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Survivability factors for Canadian cyclists hit by motor vehicles

Simon Demers*

ABSTRACT

Police-reported data from Transport Canada's National Collision Database (NCDB) are analyzed with a view to identify and quantify various factors that can impact the survivability of cyclists involved in a motor vehicle collision. A Least Absolute Shrinkage and Selection Operator (LASSO) regression and a multiple imputation (MI) process address the variable selection and missing data problems, respectively. The resulting probabilistic model suggests that collision survivability depends largely on the cyclist's age and helmet usage. Survivability improves with age up to age 21, peaks for cyclists aged 21 to 34, and falls after age 35. Controlling for age and other factors, a bicycle helmet reduces the risk that a cyclist fatality will occur by approximately 34% (OR: 0.66, 95% CI: 0.56-0.78). Survivability in general, and the apparent safety benefits of bicycle helmets in particular, do not appear to depend on the sex of the cyclist once the type of collision and other factors are controlled for. Head-on and rear-end collisions tend to be more deadly. Certain environmental and situational variables, like strong winds and traffic control devices, also appear to impact survivability. There might be opportunities to sensitize cyclists of various age groups about the risks they are exposed to while cycling, and prevent or better protect cyclists from head-on and rear-end collisions.

Key Words Bicycle; helmet; injury; fatality; motor vehicle; collision; National Collision Database; Transport Canada

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INTRODUCTION

Although there is already an extensive body of empirical research on cyclist safety and cyclist injuries, few studies have been able to analyze cyclist fatalities on a large scale. This reflects the fact that fatal cyclist incidents are relatively rare occurrences, which means extensive data collection procedures are typically required before there is enough data available to make reliable inferences. Pinpointing and quantifying fatality risk factors for cyclists remain elusive objectives, especially in the Canadian context (Gaudet, Romanow, Nettel-Aguirre et al., 2015).

The motivation for this research note is to fill a gap in the literature on cyclist safety by studying cyclist fatalities using 16 years of police-reported data on cyclist-involved motor vehicle incidents collected as part of Transport Canada's National Collision Database (NCDB).

We model the mortality risk for cyclists using a probabilistic (logit) regression model that controls for some situational variables and personal characteristics of the cyclists involved. The empirical strategy consists in comparing cyclists who died with those who did not die after being involved in a motor vehicle collision. The analysis is based on police-reported incident data, which follows in the footsteps of Kim, Kim, Ulfarsson et al. (2007) using North Carolina data, Wang, Lu and Lu (2015) using Kentucky data, and Bíl, Bílová and Müller (2010) using data from the Czech Republic.

With some exceptions (Rivara, Thompson, & Thompson, 1997; Curnow, 2003), previous epidemiological studies on bicycle injuries have generally concluded that bicycle helmets provide substantial, measurable protective benefits. More specifically, researchers have found empirical evidence suggesting that bicycle helmets contribute to reduce the risk of loss of consciousness, intracranial injuries, and significant traumatic brain injuries (Sethi, Heidenberg, Wall et al., 2015), head and brain injury (Thompson, Rivara, & Thompson, 1989; Thompson, Rivara, & Thompson, 1996), concussion or other injuries requiring hospital admission (Linn, Smith, & Sheps, 1998), major head injuries (Spaite, Murphy, Criss et al., 1991), as well as severe or incapacitating injuries (Moore, Schneider, Savolainen et al., 2011). Despite all this evidence, few studies until now have been able to quantify how helmet usage impacts the risk of a cyclist fatality at the incident- and person-level. The NCDB data offer a rare opportunity to fill that gap.

METHODS

Through the NCDB, Transport Canada has made available to the public detailed records of all police-reported motor vehicle collisions on public roads in Canada from the

Correspondence to: Simon Demers, Affiliation: Planning, Research & Audit Section, Vancouver Police Department, 3585 Graveley St., Vancouver, BC V5K 5J5, Canada.
E-mail: simon.demers@vpd.ca

1999-2014 period. Each province and territory provides the data to the Canadian government for national reporting and analysis purposes.

