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

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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.

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, educational and technical 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 focus on 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

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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. Specifically, a stricter legislation governing extreme speeding offenders and drunk or reckless drivers was introduced in January 2013, at the very beginning of the program; besides increased fines and longer license withdrawals, this new legislation also includes the possibility of prison sentences for repeat offenders and drivers who commit particularly serious offenses.

The first official assessment of the program, published in 2016, highlights the positive effect of its measures 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; Federal Roads Office, 2017). According to their results, an average of 33 fatal injuries *per year* were prevented during the three first years of the program, 17 of which are entirely attributed to the new legislation governing extreme offenders. Because it focuses on yearly totals, however, the followed approach suffers two drawbacks: (i) heterogeneity at the accident, vehicle and individual levels is ignored entirely; and (ii) the impact of Via Sicura identified by their model is actually the combination of two distinct effects of the road safety program, namely on accident occurrence and on the severity of their outcomes, and those may have very different magnitudes.

In this paper, we propose an alternative approach to measuring the impact of Via Sicura that overcomes these limitations. Namely, we design a disaggregate model to capture the dissuasive effect of Via Sicura's repressive measures on the behavior of drivers and, in turn, to assess the impact of the resulting change in behavior on accident outcomes. 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 and main contribution, which consists in using the presented framework to evaluate the efficacy of Via Sicura's repressive measures in a comprehensive manner. The model developed for this purpose is estimated on a dataset derived from the police records of all accidents that were reported in Switzerland between 1992 and 2022, which represent over 3.4 million events 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 on accident outcomes; 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 road safety program; Section 5 gathers the results obtained from its estimation; and 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 accident 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 regards the latter, the existing literature deals with explaining the influence of directly observable variables on the vulnerability of individuals in different types of vehicles (*e.g.*, de Lapparent, 2005, 2006; Xin et al., 2017; Chang et al., 2021), seat positions (de Lapparent, 2008; Bogue et al., 2017), on different road types (Huang et al., 2008; Choudhary et al., 2018; Qiu and Fan, 2021) or when involved in different types of accidents (Shankar and Mannering, 1996; Kockelman and Kweon, 2002; Wang et al., 2023).

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 in 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 an indisputable 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 reduce injury severity by preventing 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, with 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 manifestations are 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 suggested indicators of risky driving — seatbelt usage and alcohol consumption — are pointed out 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 design 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 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 $v \in \mathcal{V}(a)$. 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.

Fig. 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 most risky of said behaviors that determines the severity of the injuries sustained by all involved individuals. This follows the observation that it takes a single reckless driver to cause a serious accident, no matter how cautious and prudent the others may be.

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.

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:

$$r^*_{av1} = \boldsymbol{\gamma}\mathbf{z}'_{av1} + \eta_{av1}, \tag{1}$$

where $\mathbf{z}_{av1}$ is a vector that contains the explanatory variables and $\boldsymbol{\gamma}$ is a vector of parameters to be estimated from the data.[1] In addition, η_{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[2]:

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

[1] For the sake of compactness in notation, the intercept term is included in the vector of parameters $\boldsymbol{\gamma}$.

[2] The motivation behind the choice of a Gumbel distribution is exposed in the next paragraphs.

