2'817'904	79.6 %
<i>minor</i>	628'621	14.9 %	498'863	16.3 %	569'888	16.1 %
<i>major</i>	159'853	3.8 %	138'296	4.5 %	142'120	4.0 %
<i>fatal</i>	13'170	0.3 %	11'057	0.4 %	10'500	0.3 %