All the statistical analysis was conducted using the statistical package R and is based on the electronic dataset released in the public domain on September 24, 2016 (Record ID: 1eb9eba7-71d1-4b30-9fb1-30cbdab7e63a). The latest version of the dataset is available directly from the Open Government Portal (Transport Canada, 2016).

Out of 5,860,405 public NCDB records, there is a subset of 122,907 cyclist records where a motor vehicle hit a bicycle (or vice versa). These cyclist records are identifiable using the variables representing the class of road user (P_USER=4) or, interchangeably, the vehicle type (V_TYPE=17).

For each cyclist, the public dataset contains collision-level data elements (incident year and month, time of day, collision severity, collision configuration, roadway configuration, weather conditions, road surface, road alignment, traffic control), vehicle-level characteristics (vehicle type and model year), and person-level data for each person involved (sex, age, injury severity, safety devices used). Within the injury severity field (P_ISEV), a collision is considered fatal if the cyclist died on impact or within 30 days after the collision (except in Quebec, where the time limit is eight days). Deaths from natural causes are excluded. The NCDB Data Dictionary provides more details on how each variable is defined and coded (Transport Canada, 2016).

Data Preparation

For analysis purposes, we merge the group of injured cyclists (P_ISEV=2) with those who did not sustain any reportable injury (P_ISEV=1) according to the NCDB data. This allows us to create a binomial response variable (Y) which captures whether the cyclist died as a result of the motor vehicle collision (Y=1) or not (Y=0). This is the outcome variable we want to model in a probabilistic manner. Our dichotomous approach has the advantage of removing a lot of subjective judgment since the severity of injuries is only assessed on a fatal or non-fatal basis, which means we do not need to rely on police injury severity scales that otherwise tend to correlate poorly with official medical assessments (Agran, Castillo, & Winn, 1990).

In order to properly capture the fact that the mortality curve may not be a linear, smooth polynomial or even monotonic function of age, we divided the data between 13 distinct age groups. The largest group consists of cyclists aged 21–34 inclusively. The youngest group consists of cyclists under seven years old. The oldest group consists of cyclists aged 70 years or older. The other groups cover ages 7–11, 12–15, 16–20, 35–39, and every subsequent five-year range up to age 65–69. Age is often taken to be a relevant risk factor for cyclists, but the level of granularity varies greatly between studies. For context, Siman-Tov, Jaffe, Israel Trauma Group et al. (2012) only compared children against adults, and Thompson et al. (1989) limited their analysis to three age groups: younger than 15, 15–24 and 25 years or older. Thompson et al. (1996) relied on four age groups: younger than 6, 6–12, 13–19, and 20 years or older. More recently, Gaudet et al. (2015) used five age categories: younger than 10, 10–19, 20–44, 45–64, and 65 years or older. Several other research efforts have focused specifically on children (Linn et al., 1998; Agran et al., 1990) or adults only (Bíl et al., 2010), in which case empirical comparisons between age groups are impossible.

Probabilistic Model

The workhorse model we rely on for statistical analysis purposes is a logistic regression where the probability of a cyclist death following a motor vehicle collision, conditional on observed person-level and incident-level characteristics (captured by vector x), is modelled in accordance with Eq. (1):

$$\Pr(Y = 1 | X = x) = \frac{\exp(\beta_0 + \beta^T x)}{1 + \exp(\beta_0 + \beta^T x)} \quad (1)$$

We first use a Least Absolute Shrinkage and Selection Operator (LASSO) regression to identify in a principled manner a subset of useful covariates and prune out those variables that have the least explanatory power. This approach encapsulates an inherent preference for sparsity and allows us to identify which factors have the strongest relationship with survivability, while minimizing superfluous interaction terms and redundant or statistically insignificant variables (Tibshirani, 1996). In other words, this serves as a regularization step that allows us to identify in the first instance which explanatory variables we should focus on for further analysis purposes.

For estimation purposes, we make available to the LASSO regression model a total of 135 regression terms: 122 individual factors plus 13 interaction terms that allow for the effect size of helmet usage to vary depending on the cyclist's sex and age group. The interaction terms allow us to test whether bicycle helmets tend to offer more life-saving benefits to cyclists in certain age groups and/or sex category.

