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Relative Risk of Causing a Road Traffic Crash: Quasi-Induced Exposure Approach and Its Possible Biases

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Abstract

This paper addresses the challenge of heterogeneity in risk exposure when estimating the relative risk (RR) of causing road traffic crashes (RTCs) for different driver types. Quasi-induced exposure is a well-established alternative to direct data collection for exposure estimation. We investigate biases imposed on RR estimates caused by errors in fault assignment and unequal driver mix. Simulations reveal the directions and magnitudes of the possible biases and empirical tests of these biases are performed on a Czech dataset (1.2 million RTCs). Results show that errors in responsibility assignment work in opposite directions, with magnitude of bias depending on the size of the error and the target group proportion. Bias caused by unequal mixing depends on the target group proportion and the extent of the heterogeneity of not-at-fault drivers. Empirical tests confirm the discussed biases and underline their importance while interpreting RR estimates, so far mostly ignored by the literature.

Keywords: Quasi-induced exposure, underlying assumptions, responsibility assignment, road traffic crash risk, simulations, bias

1. Introduction

Differences in the risk of causing a road traffic crash (RTC) that correlate with differences in driver characteristics are one of the key focuses of ongoing investigations in traffic safety research. A number of detailed comparisons of risk based on age, gender, and other factors have already been produced. However, a persistent challenge in estimating the relative risk (RR) of different driver groups is accounting for heterogeneity in risk exposure. Exposure may be defined as "being in a situation which has some risk of involvement in a road traffic accident" (Wolfe, 1982, p. 337) and is one of the key

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confounding factors of RTC involvement. However, collecting direct data on individual drivers' exposure could be either costly or problematic in terms of personal data protection. Thus, indirect estimates of exposure from data on traffic crashes remain relevant both for current research and institutions.

One of the well-established approaches based on indirect estimates is quasi-induced exposure method (QIE). This approach is based on comparison of composition not-at-fault RTC participants vs. their at-fault counterparts in selected types of RTCs. QIE approach asserts that the driver group presence among not-at-fault RTC participants may serve as an approximation of its relative occurrence in the driver population. The RR is then estimated by relating this occurrence to the group´s occurrence among at-fault participants. This idea was first mentioned by Thorpe (1964) and later developed by Haight (1971) and Lyles et al. (1991). It has been applied by a number of authors to various types of crashes and risk factors to yield RR estimates (e.g. Claret et al., 2003; Taylor & Rehm, 2012; Curry et al., 2016; Voas, 2018; Morita & Sekine, 2018; Shen et al., 2019; Gomes-Franco et al., 2020). Despite its widespread use, QIE relies on key assumptions that require further scrutiny. Theoretical studies have refined these assumptions (Mendez & Izquierdo, 2010), developed tests for their validity (Jiang & Lyles, 2010), and explored appropriate crash type selection (Keall & Newstead, 2009; Wahlberg & Dorn, 2024). Recent work, such as Zhang et al. (2023), has examined how different hazardous driving actions influence QIE estimates, highlighting potential sources of bias in its application. Even though the assumptions behind the QIE approach had been analysed by the number of works, we haven´t found a work offering simulations of the magnitudes of the biases based on the key parameters. Furthermore, unequal mixing of driver groups (defined below in detail) had been identified as a potential source of bias more than two decades ago (Levitt & Porter, 2001), but have been (to our knowledge) ignored by the QIE literature. Our intention is to address both these gaps in the literature.

Building on line of research above, the objective of this paper is to examine potential violations of the main assumptions and their impact on RR estimates in terms of direction and size. More specifically, using the original test suggested by Lighthizer (1989), we simulate biases created by errors in responsibility assignment and suggest novel related empirical tests. Moreover, we combine this discussion with seemingly unrelated tests concerning the homogeneity of the driver population (introduced by Levitt & Porter (2001)) to show that these possible sources of bias influence the results of the statistical tests, and hence also the RR estimates. Our results confirm that Lighthizer's test is a good indicator of possible biases when estimating RR. Next to contribution to academic discussion, we find this important also in the context of RTC data analysis for practical purposes. When assessing driver group risk (for example to design a new policy), it is crucial to work with unbiased RR estimates or at least to understand possible biases, their directions and sources.

The paper is structured as follows. In the following section we describe our methods and the principle behind our simulations in detail. In the next section we present the results and discuss them. We conclude by summarizing the limitations of our study and avenues for future research.

2. Method

The QIE method has been frequently discussed in the context of risk exposure estimations over the last three decades (see Jiang et al., 2014 for review). It relies on the assertion that a certain subset of RTCs may be understood as a randomizing mechanism drawing not-at-fault drivers from the population of all drivers on the road. Under the key assumption, the sample of not-at-fault drivers is representative of the population and may be compared with at-fault drivers to estimate the RR of the group of interest in order to control for driver group exposure (Jiang et al., 2014). The method is usually applied to multiple-vehicle crash data with one at-fault driver that include similar vehicle types and are recorded without errors or missing values (Jiang & Lyles, 2010).

To illustrate the QIE principle, we focus our work on the youngest and oldest drivers on the roads (for purposes of this paper by youngest drivers we mean drivers <25 y.o. and oldest drivers >65 y.o., unless defined otherwise). The increased risk of causing a RTC for these groups is well documented in the literature. Furthermore, these groups of drivers constitute sufficiently large proportions of the drivers on the roads, so we have a good chance of identifying relevant patterns in our data.

Assume that we aim to estimate the RR of drivers <25 y.o. as compared to that of their 25–65 y.o. counterparts. In other words, we are interested in whether on average there is a significant difference between the risk of a young driver causing an RTC and the risk of their older counterparts doing so, controlling for exposure. Let us label the group of drivers we are interested in (drivers <25 y.o.) as the *target* and the relevant comparison group of drivers (drivers 25–65 y.o.) as the *baseline*. Following the definition of Stamatiadis & Deacon (1995) the relative crash involvement (RCI) of the two groups in question can be defined:

$$RCI = \frac{T_f \;/\; B_f}{T_n \;/\; B_n} \qquad (1), \text{ where}$$

T_f is the number of *target* drivers among all at-fault drivers *(f)* and T_n is the number of *target* drivers among all not-at-fault drivers *(n)*, B_f is the number of *baseline* drivers among at-fault drivers and B_n is the number of *baseline* drivers among not-at-fault drivers, all within a given type of crash.