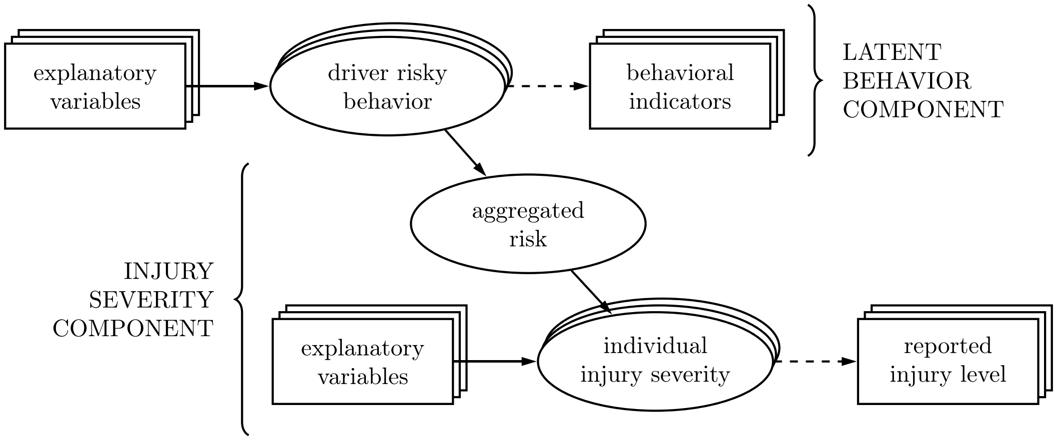

Fig. 1. Structure of the integrated ordered logit and latent variable model for accident injury severity and risk-taking behavior. The observable variables are depicted as rectangles and the latent ones as ellipses. Solid arrows stand for structural equations, whereas dashed arrows represent the measurement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

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:

$$I^*_{av1p} = \boldsymbol{\theta}_p \mathbf{s}'_{av1p} + \lambda_p r^*_{av1} + \nu_{av1p}, \tag{3}$$

where $\boldsymbol{\theta}_p$ and λ_p are parameters to be estimated from the data and ν_{av1p} are idiosyncratic terms that account for unobserved variables.[3] The error terms are assumed to be independently and identically distributed across all observations, as well as uncorrelated with observable factors. They follow a logistic distribution with scale parameter $\delta_p > 0$:

$$\nu_{av1p} \overset{\text{iid}}{\sim} \text{Logistic}\left(0, \delta_p\right). \tag{4}$$

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. Following our assumption that the most risk-taking behavior determines the severity of the accident, we define the aggregated risk r^*_a as the maximum risk-taking behavior among all involved drivers:

$$r^*_a = \max_{v \in \mathcal{V}(a)} (r^*_{av1}). \tag{5}$$

Given that extreme value distributions are max-stable and that the risk-taking behaviors of all drivers in an accident follow the same Gumbel distribution, the resulting aggregated risk r^*_a may be written as:

$$r^*_a \overset{\text{iid}}{\sim} \text{Gumbel}\left(\mu \sum_{v \in \mathcal{V}(a)} \exp\left(\frac{\boldsymbol{\gamma} \mathbf{z}'_{av1}}{\mu}\right), \mu\right), \tag{6}$$

where μ is the same scale parameter as in (2).[4]

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

$$U_{avi} = \boldsymbol{\beta} \mathbf{x}'_{avi} + \alpha r^*_a + \varepsilon_{avi}, \tag{7}$$

where $\mathbf{x}_{avi}$ is a vector containing the observable variables that are deemed to be explanatory of individual levels of injury, $\boldsymbol{\beta}$ and α are vectors of parameters to be estimated from the data, and ε_{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:

$$\varepsilon_{avi} \overset{\text{iid}}{\sim} \text{Logistic}\left(0, \sigma\right). \tag{8}$$

[3] For the sake of compactness in notation, the intercept term is included in the vector of parameters $\boldsymbol{\theta}_p$.

[4] Alternative approaches to aggregating risk-taking behaviors could assume normally distributed risk-taking behaviors and then rely on summing or averaging them. However, the former would make the aggregated risk dependent on the number of involved vehicles — wrongly implying that larger accidents are more serious — while the latter would get rid of extreme behaviors and imply that cautious drivers might compensate for risk-taking ones. Therefore, both are neither realistic nor desirable.