As a second step, we build a standard logistic regression model (Model A) incorporating only the explanatory variables deemed to be important by the LASSO regression. This allows us to confirm that the preliminary findings from the regularization step are plausible and establishes a baseline model against which we will be able to compare our final results.

Missing Data

Unfortunately, several data records in the NCDB are incomplete or are not coded in an internally consistent manner. This includes, for example, the sex (20.4% missing) and age (26.0% missing) fields. The field intended to capture whether the cyclist was wearing a helmet at the time of the incident (P_SAFE) is especially problematic because it is impossible to conclusively confirm helmet usage in 76,731 cases, representing 62.4% of the entire NCDB sample.

In order to address the loss of statistical power and possible regression bias created by the missing data points (Fichman & Cummings, 2003), we rely on a multiple imputation (MI) process. This consists in filling in the missing values in a principled manner so that the analysis can proceed as if the dataset contained complete observations instead of automatically dropping all incomplete cases for which some data point is missing. The key is to properly reflect imputation uncertainty and this is accomplished by creating multiple synthetic datasets containing different imputed data points.

We accomplish the MI task and simulate five synthetic, but complete, datasets using the *Amelia* package in R

(Honaker, King, & Blackwell, 2011). The data are repeatedly simulated (imputed) based on the information available in the dataset. In each imputed dataset, the missing values are filled in using different imputed values that reflect approximately the uncertainty around the missing data.

Once MI has been used to fill in the missing values, all the usual statistical tools designed for complete cases can be used to conduct the analysis. In the pooled MI regression (Model B), the reported coefficient estimates simply reflect the average of the point estimates obtained from the five separate regressions based on each imputed dataset. The variance associated with each coefficient estimate in the pooled regression, for its part, reflects the average within imputation variance that captures model uncertainty plus a measure of between imputation variance that captures imputation uncertainty (Rubin, 1987; Marshall, Altman, Holder et al., 2009).

For reference, the flowchart in Figure 1 summarizes the analysis steps.

RESULTS

Out of the 122,907 individual cyclists involved in a police-reported motor vehicle collision on a public road in Canada between 1999 and 2004 inclusively, 895 died according to the NCDB. Table I shows the number of cyclist collisions and deaths in the NCDB by year.

This represents an average rate of approximately 73 cyclist fatalities per 10,000 collisions (95% CI: 68-78) or 1.7 cyclist fatalities per million person-years based on Statistics Canada's population numbers (Statistics Canada, 2018). This cyclist fatality rate is slightly lower than (but still comparable to) previously published estimates. Based on data from the Office of the Chief Coroner of Ontario, Wesson, Stephens, Lam et al. (2008) reported a mortality rate of 2.3 per million person-years across the 1991–2002 period, but observed a lower rate of 2.0 per million person-years specifically after the introduction of bicycle helmet legislation targeting children under 18 years old. In the United States, based on FARS data, Meehan, Lee, Fischer et al., (2013) found annualized fatality rates of 2.0 per million children and 2.5 per million children

TABLE I Police-reported cyclist collisions and deaths in the NCDB

Year	Collisions	Deaths
1999	8,674	69
2000	8,029	40
2001	8,221	59
2002	8,019	63
2003	8,062	45
2004	8,494	58
2005	8,390	52
2006	8,025	75
2007	7,746	67
2008	7,082	44
2009	7,144	44
2010	7,199	61
2011	7,078	56
2012	7,415	61
2013	7,109	62
2014	6,220	39
TOTAL	**122,907**	**895**