The intuitive understanding of the RCI is that if it is statistically significantly greater than 1 (determined by Fisher's exact test, for example), then the proportion of *target* drivers is larger among those who cause a crash than among those who are victims (who may be seen as randomly drawn from the population of all drivers). An estimated value of RCI>1 may (at least partly) be attributed to an increased risk of causing a RTC that is systematically connected to the driver's age. However, using RCI as an estimate of RR would yield unbiased results only under key assumptions.

First, while using standard RTC data we do not know whether the at-fault driver caused the crash or not, all we know is that he or she was assigned as the at-fault party in the crash (see e.g. Jiang & Lyles, 2010). In other words, what we see in the RTC data is only the probability of being assigned as at-fault by the documenting police officer. That probability depends not only on the crash situation but also on potential error made by the police officer. The size of the error, furthermore, may not be independent of whether the driver in question is from the *target* group, hence this is a possible source of bias for an RR estimate (see a detailed discussion in Jiang et al. 2012).

Second, involvement in an RTC depends on several other factors that differ across the groups of drivers in question. These factors would include: miles driven during a given period of time, driving timing and location, crash avoidance ability, differences in risk of injury, crash type, hit-and-run propensity, vehicle type and speed. The potential differences in these factors across groups of drivers can cause different types of biases when using RCI (e.g. Méndez & Izquierdo, 2010; Keall & Newstead, 2009).

The literature cited above has identified a number of biases, and proposed possible remedies to avoid them. Tests of the representativeness assumption have included comparisons of not-at-fault drivers' characteristics based on selected criteria. Lighthizer (1989) suggested applying such a test to the responsibility criterion: if the at-fault drivers "choose" their crash victims randomly, then the subsets of not-at-fault drivers should not differ across the different types of at-fault drivers. Later works (e.g. Jiang & Lyles, 2010; Curry et al. 2016) develop this idea and look at comparisons of second and third (etc.) participants in multiple vehicle RTCs or compare not-at-fault driver data with other sources of data such as surveys (Shen et al. 2019).

In this paper, we expand on the original version of the Lighthizer test, which focused on the characteristics of the not-at-fault drivers involved in RTCs with different types of at-fault drivers. We argue that this test has multiple applications and may lead us to simulations of the directions of possible biases in RR estimates.

To put this more formally, let us return to Eq. (1) and separate the set of 2-vehicle RTCs into a set of cases when *target* (<25 y.o.) is at-fault vs. a set of cases where *baseline* (25–65 y.o.) is at-fault. Using these sets, we may inspect and compare the characteristics of the not-at-fault drivers conditional on the type of at-fault driver. The test suggested by Lighthizer can be formally applied as a test of whether not-at-fault *target* drivers are equally represented across these two sets of RTCs calculated as follows.

$$\frac{T_n}{B_n}|T_f = \frac{T_n}{B_n}|B_f \qquad (2)$$

Both sides of the Eq. (2) show the proportion of *target* to *baseline* among the not-at-fault drivers, conditional on *target* vs. *baseline* being at-fault, respectively. The null hypothesis states that the proportion of *target* among not-at-fault drivers is independent of the type of at-fault driver. This hypothesis may be tested by the Fisher exact test, yielding standard statistical inference. The test is performed by relating the left- and right-hand sides of Eq. (2) leading to an odds ratio we will call Lighthizer statistics (LS) calculated as follows.

$$LS = \frac{T_n\,|\,T_f}{B_n\,|\,T_f} / \frac{T_n\,|\,B_f}{B_n\,|\,B_f} \quad (3)$$

LS takes a value between 0 and infinity and tells us how many times more (or less) *target* are present as not at-fault drivers in RTCs when *target* is at-fault, in comparison to the situation when *baseline* is at-fault.

In this paper, we focus on possible biases identifiable by this Lighthizer test and their closer classification. We argue that this test may shed more light than previously understood on the possible causes and directions of the biases. Specifically, we focus on biases caused by errors in responsibility assignment and biases caused by the heterogeneity of driver populations across time/space. In the following section, we will explain these possible causes of bias in detail.

3. Error in responsibility assignment

Since the core of the QIE approach is based on a comparison of proportions among at-fault vs. not-at-fault drivers, the correct assignment of driver responsibility is crucial to the validity of the results. While focusing on two-vehicle RTCs with one at-fault driver we may observe four scenarios: a) T_f encountered T_n, b) T_f encountered B_n, c) B_f encountered T_n and d) B_f encountered B_n. Clearly, if a responsibility assignment error is made in RTCs of type a) or d), the comparisons between *target* and *baseline* in Eq. (1) will not be affected. However, errors related to types b) and c) might influence the distributions among the groups and thus RCI would cease to serve as an unbiased estimate of RR. Two types of assignment errors may occur: systematic and random.

3.1 Systematic error in responsibility assignment

A systematic error in responsibility assignment would occur if particular groups of drivers are "preferred" to be selected as at-fault. If we assume that the "preferred" group is *target*, T_f in Eq. (1) would increase and T_n would decrease; at the same time B_f would decrease and B_n would increase. Consequently, the RCI as an estimate of RR for *target* would increase (Jiang et al., 2014). DeYoung et al. (1997) named this phenomenon a "negative halo effect." This type of systematic error would mean that the error e is only made with crashes type c), which are wrongly classified as type b).

The consequences for the result of the Lighthizer test may be easily simulated. In the following equation, we present the Lighthizer statistics from Eq. (3) already adjusted for the presence of systematic error e calculated as follows.

$$LS = \frac{T_n \mid T_f}{B_n \mid T_f + eT_n \mid B_f} / \frac{T_n \mid B_f - eT_n \mid B_f}{B_n \mid B_f} \quad (4)$$

The rationale is that the numbers of drivers involved in crashes of the same type (types a) and d)) remain unbiased in the data and thus the expressions $T_n|T_f$ and $B_n|B_f$ remain unchanged. However, the systematic error in responsibility assignment causes a certain proportion of type c) crashes to be classified as type b). Thus, the number of type b) crashes is increased by $e \cdot T_n|B_f$. Analogically, the number of type c) crashes is decreased by the same amount.