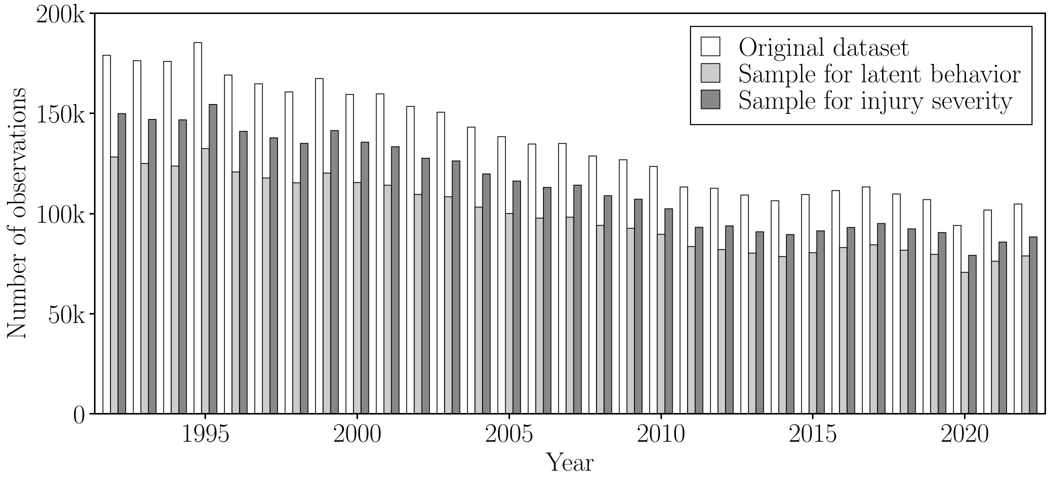

Fig. 2. Number of observations per year in the original dataset and amounts retained from each year for the estimation of the two model components.

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.[5] 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.[6]

Fig. 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 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 Tables 1 and 2, respectively. The original dataset distinguishes between 54 distinct vehicle types. For the sake of simplicity, we group those into categories that we define based on the maximum speed each vehicle type can reach and the level of protection it offers to its occupants. We obtain six categories: (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.

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

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

where I^*_{av1p} is the underlying continuous variable of indicator I_{av1p}, as defined in (3), and κ_{p1} is the associated threshold parameter, to be estimated from the data. For the sake of compactness in notation, let $\boldsymbol{\Theta}_p = (\theta'_p, \lambda_p, \delta_p, \kappa_{p1})'$ be the vector of unknown parameters.

[5] Verkehrsunfall Jahresdatensatz (DWH-VU), Federal Roads Office.

[6] 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.

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

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

Table 2
Description of the explanatory variables of injury severity.

Variable	Type	Description
Age	ratio	*Age of the individual in years.*
Gender	binary	*1 if female and 0 otherwise.*
Vehicle category	categorical	*We distinguish six: (i) pedestrians, (ii) slow modes, (iii) e-bikes & mopeds, (iv) motorcycles, (v) cars & vans, and (vi) heavy vehicles.*
Seatbelt	binary	*1 if the individual is wearing a seatbelt and 0 otherwise.*
While driving	binary	*1 if the accident occurred while driving, and 0 if while parking.*
Single vehicle	binary	*1 if a single vehicle was involved in the accident, and 0 otherwise.*
Speed limit	ratio	*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	continuous	*Defined as the maximum risk-taking behavior among all drivers involved in the accident.*

Conditional on r^*_{av1}, the probability that the discrete indicator I_{av1p} takes value $\ell \in \{0, 1\}$ is computed as

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

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, Fig. 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. Fig. 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. Fig. 5 shows their distribution through the years in the sample used for the estimation of the injury severity component. In our model, these outcomes are generated by their corresponding latent injury severity U_{avi}, as follows:

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

where τ_1, τ_2 and τ_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 h". This change is taken into account by defining two different parameters for threshold τ_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 $\boldsymbol{B} = \left(\boldsymbol{\beta}', \alpha, \sigma, \tau_1, \tau_2, \tau_3\right)'$ 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