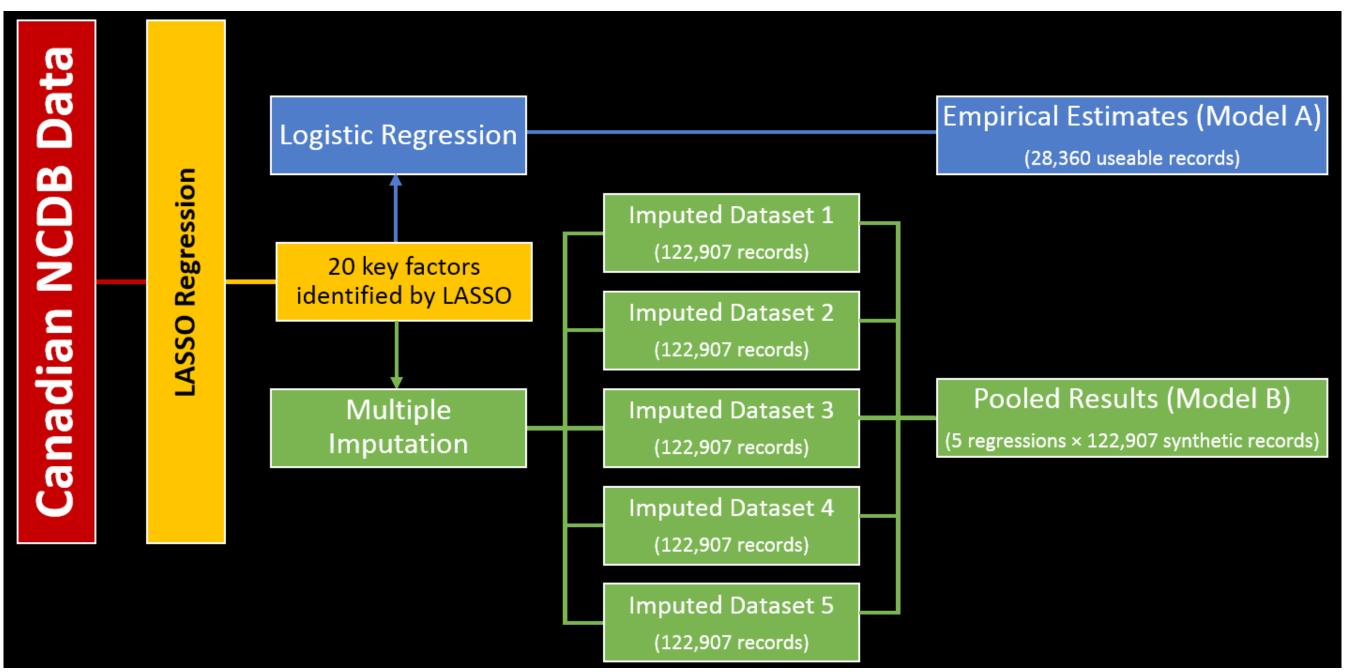

FIGURE 1 Analysis flowchart. The LASSO regression is used to identify which variables are included in the baseline logistic regression (Model A) and need to be manually imputed (Model B). The reported estimates from Model B reflect the pooled analysis results combining all five imputed datasets.

in states, respectively, with and without bicycle helmet safety laws. For the period between 1996 and 2005, Nicaj, Stayton, Mandel-Ricci et al. (2009) reported annualized rates of 1.8 to 2.3 per million residents for Chicago, Boston, Washington, Los Angeles, Philadelphia, and New York (in increasing order).

The main regression results from Model A and Model B are summarized side-by-side in Table II. For greater clarity, Model A is the regular logistic regression model that combines the relevant subset of factors identified by the sparse LASSO regression. Model B includes the same subset of explanatory variables as Model A, but is able to leverage the entire NCDB dataset instead of just the complete cases because it relies on the pooled MI data. Both models use only 20 explanatory variables (plus an intercept coefficient): a relevant subset of eight plausible predictors of survivability as identified by the LASSO model (including helmet usage) and dummy variables representing each age group (except the 21–34 baseline group).

Age is correlated strongly with cyclist survivability. This finding is consistent with earlier studies, including, most recently, Gaudet et al. (2015) and Behnood and Mannering (2017). As anticipated, however, the relationship is not linear or monotonic. This is illustrated by Figure 2.