To see how this error affects the LS and RCI, we transform both expressions LS and RCI using the true RR. We start with the expression for $T_n|T_f$. We assume that for each RTCs both drivers belong to either *baseline* or *target* group. Then, we denote by p the overall proportion of *target* among the *target* and *baseline* not-at-fault participants. Given that, p of T_n drivers encounter pRR of T_f drivers, resulting in a total number of type a) crashes of $p(pRR)$. Similarly, $B_n|T_f$ could be seen as the residual proportion where $(1-p)$ of B_n drivers encounter pRR T_f drivers, resulting in $B_n|T_f \sim p(1-p)RR$. In the same fashion, $B_f|T_n \sim p(1-p)$, and $B_n|B_n \sim (1-p)^2$. Thus, LS can be expressed as follows.

$$LS = \frac{p^2 RR}{p(1-p)RR + ep(1-p)} / \frac{p(1-p) - ep(1-p)}{(1-p)^2} = \frac{RR}{RR+e} / \frac{1-e}{1} = \frac{RR}{(RR+e)(1-e)} \quad (5)$$

As the right-hand side shows, p is cancelled out from the expression, thus the bias of LS is independent of the proportion of the driver group in question.

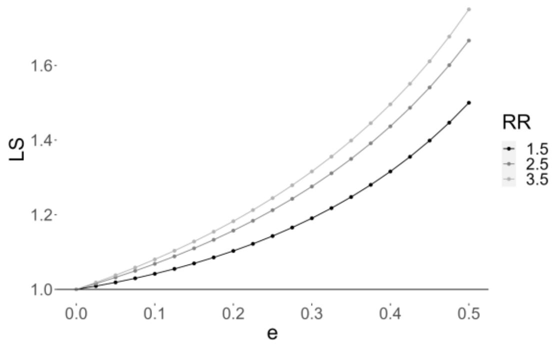
We apply a similar principle to transformation of the RCI. First, we plug in the adjustment of relevant parts into the Eq. (1) with errors e that increase and decrease selected *target* and *baseline* driver counts, which yields

$$RCI = \frac{T_n \mid T_f + B_n \mid T_f + e(T_n \mid B_f)}{B_n \mid B_f + T_n \mid B_f - e(T_n \mid B_f)} / \frac{T_n \mid T_f + T_n \mid B_f - e(T_n \mid B_f)}{B_n \mid T_f + e(T_n \mid B_f) + B_n \mid B_f} = \frac{RR + e(1-p)}{1-ep} / \frac{pRR + (1-p) - e(1-p)}{pRR + ep + (1-p)}. \quad (6)$$

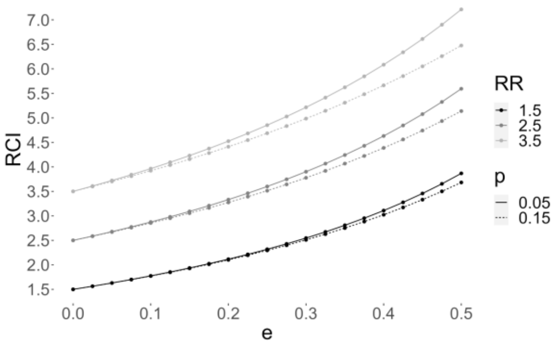
The right-hand side of this equation again shows the transformation described in relation to Eq. (5) using true RR and p. In this case, p remains a parameter that influences the resulting bias of the RR estimate.

We present the results of both simulations based on Eqs. (5-6) in Figures 1(a) and 1(b), respectively. The curves in Figure 1(a) show the size and the direction of the bias for LS for different sizes of systematic errors e. If we assume that there is no statistically significant difference between the populations of not-at-fault drivers (Eq. (3)), LS would be equal to 1 (or we would not reject the null hypothesis stating this). However, if there is error in the responsibility assignment, LS will be biased upwards. For example, if

RR=2.5, there are 15 percent *target* drivers in the population (p=0.15), and the police wrongfully assigns the responsibility in 10% of type c) crashes (e=0.1) we get LS=1.07, a 7% upward bias.



(a)



(b)

Figure 1: Impact of systematic error on LS (a) on LS, (b) on RCI for different values of relative risk (RR) and target driver proportions (p)

Figure 1(b) shows the bias for the estimate of RR based on Eq. (6). In this case, the size of the bias also depends on p, giving different scenarios for different proportions of *target* in the population. Using the same values, with true RR=2.5, p=0.15 and e=0.1, we get RCI=2.85, i.e. a 14% upward bias in the RR estimate.

3.2 Random error in responsibility assignment

Besides systematic assignment error, the data may also contain random assignment error: the records are made on the spot (and rather rarely corrected ex post) and the responsibility is assigned based on the information and knowledge available to the officer at that moment (Jiang et al., 2011). This may cause a certain fraction of wrongfully assigned responsibility, which we again denote "e". Remember that errors in crash types a) and d) would not affect our estimates and thus we focus on RTC types b) and c) only. Assume that the proportion of wrongfully assigned responsibility is e for both. Then, LS becomes:

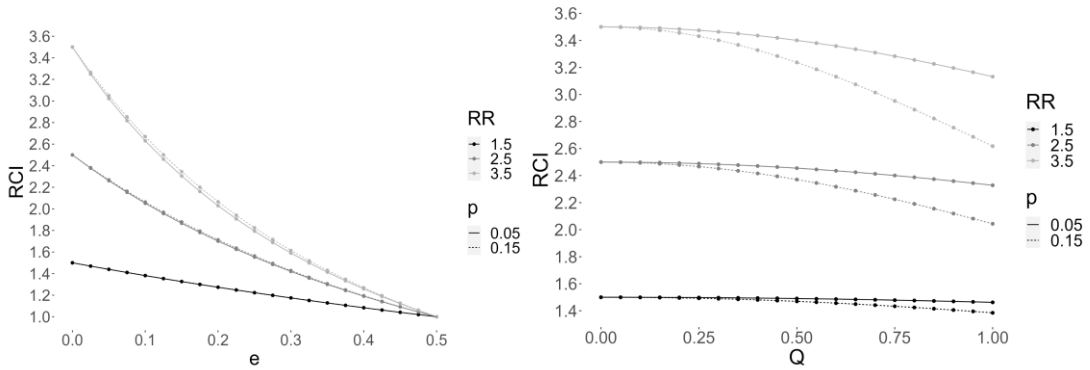
$$LS = \frac{T_n\,|\,T_f}{B_n\,|\,T_f - e(B_n\,|\,T_f - T_n\,|\,B_f)} \Big/ \frac{T_n\,|\,B_f - e(T_n\,|\,B_f - B_n\,|\,T_f)}{B_n\,|\,B_f}. \qquad (7)$$