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

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

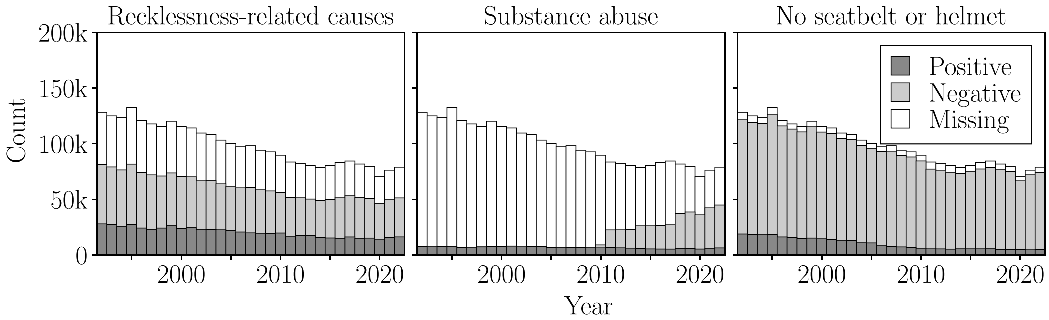

Fig. 3. Evolution of the values of the indicators over time.

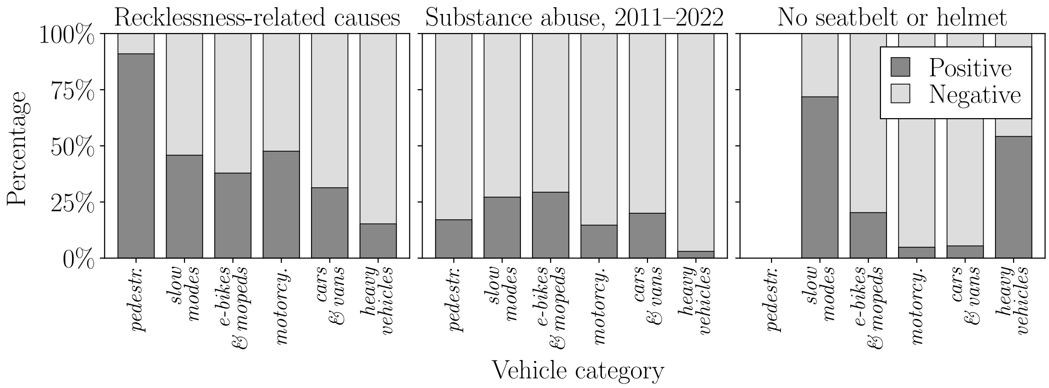

Fig. 4. Distribution of the values of the indicators for each vehicle category, missing values excluded. The indicator related to substance abuse only reports the values from 2011 onward to account for the change of accident report template.

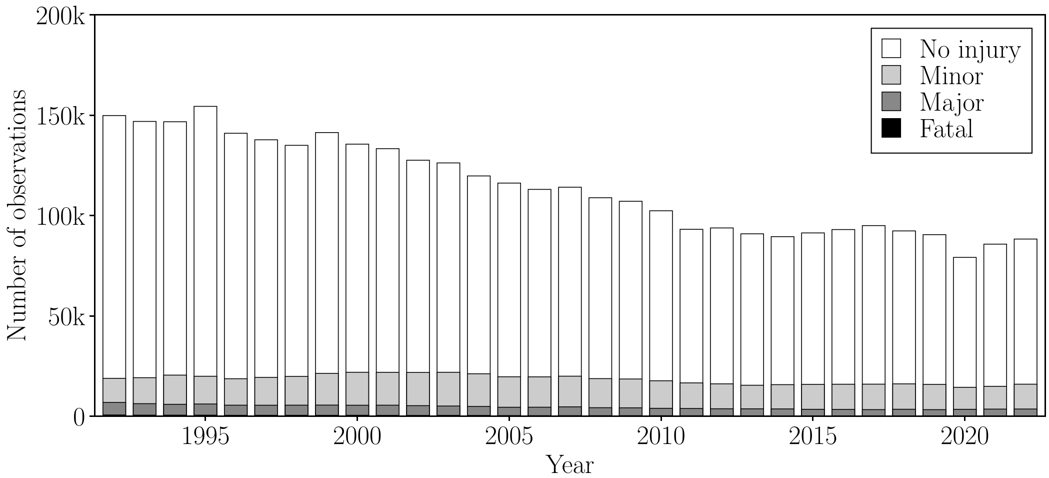

Fig. 5. Number of observations per year and injury severity level in the sample used for the estimation of the injury severity component.