Cyclists younger than 21 years old are roughly 45–55 per cent more likely to die subsequent to a cyclist collision relative to those in the baseline 21–34 age group. This is consistent with previous empirical evidence that suggested children may be more vulnerable than adults to serious injury in general (Rivara et al., 1997) and head injury in particular (Thompson et al., 1989), especially in a cycling setting. Always relative to the 21–34 age group, the mortality risk becomes 80 per cent higher by age 35–39 (OR: 1.80, 95% CI: 1.34-2.43), doubles for cyclists aged 40–54, triples for cyclists aged 55–59 (OR: 3.05, 95% CI: 2.22-4.19), more than quadruples for cyclists aged 60–69, and continues to worsen for cyclists who are 70 years or older (OR: 8.53, 95% CI: 6.35-11.46).

The mortality risk for a cyclist involved in a head-on collision increases three-fold (OR: 3.12, 95% CI: 2.37-4.12). Rear-end collisions (OR: 4.87, 95% CI: 4.03-5.88) and collisions where the cyclist was run off the right shoulder (OR: 5.94,

TABLE II Regression results: the corresponding odds ratio (OR) is reported to the right of each estimated regression coefficient; all the reported coefficients except two are statistically significant at least at the 95% confidence level; confidence intervals are provided for Model B (95% CI), reflecting the fact that it is intended to be the final empirical model

	Model A (Reduced)		Model B (Pooled MI Data)		
Factor	**Estimate**	**OR**	**Estimate**	**OR**	**[95% CI]**
Helmet	-0.53[a]	0.59	-0.41[a]	0.66	[0.56-0.78]
Ran off right shoulder	2.61[a]	13.60	1.78[a]	5.94	[3.07-11.50]
Rear-end collision	1.58[a]	4.85	1.58[a]	4.87	[4.03-5.88]
Head-on collision	1.52[a]	4.57	1.14[a]	3.12	[2.37-4.12]
Passing or climbing lane	5.25[a]	191	1.88[b]	6.54	[1.01-42.23]
Strong wind	2.25[a]	9.50	1.63[a]	5.11	[2.02-12.93]
Stop sign	-0.55[a]	0.58	-0.53[a]	0.59	[0.46-0.76]
No traffic control	0.30[b]	1.36	0.42[a]	1.53	[1.31-1.79]
Age 6 and younger	1.73[a]	5.63	0.45[b]	1.56	[1.04-2.35]
Age 7 to 11	0.66[b]	1.94	N.S.	N.S.	[0.90-1.74]
Age 12 to 15	0.45[c]	1.57	0.38[a]	1.46	[1.10-1.95]
Age 16 to 20	0.57[b]	1.76	0.37[a]	1.45	[1.11-1.90]
Age 21 to 34	Baseline	1.00	Baseline	1.00	Baseline
Age 35 to 39	0.93[a]	2.54	0.59[a]	1.80	[1.34-2.43]
Age 40 to 44	0.68[a]	1.98	0.65[a]	1.92	[1.44-2.58]
Age 45 to 49	0.64[b]	1.90	0.68[a]	1.98	[1.44-2.73]
Age 50 to 54	0.82[a]	2.27	0.71[a]	2.03	[1.47-2.80]
Age 55 to 59	1.59[a]	4.90	1.11[a]	3.05	[2.22-4.19]
Age 60 to 64	2.01[a]	7.49	1.43[a]	4.20	[3.03-5.82]
Age 65 to 69	1.83[a]	6.24	1.63[a]	5.08	[3.54-7.29]
Age 70 and older	2.38[a]	10.85	2.14[a]	8.53	[6.35-11.46]
No. of observations	**28,360**		**122,907**		

[a] Statistically significant at the 99% confidence level.
[b] Statistically significant at the 95% confidence level.
[c] Statistically significant at the 90% confidence level.
N.S. = not statistically significant (or different from the baseline).