Given that *target* drivers have a higher expected RR, it is reasonable to assume that $B_n|T_f > T_n|B_f$ which means that with e=0, there would be more type b) crashes than type c) crashes. Introducing e>0 implies that $B_n|T_f - e(B_n|T_f - T_n|B_f) < B_n|T_f$ and $T_n|B_f - e(T_n|B_f - B_n|T_f) > T_n|B_f$. That leads to a modified LS (the left-hand side), which we compare to the LS without the error (the right-hand side):

$$\frac{T_n\,|\,T_f}{B_n\,|\,T_f - e(B_n\,|\,T_f - T_n\,|\,B_f)} \Big/ \frac{T_n\,|\,B_f - e(T_n\,|\,B_f - B_n\,|\,T_f)}{B_n\,|\,B_f} < \frac{T_n\,|\,T_f}{B_n\,|\,T_f} \Big/ \frac{T_n\,|\,B_f}{B_n\,|\,B_f}. \qquad (8)$$

LS with random error present is systematically biased downwards.

In similar fashion as in the case of systematic error, we express both LS and RCI in terms of p and true RR. To do that, we express $T_n|T_f$, $B_n|T_f$, $B_n|B_f$ and $T_n|B_f$ in the same way as when deriving Eq. (5). The results suggest that both LS and RCI are biased downwards. RCI estimate simulations are presented in Figure 2(a).



(a) (b)

Figure 2: Impact of (a) random error in responsibility assignment, (b) heterogeneity of driver populations on RCI for different values of relative risk (RR) and target driver proportions (p)

The bias of RCI depends on *p*, whereas the bias of LS does not. Our simulations suggest that, for example, if RR=2.5, *p*=0.15 and *e*=0.1 (random error), then LS=0.93 and RCI=2.05, leading to an 18% downward bias of RR.

Figures 1(b) vs. 2(a) (the dependence of RCI bias on *e* for systematic and random error), show that these biases work in opposite directions. The intuition is that under systematic error, *target* are more often mistakenly assigned as at-fault, which increases the estimate of their relative risk. Conversely, the random error introduces some random noise into the crashes where the types of drivers differ. Because crashes where the *target* driver is at-fault and *baseline* driver is not-at-fault are more likely to happen, they are more impacted by this noise. That leads to an underrepresentation of this type of crashes in the data, driving down the estimate of relative risk.

4. Unequal mixing of driver groups

Now, assume that responsibility is assigned correctly and consider the concept of exposure. Exposure to the risk of being involved in the crash, by mere presence on the road, has at least three dimensions. The first of these is the distance driven per person per unit of time and it is thought to be controlled for in the comparison of proportions in Eq. (1) by including the proportion of not-at-fault drivers (T_n /B_n). However, another two dimensions (where and when the miles are driven) also co-determine the RR since the risk varies across both time and space. If the driver groups in question tend to drive in clusters (their incidence is correlated in time and/or spaces) this may affect the RCI expressed in Eq. (1). To our knowledge, Levitt & Porter (2001) were the first to introduce this assumption, which they referred to as “equal mixing of drivers”.

Assume that *target* drivers have higher RR than *baseline* drivers. If *target* drivers form time or/and space clusters (segments when they constitute significantly higher proportions of drivers in comparison to other segments), in these clusters we will observe more crashes per unit of time / space. However, the data related to these crashes will also have a higher count of *target* among the not-at-fault drivers (T_n). If we assume that the risk of causing a crash is exogenous (does depend only on the type of at-fault driver), the overall proportion T_f/B_f in Eq. (1) will be unchanged. What will however change is T_n/B_n since in the clustered hours (or/and locations), T_n will increase relative to B_n and thus the whole RR estimate will be biased downwards.

Even though there has been a rich discussion of Levitt & Porter´s (2001) paper, including a number of additional applications (Edlin & Karaca-Mandic, 2006 or Rodríguez-López 2019, for example) and successful replications (Dunn & Tefft, 2020 or Karl et al. 2023), there seems to be a gap in the systematic application of this important concept in the current stream of QIE literature. Since – as we show below – the equal mixing assumption affects the results of Lighthizer's test, we would like to fill this gap and follow up on our discussion of the responsibility assignment problem.

Clearly, if the composition of the not-at-fault population varies across at-fault *target* drivers vs. at-fault *baseline* drivers due to time or space clusters, it also may alter the outcome of LS. For example, if the equal mixing assumption is violated in the positive direction (*target* drivers drive in clusters), then *target* at-fault drivers meet a not-at-fault population that contains an unproportionally high portion of *target* drivers. Similarly, under this assumption, *baseline* drivers would more often crash with other *baseline* drivers. Consequently, the ratio on the left-hand side of Eq. (3) would be biased upwards, whereas the ratio on the right-hand side of Eq. (3) would be biased downwards, leading to systematic upward bias to LS (Eq. (4)).

As we did above for errors in responsibility assignment, we now simulate the extent of this bias of LS and RCI for different scales of equal mixing violation. For simplicity, we assume that there are two[2] space/time slots (of equal size), one where *target* drivers are more exposed, and one where *baseline* drivers are more exposed. Let us again focus on RTCs where both drivers belong to either *target* or *baseline* group and denote by p the overall proportion of *target* among the *target* and *baseline* not-at-fault participants. The two sets of drivers are unequally distributed across the two time slots, which are of equal length. In the first time slot, *target* drivers are overrepresented and their proportion is $p(1+Q)$, where $Q \in [0;1]$. In the second time slot, *target* drivers are underrepresented and their proportion is $p(1-Q)$. Q could then be interpreted as a proxy for the heterogeneity in population composition: the higher Q, the more serious violation of the equal mixing assumption.

Under these assumptions, we can compute the biased values of LS and RCI. First, for LS, we need to express the probability of *target* at-fault drivers crashing with a *target* not-at-fault driver (and all other combinations of driver status). That probability can be computed using the following logic: in the first time slot, the proportion of *target* drivers equals $(p+pQ)$. These drivers are more prone to cause a crash than *baseline* drivers by factor RR. Thus, the relative number of crashes these drivers cause is $(p+pQ)RR$. To compute the probability of the *target* driver crashing with a *target* not-at-fault driver in the first time slot, we need to multiply this expression with the proportion of *target* drivers in that time slot $(p+pQ)$. Thus, for the first time slot the probability of a *target* at-fault driver crashing with a *target* not-at-fault driver is $(p+pQ)^2RR$.