5. Identification and estimation

We start by setting the observations from 2012 and 2013 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. Then, the two components of the model are estimated sequentially, primarily to address the computational demands imposed by the vast amount of data. Although theoretically desirable, simultaneous estimation is simply not viable given the size of the dataset and the added complexity of the aggregated risk. Yet, sequential estimation, while consistent, can lead to potentially inefficient second-stage estimates, which require correction (Ben-Akiva et al., 2002; Bahamonde-Birke and Ortúzar, 2014). This is achieved by resampling 100 times the samples used to estimate the injury severity component and then bootstrapping the standard errors of all second-stage parameters. 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:

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

where g is the probability density function of η_{av1}, conditional on μ, and ℓ_{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 Fig. 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.[7] 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.

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, Fig. 6 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. These findings coincide with those reported by Tasca (2000). 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 cyclists and drivers under 13 are wearing either, against 89.3% in the whole sample. Moreover, the “recklessness-related causes” indicator is positive for 52.9% of pedestrians under 18, against 28.6% for adult pedestrians.[8]

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, such as 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 appear 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 Fig. 7, 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, Fig. 7 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.

[7] 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.

[8] We remind the reader that the indicator “no seatbelt or helmet” is not used for pedestrians, which means that their risk-taking behavior is only determined using the two other indicators.

Table 3
Estimation results of the latent behavior component.

Parameter	Value	Rob. t-test
Recklessness-related causes		
θ–intercept, pedestrians	2.90	44.8
θ–intercept, slow modes	0.264	4.01
θ–intercept, e-bikes & mopeds	−0.337	−3.65
θ–intercept, motorcycles	0.498	3.12
θ–intercept, cars & vans	−0.680	−2.98
θ–intercept, heavy vehicles	−2.01	−11.1
θ–poor weather	1.53	86.4
λ–risk-taking behavior, pedestrians	0.381	18.3
λ–risk-taking behavior, slow modes	0.559	16.1
λ–risk-taking behavior, e-bikes & mopeds	0.588	13.9
λ–risk-taking behavior, motorcycles	0.829	59.4
λ–risk-taking behavior, cars & vans	1.12	94.9
λ–risk-taking behavior, heavy vehicles	0.866	37.3
Substance abuse		
θ–intercept, pedestrians	−0.591	−0.657
θ–intercept, slow modes	1.98	1.46
θ–intercept, e-bikes & mopeds	−0.407	−0.423
θ–intercept, motorcycles	−3.31	−8.41
θ–intercept, cars & vans	−3.94	−4.98
θ–intercept, heavy vehicles	−5.13	−16.2
θ–old template	28.6	19.0
λ–risk-taking behavior, pedestrians	4.37	8.02
λ–risk-taking behavior, slow modes	6.17	21.9
λ–risk-taking behavior, e-bikes & mopeds	4.50	20.9
λ–risk-taking behavior, motorcycles	3.27	7.12
λ–risk-taking behavior, cars & vans	4.04	20.8
λ–risk-taking behavior, heavy vehicles	1.18	13.3
No seatbelt or helmet		
θ–intercept, pedestrians	0	–
θ–intercept, slow modes	1.52	16.6
θ–intercept, e-bikes & mopeds	−1.22	−37.3
θ–intercept, motorcycles	−2.84	−88.8
θ–intercept, cars & vans	−2.74	−118
θ–intercept, heavy vehicles	−1.99	−107
θ–no protection needed	4.03	219
λ–risk-taking behavior, pedestrians	0	–
λ–risk-taking behavior, slow modes	0.336	16.6
λ–risk-taking behavior, e-bikes & mopeds	0.165	16.1
λ–risk-taking behavior, motorcycles	0.143	15.9
λ–risk-taking behavior, cars & vans	0.113	45.2
λ–risk-taking behavior, heavy vehicles	0.0368	4.27
Risk-taking behavior		
γ–age, 0–18	−0.108	−10.8
γ–age, 18–35	−0.0245	−32.2
γ–age, 35–65	−0.0105	−21.8
γ–age, 65–100	0.00296	2.31
γ–age, with passenger, 0–18	0.0275	27.8
γ–age, with passenger, 18–35	−0.0278	−16.8
γ–age, with passenger, 35–65	−0.00877	−7.58
γ–age, with passenger, 65–100	0.00134	0.448
γ–age, female driver, 0–18	−0.0488	−43.0
γ–age, female driver, 18–35	0.0195	13.0
γ–age, female driver, 35–65	0.00316	3.32
γ–age, female driver, 65–100	0.00619	2.41
γ–age, female driver, with passenger, 0–18	−0.0188	−9.56
γ–age, female driver, with passenger, 18–35	0.0219	6.70
γ–age, female driver, with passenger, 35–65	−0.00174	−0.701
γ–age, female driver, with passenger, 65–100	−0.00342	−0.443
γ–learner driver	−0.239	−16.9
γ–child passenger	−0.254	−13.3