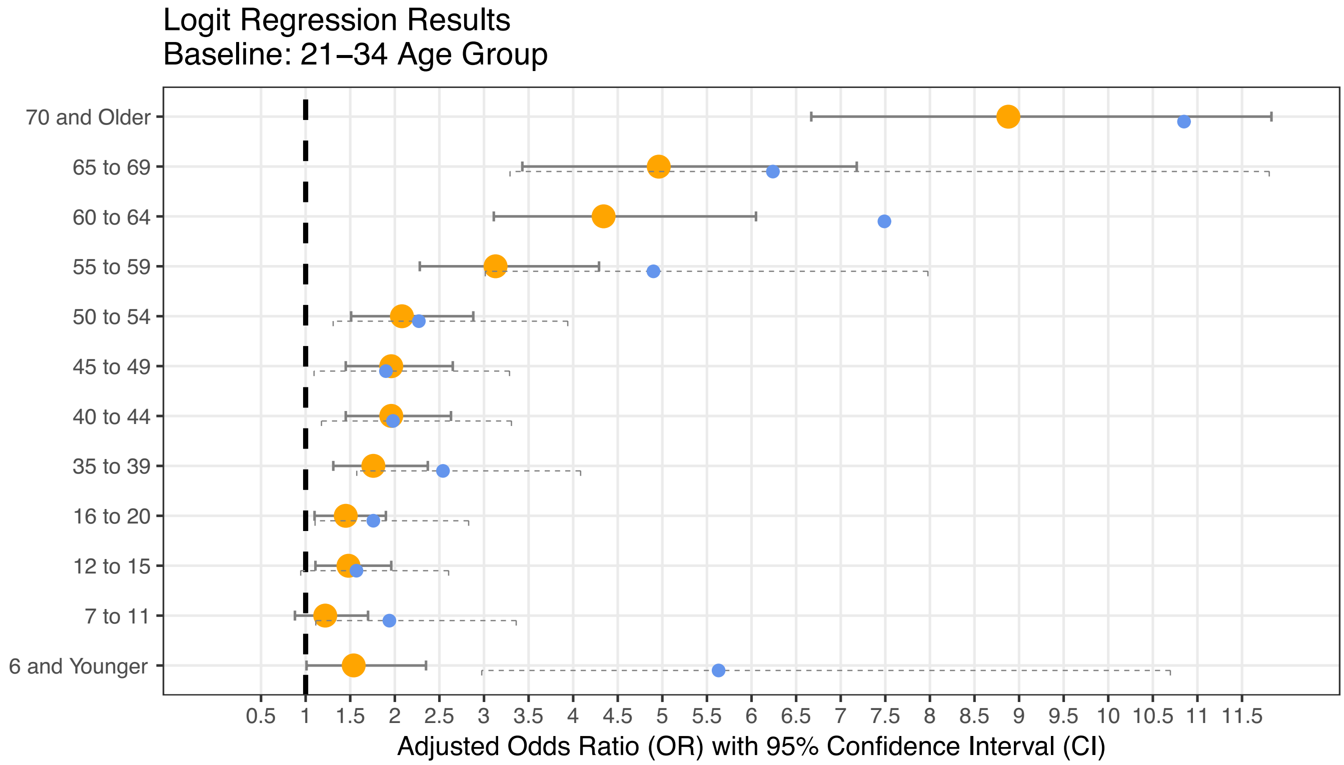

FIGURE 2 Adjusted odds ratios and 95% confidence intervals by age group. For comparison purposes, the pooled analysis results from Model B (top lines) are presented side-by-side with Model A estimates (bottom dashed lines). Model B tends to deliver estimates that are simultaneously more conservative (ORs usually closer to 1) and more precise (with shorter confidence intervals) relative to Model A. The confidence intervals produced by Model A for two age groups (60–64 and 70 years and older) are not shown because they extend beyond the maximum range of the horizontal axis.

95% CI: 3.07-11.50) are, respectively, five and six times more deadly than other types of cyclist collisions. Cyclist collisions that occur in strong wind conditions are also five times more deadly (OR: 5.11, 95% CI: 2.02-12.93). We hypothesize, without being able to offer any supporting evidence, that this might be because the cyclists or motorists involved in these types of collisions may not have as much opportunity to mitigate the force of the impact (e.g., by applying the brakes, swerving, or bracing themselves just before the accident).