In the second time slot, the proportion of *target* drivers is $(p-pQ)$, thus, using the same logic, we obtain that the probability of *target* at-fault driver crashing with a *target* not-at-fault driver is $(p-pQ)^2RR$. Since both time slots are of equal length, the overall probability across the whole time period is equal to their sum $(p+pQ)^2RR+(p-pQ)^2RR$. This expression takes the place of $T_n|T_f$ in the LS Eq. (3). All the other parts of LS can be computed using similar logic. The final expression is independent of RR, which cancels out from the equation.

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[2] Our approach could be easily generalized to any finite number of time slots. To show the basic impacts of heterogeneity on RCI and LS, we use this simple model, as it has a universal and easily interpretable measure of heterogeneity - Q.

To compute the RCI we express T_f, T_n, B_f, B_n as given by Eq. (1). For instance, T_f could be expressed as $T_f = T_n|T_f + B_n|T_f = (p+pQ)(1-p-pQ)RR + (p-pQ)(1-p+pQ)RR$. The same principle applies to the other proportions.

The simulations show that the bias induced by violation of equal mixing impacts both LS and RCI. If equal mixing is violated, LS is biased upwards, and its bias depends on p (however, it does not depend on RR). The RCI bias depends on both p and RR, and it is always in a downward direction. Both biases of LS and RCI grow with growing p. Figure 2(b) shows the relationship between Q (inequality of mixing) and the observed RCI.

Our simulations suggest that, for example, if RR=2.5, there are 15 percent *target* drivers in the population (p=0.15), and Q=0.5, then LS=1.38 and RCI=2.37. The LS is biased upwards by 38%, the RR downward bias is only 5%. If Q took the extreme value of Q=1, the estimated RR in our example would be 2.04, with 18% of downward bias.

The presented simulations predict the direction and size of these possible biases. Since the biases cannot be identified directly through the Lighthizer test results, we need to rely on an estimation of the parameters in question. We suggest this in the following section, where we also offer additional tests that may help to decide the cause and direction of the dominant bias.

5. Empirical identification of possible biases

The simulations presented above contain parameters of *RR*, *p, Q* and errors made while assigning responsibility. At least a range of the first of these (*RR*) can be estimated based on RCI from Eq. (1). Parameters p and Q may be estimated in an approach that we present below. Estimating errors in assignment (both, systematic and random) is beyond the scope of this paper, however we may rely on empirical estimates from other works.

In order to perform further tests, the RTC-level data that are usually used in empirical research (an observation corresponds to one particular RTC) need to be transformed into counts (sums) of at-fault and not-at-fault target and baseline drivers per each hour-per-week. This leads to 168 slots where each represents a specific hour in the week and we aggregate relevant sums across the RTC dataset to construct variables of interest. The dataset used in this paper are described in detail in the section 6 below. For example, the number of *target* at-fault (T_f) during hour of the week h would be computed as a sum of all *target* at-fault (T_f) recorded during hour h across the whole time period of the dataset. The sample should be restricted to the RTCs where both drivers were from either the *target* or the *baseline* group (we omit e.g. cases where a driver < 25 y.o. collided with a driver >65 y.o.).

The first parameter of interest is the proportion of *target* drivers in the population of not-at-fault drivers p. Since we are focused on RTCs involving *target* and *baseline* drivers, this can be defined as $p = T_n/(B_n+T_n)$. To capture the time heterogeneity in p, we group the crashes by hour across the week and compute the population of *target* drivers for each hour h separately, obtaining $p_h = T_{nh}/(B_{nh}+T_{nh})$ yielding 168 observations of p_h. A valid estimator $\hat{p}$ would be a weighted average of these, weighing each observation by the number of crashes within that hour of the week n_h resulting in the equation:

$$\hat{p} = \sum_{h=1}^{168} \frac{T_{n_h}}{B_{n_h}+T_{n_h}} \cdot \frac{n_h}{N} = \sum_{h=1}^{168} p_h \cdot \frac{n_h}{N}, \qquad (9)$$

where N stands for total number of RTCs in given dataset, $N = \sum_{h=1}^{168} n_h$. Next, we notice that in the simplified theoretical case with two time slots, the variance of p_h corresponds to the following

$$Var(p_h) \sim \sum_{h=1}^{N} \frac{n_h}{N} (p_h - \hat{p})^2 = [(p+pQ-p)^2 + (p-pQ-p)^2] = p^2Q^2 \qquad (10)$$

Eq. (10) implies that for a non-zero p, we can introduce an estimator of Q computable from the data:

$$\hat{Q} = \frac{\sqrt{\widehat{Var(p_h)}}}{\hat{p}} = \frac{\sqrt{\sum_{h=1}^{168}\left(\frac{T_n}{B_n+T_n}_h - \hat{p}\right)^2 \cdot \frac{n_h}{N}}}{\hat{p}}, \qquad (11)$$

where we use the same system of weights as in all examples above.

The simulations above show three different biases of LS and RR may be present in estimates due to errors in responsibility assignment and/or due to unequal mixing. The dominant effect may be revealed by the value of LS: values <1 would signal the dominance of random error in assignment and values >1 signal the prevalence of systematic error in assignment and/or unequal mixing. In order to identify the presence of unequal mixing, we suggest a simple test that may identify the dominant cause of bias.

Following the logic above of dividing a week into 168 time segments and summing up the RTC participants hour by hour, we may compute the correlations between T_f/B_f and T_n/B_n across these segments. In general, if we detect $corr(T_f/B_f, T_n/B_n)>0$, this means that the time segments with above-average proportions of *target* at-fault are positively associated with above average presence of *target* among the not-at-fault. That would indicate the presence of unequal mixing. In order to control for more variables, such as traffic volume (by including total number of crashes per time/space cluster), we suggest extending this test to a regression model:

$$\frac{T_f}{B_f}_h = \beta_0 + \beta_1 \frac{T_n}{B_n}_h + e_h \qquad (12), \text{ where}$$

$(T_f/B_f)_h$ and $(T_n/B_n)_h$ are defined above, each computed per time segment h. Coefficient β_1 gives us an estimate of the linear relationship between the proportions: a statistically significant positive value would point to the presence of unequal mixing.