(*continued on next page*)

Table 3 (*continued*).

γ–adverse weather	−0.227	−14.3
γ–late night	2.09	88.5
γ–urban	0	–
γ–rural	1.16	76.6
γ–highway	1.21	76.2
γ–year	0.0175	14.1
γ–year, squared	−0.000874	−16.2
γ–via sicura	−0.240	−14.9
μ	1.50	79.7

Table 4
Estimation reports of the latent behavior and injury severity model components. The reported out-of-sample log likelihoods are obtained on the data from 2012 and 2013, as those are the years immediately preceding and following the entry into force of the Via Sicura road safety program.

	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

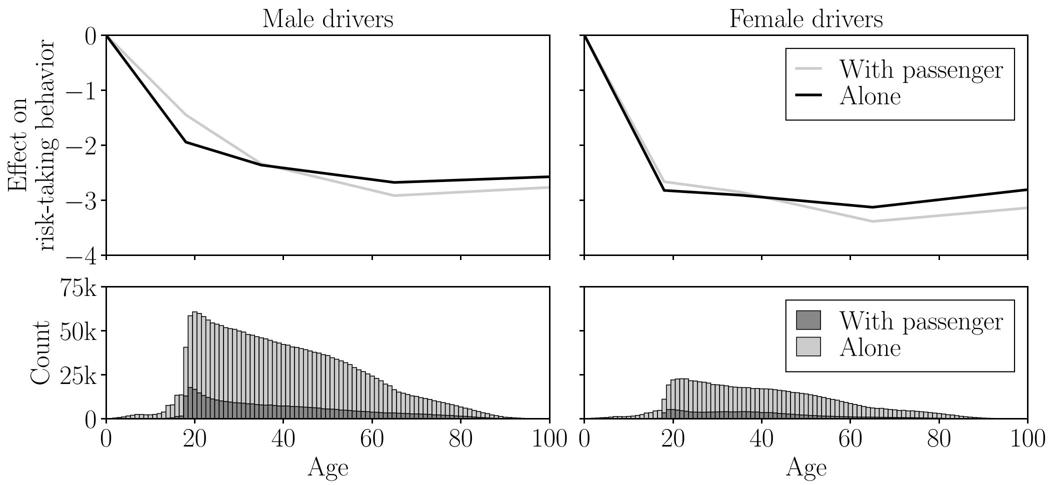

Fig. 6. Age distribution and effect on risk-taking behavior for each segment of drivers.

5.2. Injury severity component

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

$$\int_{\mathbb{R}} \Pr\left(y_{avi} = k \mid \mathbf{x}_{avi}, r_a^*; \boldsymbol{B}\right) g\left(r_a^* \mid \mu\right) \mathrm{d}r_a^*. \tag{14}$$

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 ω 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 τ_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 breakpoints and segmented based on the gender of the individual. Fig. 8 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.[9] 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.