6. Results

We work with a database covering the universe of RTCs in the Czech Republic administered by the Czech Traffic Police. Our merged dataset contains data on all RTCs that occurred in the Czech Republic and were reported to police[3] between 2011 and 2022, about 1.2 million RTCs in total, with nearly 2 million drivers involved. The unit of observation is at the vehicle-driver level and the data identify the driver that caused the crash, as determined by the investigating officer. Additionally, the data contains detailed information about each crash, its participants and circumstances with 59 detailed attributes of the RTC including the participant's role in the RTC, their characteristics (e.g. age, gender, driver experience, alcohol blood content, intoxication by illegal drugs), vehicle characteristics, type of collision, location and other circumstances (weather, road condition, etc.). With respect to the severity of injury, all crashes are classified by the investigating officer into one of four ordinal categories: fatal injury (F), serious injury (S), slight injury (L), and property damage only ($)[4]. Table 1 summarizes the number of available observations by the severity of the RTC.

[3] According to Czech Act on Road Traffic (361/2000), the RTC must be announced to the police if it resulted in injury or property damage to the 3rd party or in damage to a vehicle in excess of CZK 100,000 (approx. EUR 4,000).

[4] The classification used in this paper reflects the classification used by Czech police. The fatal injury crashes (updated/corrected ex post on a monthly basis) and property damage only crashes are in line with the widely used international classification. Serious injuries are those that may lead to work incapacity longer than 1 week. Slight injuries include all other injuries.

Table 1: Overview of data availability in the Czech RTA database (2011 to 2022)

	F	*S*	*L*	*$*	*All*
All RTCs	6,243	25,104	214,159	881,311	1,126,817
Multiple vehicle crashes	3,166	11,705	111,597	523,396	649,864
2 motor vehicle crashes	2,213	7,674	76,134	478,234	564,255
Crashes caused by driver error	2,194	7,600	75,620	472,907	558,321
Data on Alcohol	2,121	7,404	72,544	313,492	395,561
Data on driver's age	2,079	7,244	70,657	229,525	309,505
Data on vehicle type	2,153	7,466	73,075	324,153	406,847
All three characteristics above	2,080	7,244	70,660	229,548	309,532

Source: Czech Traffic Police Headquarters. Unit of observation is one road traffic crash.

First, we present standard estimates of relative risk (RR) based on RCI defined in Eq. (1) for the selected age groups. These are divided according to the severity of the RTC. The upper part of Table 2 contains all RTCs relevant for the RR estimates (2 motor vehicles, driver fault, clean data), whereas the lower part contains rear end crashes only (same filters as above and further restricted to cases when the “back” driver was at-fault). The estimates of RR are presented with 95% confidence intervals of Fisher's exact test. All estimated RRs from the unrestricted sample show values significantly larger than 1. Drivers <25 y.o. and especially drivers >75 y.o. show consistently higher RTC involvement as at-fault drivers in comparison to their 25–65 y.o. counterparts.

Table 2: Estimates of relative risk for selected age groups and RTC types

All RTC types								
	F		*S*		*L*		*$*	
	RR*	CI	RR*	CI	RR	CI	RR	CI
Age <25	2.45*	1.99-3.04	1.95*	1.76-2.15	1.80	1.74-1.86	1.61	1.58-1.64
Age 65-74	2.23*	1.72-2.9	1.35*	1.18-1.55	1.45	1.39-1.52	1.36	1.32-1.39
Age 75+	3.37*	2.39-4.81	2.53*	2.07-3.1	2.34	2.2-2.49	2.28	2.19-2.37
n	2,194		7,600		75,620		472,907	

Rear End RTCs								
	F		*S*		*L*		*$*	
	RR*	CI	RR*	CI	RR	CI	RR	CI
Age <25	1.69*	0.73-4.12	2.31*	1.69-3.17	2.32	2.17-2.47	2.02	1.95-2.09
Age 65-74	1.04*	0.39-2.73	1.03*	0.65-1.63	1.35*	1.23-1.47	1.10	1.05-1.16
Age 75+	0.62*	0.09-3.27	1.94*	0.95-4.09	2.53	2.22-2.89	1.97	1.83-2.13
n	168		837		19,557		80,227	

If CI <1, RR is statistically significantly higher than 1 at 5% significance level.

* The Lighthizer test is not rejected at 5% significance level.

Across all the results in Table 2, the (*) sign marks the RR estimates when the Lighthizer test (Eq. (4)) does not reject the null hypothesis about the equality of the proportions at 5% significance level. The statistical inference was computed with Fisher's exact test. In these cases, the groups of drivers that the at-fault encounter as not-at-fault drivers do not significantly differ.

Table 3: Lighthizer statistics for selected age groups and RTC types

All RTC types								
	F		*S*		*L*		*$*	
	LS	CI	LS	CI	LS	CI	LS	CI
Age <25	1.24	0.76-1.97	0.83	0.66-1.03	1.12^{+}	1.05-1.2	1.28^{+}	1.22-1.33
Age 65-74	1.20	0.54-2.4	0.95	0.63-1.39	1.13^{+}	1-1.28	1.27^{+}	1.18-1.35
Age 75+	1.42	0.36-4.14	1.58	0.73-3.08	2.46^{+}	2.07-2.9	2.43^{+}	2.15-2.74
n	2,194		7,600		75,620		472,907	

Rear End RTCs								
	F		*S*		*L*		*$*	
	LS	CI	LS	CI	LS	CI	LS	CI
Age <25	0.97	0.02-8.13	0.92	0.43-1.81	1.33^{+}	1.17-1.51	1.38^{+}	1.28-1.49
Age 65-74	1.80	0.04-16.77	2.37	0.68-6.70	1.13	0.85-1.48	1.41^{+}	1.22-1.62
Age 75+	0.00	0.00-176.16	0.00	0.00-13.17	3.60^{+}	2.50-5.08	3.22^{+}	2.50-4.10
n	168		837		19,557		80,227	

$^{+}$ The difference is statistically significant at 5% significance level.

Table 3 presents the LS resulting from the ratio in Eq. (4). The reported rate 1.24 means that the proportion of young not-at-fault drivers is 24% higher when the at-fault driver is <25 y.o. than when the at-fault driver is 25–65 y.o. The confidence interval (95%) is computed using Fisher's exact test. The cases when we can reject the null hypothesis at 5% significance level are clearly inverse to those denoted in Table 2, where we were looking for cases where the results passed the LS test.

In most cases the value of LS is greater than 1, which may lead us to the intuitive conclusion that the proportions of drivers seem to be positively correlated and therefore that there are particular times and/or locations at which young (or older) drivers tend to be active on the road. However, our simulations show that this may also be an outcome of systematic error in responsibility assignment and that the value of LS cannot distinguish between these two causes.

To shed more light on this distinction we perform the regression analysis from Eq. (12). We divide the week into 168 hours and compute the relevant proportions for slight injury crashes (L) that provide us with a sufficient number of observations and show statistically significant values for LS. Figure 3 plots the data that enter this regression.

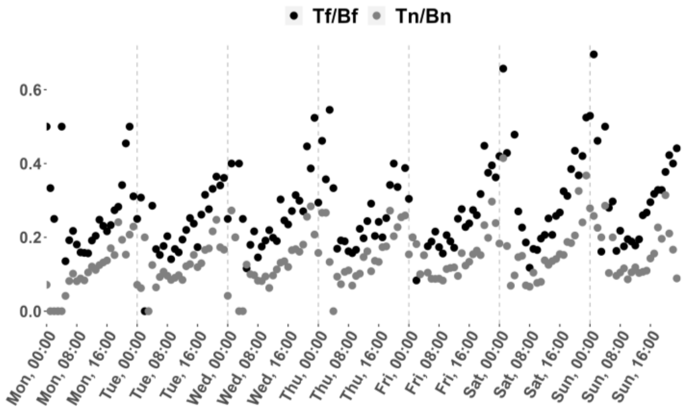

Figure 3: Proportions of target drivers among RTC participants (at-fault and not-at-fault) across the week

The involvement of drivers <25 y.o. in RTCs (measured by the proportions T_f/B_f and T_n/B_n) shows a clear time pattern (nearly uniform steady increase across the daytime, peaking around midnight). The correlation coefficient of 0.43 (95% CI 0.29-0.55) confirms that higher proportions of at-fault drivers <25 y.o. are positively associated with higher proportions of not-at-fault drivers <25 y.o. Similar results apply to drivers above 65 years, whose driving is spread more uniformly across the day time, with low/zero values at night (not reported in this paper).

Table 4: Regression coefficients based on proportions of drivers <25 y.o.

	Dependent variable: T_f/B_f					
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
Intercept	0.174*	0.032	0.244*	0.039	0.266*	0.044
T_n/B_n	0.756*	0.180	0.657*	0.146	0.662*	0.135
n			-0.00017*	0.00005	-0.00043*	0.000145
n^2					0.0000*	0.0000
N	57,335		57,335		57,335	
Hours	167		167		167	
R^2	0.163		0.267		0.291	

* The coefficient is statistically significant at 5% level. Newey-West standard errors reported.

The regression results resulting from Eq. (12) are presented in Table 4. We offer three specifications of the model, the first with simple regression, the second extended to include total number of crashes in given hour (n as a proxy for total volume of traffic that may affect the T_f/B_f proportion), and the third adding the term n^2 to allow for non-linearity. Since the time-of-the-week clusters are not independent (adjacent values are correlated), we report Newey-West standard errors correcting for possible autocorrelation (also correcting for the cyclical character of our data, in which the start and end of the series are connected). All the regression coefficients have the expected signs and are statistically significant at conventional levels.

The coefficients range from 0.662 to 0.756 with very small standard errors, meaning that an increase of T_n / B_n 10% is associated with around a 7% increase in T_f / B_f . The negative and statistically significant values of coefficient *n* suggest that the largest portion of RTCs with above-average values of T_f / B_f for *target* <25 y.o. happens at times with relatively lower volumes of total traffic. As for the size of the coefficient, the value of -0.00017* means that an increase of traffic volume (measured by RTCs) in a given hour by 100 crashes is associated with a 1.7 % decrease in T_f / B_f (controlling for T_n / B_n).

In order to estimate the possible influence of this unequal mixing on values of LS and RR, we need to return to our simulations and estimate the key parameters $\hat{p}$ and $\hat{Q}$. For this purpose, we first restrict the sample to the set of crashes in which both drivers were from the *target* or *baseline* groups (i.e. excluding any crashes involving drivers >65 y.o.). This means that *p* represents the proportion of *target* drivers in the total sum of all baseline plus *target* drivers. We then use the estimators introduced by Eqs. (9) and (11) with the data on slight injury crashes (L). Our approach divides the observed time period into two slots using the median proportion of *target* drivers and describes the heterogeneity in mean *p* for each slot. We acknowledge that using only two time slots represents a simplification and that the data might elicit a more complicated structure, but we find the simplification useful as an explanatory tool since it has a straightforward interpretation. We report the estimates of $\hat{p}$ and $\hat{Q}$ in Table 5.

Table 5: Estimates of proportion of target drivers p and the measure of heterogeneity Q

	$\hat{p}$	*s.d.*	$\hat{Q}$	*s.d.*
Age < 25	0.116	0.036	0.31	0.011
Age 65-74	0.065	0.025	0.38	0.018
Age 75 +	0.028	0.013	0.47	0.026

The standard deviation of *p* is computed in the usual way, and the standard deviation of *Q* is bootstrapped using 1,000 bootstrap replications. The estimates of $\hat{p}$ are in the expected ranges with reasonable values of variability when using $\hat{Q}$. For example, coming back to partition to two slots, the mean proportion of < 25 y.o. drivers (out of all drivers < 25 y.o. and 25–65 y.o.) would be 15.2 % $(\hat{p} + \hat{p}\hat{Q})$ for the first slot and 8.0 % $(\hat{p} - \hat{p}\hat{Q})$ for the second slot.

7. Discussion

The estimated RRs are consistent with existing research. For example, Gomes-Franco et al. (2020) estimated that the risk of causing a serious crash is 2.68 higher for drivers <25 y.o. compared to drivers 35–44 y.o.. For 65–74 y.o. drivers, Gomes-Franco et al. (2020) estimate that the risk of causing a crash is 1.75 times higher than it is for drivers 35–44 y.o. and for drivers >74 y.o. 2.94 times higher. Similar results are reported by Claret et al. (2003) or Morita a Sekine (2018).