[9] The speed limit is included as a proxy of the actual driving speed, which unfortunately is not available.

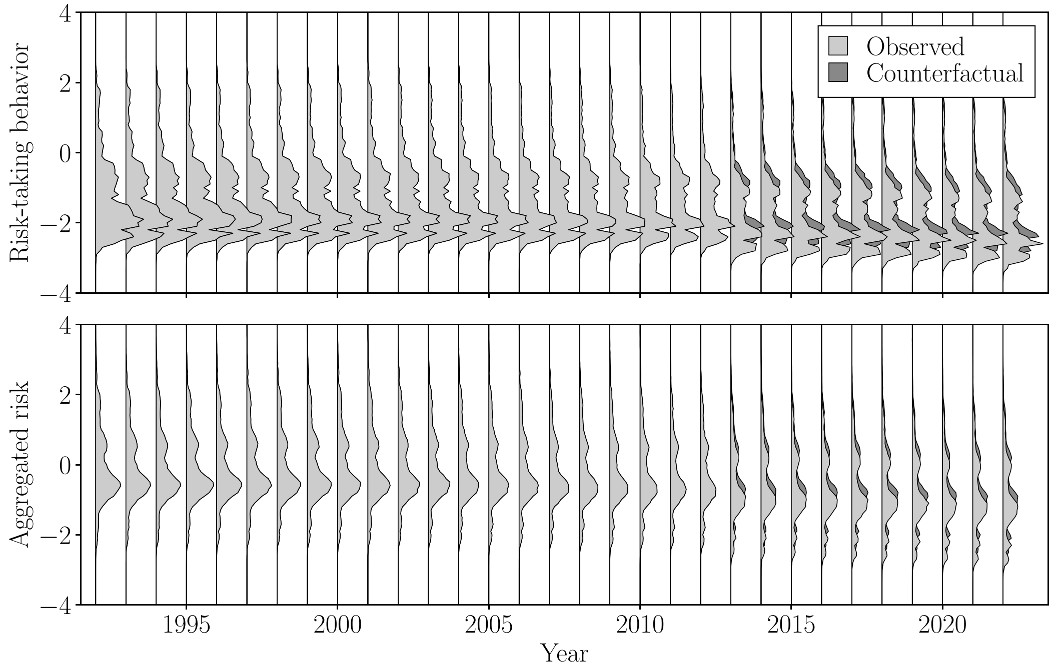

Fig. 7. Distribution of driver risk-taking behavior and resulting aggregated risks for each year of data. The counterfactual distributions refer to ignoring the effect of Via Sicura, as if the measures of the road safety program were never implemented.

Table 5
Estimation results of the injury severity component.

Parameter	Value	Rob. t-test	Boot. t-test
Individual injury severity			
α–aggregated risk	0.136	76.0	75.4
β–age, 0–18	0.0223	29.9	28.7
β–age, 18–35	0.000874	2.05	2.32
β–age, 35–65	0.00563	20.2	21.4
β–age, 65–100	0.0190	26.9	27.6
β–age, female, 0–18	0.0395	94.9	92.4
β–age, female, 18–35	0.0000581	0.0868	0.0791
β–age, female, 35–65	−0.00227	−5.20	−4.75
β–age, female, 65–100	−0.00696	−6.47	−6.03
β–pedestrians	0.635	49.9	49.5
β–slow modes	0.238	18.3	17.7
β–e-bikes & mopeds	−0.0654	−4.23	−4.34
β–motorcycles	−0.0692	−5.03	−5.35
β–cars & vans	−2.12	−161	−163
β–heavy vehicles	−3.89	−203	−205
β–seatbelt	−1.34	−215	−199
β–while parking	−1.34	−82.9	−81.4
β–while driving, single-vehicle accident	0.559	138	131
β–while driving, speed limit	0.00963	141	134
Reported injury level			
τ_1	0	–	–
τ_2*–until 2014*	2.38	631	623
τ_2*–since 2015*	2.65	405	430
τ_3	5.37	513	457

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 of (11) 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