Both relationships between age and RR are confirmed when we divide the drivers into smaller cohorts. We perform this robustness check with fatal RTCs (F). Cohorts of drivers aged 18–20, 21–22 and 23–24 yield RR estimates of 3.09, 2.49 and 1.99, respectively. Cohorts of drivers aged 65–69, 70–74 and 75+ yield RR estimates of 1.92, 2.69 and 3.37, respectively. These values are in line with the “J-curve” which predicts that RR will rise exponentially when approaching both extremes of the driver age interval (Stamatiadis & Deacon, 1997; Claret et al., 2003).

We also estimate RRs for rear end crashes, because this should address other potential sources of bias, such as differences in crash avoidance ability (Mendez & Izquierdo, 2010). Our results are fairly consistent with our estimates based on the unrestricted sample, with RR consistently higher for drivers <25 y.o. That could mean that in case of general crashes, <25 y.o. drivers show up more often among the not-at fault compared to rear end crashes which may signal their lower crash avoidance ability.

Moreover, we also estimated the LS for both, the general sample of RTCs and for rear and crashes. Again, both groups of results seem to be consistent. For (L) and ($) crashes, we observe that the LS is consistently higher for all rear end crashes with sufficient numbers of observations. There could be multiple explanations of this phenomenon. First, it might be that rear end crashes suffer less from random error than the general sample. Second, the sample of rear end crashes might suffer more by unequal mixing or systematic error (which seems not to be much likely). Finally, there might be an even more sophisticated reason. For instance, the relative risk of causing a rear end accident might be significantly different from the risk of causing a general accident. We have shown that the true value of RR influences the magnitude of responsibility assignment biases. Thus, the difference between LS for general sample and rear end accidents could also be explained by these different notions of RR.

Table 6: Potential biases caused by assumptions violations

	Impact on		
	Lighthizer statistics		RR estimate
	Bias	RR size	Bias
Responsibility: Systematic error	↑	matters	↑
Responsibility: Random error	↓	matters	↓
Unequal mixing	↑	not	↓

The simulations presented above had given us clues about the direction and the possible magnitudes of biases to LS and RR, as summarized in Table 6. Since the biases point in both directions, we cannot consider the estimated RR values as upper or lower bounds for the true value of RR. To illustrate the size of the possible biases, we use the example of crashes causing slight injury. If we assume that for drivers < 25 y.o. there was systematic fault assignment error in 10% of cases, the true RR would be 1.53 (implying an 18 % upward bias of our estimate RR=1.80 reported in Table 2). Similarly, if there was a random fault assignment error in 10% of cases, the true RR would be 2.10 (14 % downward bias of our estimate).

We estimate the consequences of unequal mixing by plugging the estimated values of RR, $\hat{p}$ and $\hat{Q}$ into the expressions for LS and RCI under unequal mixing. For example, using the values obtained on the sample of slight injury crashes (L) for drivers < 25 y.o., we estimate an LS value of 1.12 (a 12 % upward bias). The true RR would then be 1.82 (which represents a 1.1 % bias compared to our RR estimate of 1.80 shown in Table 2).

In the next step, we have employed a regression that reveals the presence of unequal mixing of driver groups on the roads. Using the sample of slight injury crashes (L) for drivers < 25 y.o., the results show a statistically significant positive association between at-fault and not-at-fault driver compositions (β_1=0.756), confirming a strong presence of unequal mixing. This presence may explain the value of LS larger than 1 (LS=1.12), however this result does not imply the absence of errors in responsibility assignment in the Lighthizer statistics: both types of bias may coexist.

8. Conclusions

We investigate potential sources of bias in the QIE method for relative risk estimation. We focus on three potential sources of bias frequently informally discussed in literature. Our main contribution is that we model these biases and rigorously describe their impacts on Lighthizer's test and RR estimate. Moreover, we empirically investigate the presence of such biases using a dataset on RTCs in the Czech Republic.

Our findings confirm that failure to pass Lighthizer's test may be a result of three possible sources of bias: systematic errors in responsibility assignment, random errors in responsibility assignment, or unequal mixing of the driver populations. Our simulations show that the expected biases caused by these errors depend both on the size of the error and the proportion of the *target* group in question. The overall direction of the RR estimate bias is determined by the type of error. On the other hand, the bias caused by unequal mixing depends on the proportion of the *target* group in question and the heterogeneity of the set of not-at-fault drivers. In this case, the direction of the RR estimate bias is downward and its size rather small.

We argue that Lighthizer´s test should be used to validate QIE assumptions, as it may reveal differences in the populations that at-fault drivers encounter, with important implications to interpretation of estimated relative risk. Distinguishing among the possible sources of biases requires additional work, however we suggest ways to estimate relevant parameters and a simple method to confirm unequal mixing.

Our work has a number of limitations that directly open avenues for further research. First, we work mostly with data on RTCs that resulted in slight injury. Expanding the inquiry to different types of RTC may help to mitigate biases. For example, for fatal crashes there is always a thorough post-accident investigation, thus, there should be less errors in responsibility assignment compared to less severe crashes. Furthermore, more observations would allow us to provide more detailed disaggregation (for example to year*hour observations) or perform spatial analysis. Our simplified approach to estimating heterogeneity, with two time slots, should be expanded to a more realistic scenario, possibly bringing new outcomes from the simulations. Lastly, we are aware that our estimates suffer from biases that we were not able to address here: differences between vehicles, differences in injury propensity, and issues with hit-and-run RTCs (where we lose all data on the driver who drove away).

Work with rear end crashes addresses part of these biases. We hypothesize that rear end crashes may be less prone to both random and systematic error in responsibility assignment and some other additional biases we did not discuss. Our tests on rear end crashes bring RR estimates very similar to the estimates on the general sample of crashes. As for the LS statistics, we see that the direction of its bias in most cases corresponds to the LS bias direction for the general sample. For the slight injury cases, the LS of rear end crashes exceeds the LS for the general sample. That brings some insights into which channels of bias the rear end crashes actually switch off. These results support reduction of random error assignment for rear end crashes, nevertheless, further exploration would be desirable.

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Declaration of Conflicting Interests

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

Data availability

The data used in this publication are freely available at Czech Police web site https://www.policie.cz/clanek/statistika-nehodovosti-900835.aspx