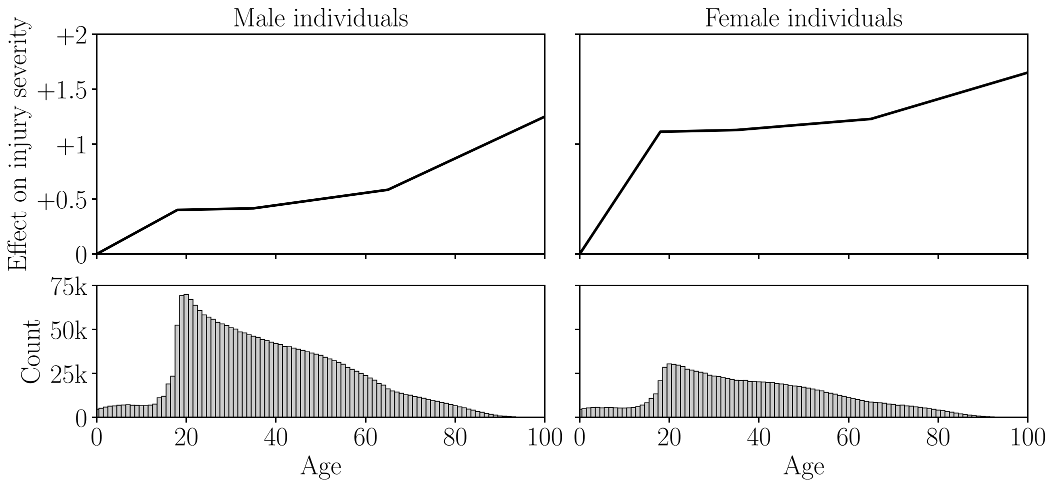

Fig. 8. Age distribution and effect on injury severity for male and female individuals.

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

Level of injury	Observed shares		Counterfactual shares [90% CI]		
None	702,739	78.4%	699,497	78.1%	[698,549, 700,514]
Minor	156,362	17.5%	158,665	17.7%	[157,835, 159,444]
Major	34,898	3.9%	35,774	4.0%	[35,454, 36,081]
Fatal	1,926	0.2%	1,989	0.2%	[1964, 2012]

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 2303 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.

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 2303 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. 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. Finally, allowing for the values of key parameters to change over time could provide deeper insights into how the effects of Via Sicura and other factors change over time, hence allowing for a more detailed examination of the temporal dynamics and the evolving impact of interventions.

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:						
urban	1,353,266	66.6%	1,149,654	63.5%	1,009,080	62.6%
rural	420,257	20.7%	405,877	22.4%	368,753	22.9%
highway	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:						
pedestrians	84,638	2.5%	83,879	2.7%	72,340	2.6%
soft modes	136,613	4.0%	133,876	4.4%	122,781	4.4%
e-bikes & mopeds	41,184	1.2%	40,161	1.3%	37,362	1.3%
motorcycles	171,716	5.0%	169,571	5.5%	154,107	5.5%
cars & vans	2,577,401	75.7%	2,509,508	81.9%	2,301,289	82.0%
heavy vehicles	135,087	4.0%	128,709	4.2%	118,276	4.2%
other/unknown	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:						
male	2,644,447	62.6%	2,206,132	72.0%	2,359,508	66.6%
female	1,299,163	30.8%	859,573	28.0%	1,180,904	33.4%
unknown	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%
unknown	294,191	7.0%	0	0.0%	0	0.0%
Level of injury:						
none	3,422,664	81.0%	2,417,489	78.9%	2,817,904	79.6%
minor	628,621	14.9%	498,863	16.3%	569,888	16.1%
major	159,853	3.8%	138,296	4.5%	142,120	4.0%
fatal	13,170	0.3%	11,057	0.4%	10,500	0.3%

CRediT authorship contribution statement

Nicola Ortelli: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Matthieu de Lapparent:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Silvia F. Varotto:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Michel Bierlaire:** Writing – review & editing, Supervision, Resources, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

See Table 7.

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