The absence of traffic control device increases the mortality risk for cyclists involved in a collision by 53 per cent (OR: 1.53, 95% CI: 1.31-1.79). It might be because these cases tend to involve faster speeds, or tend to occur in more isolated areas where the ambulance response times are longer or in rural areas where emergency care is less specialized. By comparison, cyclist collisions that occur at or near an intersection controlled by a stop sign tend to be 41 per cent less deadly (OR: 0.59, 95% CI: 0.46-0.76).

Everything else being the same, wearing a helmet improves survivability for cyclists involved in a traffic collision, but there is no measurable difference between sex or age groups in terms of life-saving benefits, which is consistent with earlier findings by Thompson et al., (1996). Helmet use reduces the risk that a cyclist fatality will occur by approximately 34 per cent (OR: 0.66, 95% CI: 0.56-0.78). This level of efficacy for bicycle helmets falls within the statistical range obtained by Attewell, Glase and McFadden (2001) based on a meta-analysis of earlier studies on bicycle helmets published between 1987 and 1998 (95% CI: 0.10-0.71), and Olivier and Creighton (2016) from another meta-analysis of quantitative studies (95% CI: 0.14-0.88). Separately, Joseph, Azim, Haider et al. (2017) reported a mortality OR of 0.56 (95% CI: 0.34-0.78) based on an analysis of National Trauma Data Bank (NTDB) data compiled by the American College of Surgeons.

DISCUSSION

Despite the fact that adult males appear to be consistently overrepresented in cyclist fatalities (even taking into account the number of collisions), as shown by several previous epidemiological studies and the raw Canadian NCDB data itself, male cyclists who are involved in a motor vehicle collision are NOT more likely to die than female cyclists, everything else being equal. This apparent contradiction can be reconciled by recognizing that male cyclists involved in motor vehicle collisions tend to be older than their female counterparts (average age of 30.8 vs. 28.8), are less likely to wear a helmet (51.2% vs. 58.1%), are more likely to be rear-ended (5.1% vs. 3.7%) or be involved in a head-on collision (2.1% vs. 1.6%), and are more likely to be involved in collisions where there is no traffic control device (50.1% vs. 47.1%) as opposed to an intersection controlled by a stop sign (20.8% vs. 23.4%). Those are all detrimental risk factors for male cyclists, as shown by Table II.

One obvious weakness with the NCDB data is that we cannot differentiate cases that involved a head impact or a head injury from those that did not involve a head impact or a head injury. Of course, if cyclists tend to die from injuries other than head injuries or head trauma, then bicycle helmets would essentially make no difference on the mortality risk. Based on a detailed review of case files from the Coroner's Office, Gaudet et al. (2015) found that 72 per cent of the cyclists who died in a motor vehicle collision in Alberta between 1998 and 2011 suffered head injuries. A similar review in New York City found that 77 per cent of the bicycle fatalities that occurred there between 1996 and 2005 involved a head injury (Nicaj et al., 2009).

Unlike Nicaj et al. (2009), Gaudet et al. (2015) and others, we are also unable to consider alcohol or drug use as possible risk factors because these factors are not available in the public NCDB dataset. We also do not know the speeds involved in each case or the type of motor vehicle that collided with each cyclist. These shortcomings would need to be addressed in follow-up studies or through supplemental data.

CONCLUSIONS

The police-reported data in Transport Canada's NCDB offer researchers a rare opportunity to analyze cyclist fatalities and, more specifically, the relative mortality risk associated with various environmental and situational factors.

Our analysis delivers new findings and reaffirms several existing ones, especially around the life-saving benefits of bicycle helmets. Among others, the NCDB data suggest that wearing a helmet can reduce the risk that a cyclist fatality will occur by approximately 34 per cent (OR: 0.66, 95% CI: 0.56-0.78). This means there might be opportunities to remind cyclists about the life-saving benefits of bicycle helmets and reinforce helmet usage through enforcement.

Head-on and rear-end collisions tend to be especially more deadly. Certain environmental and situational variables like strong winds and traffic control devices also appear to influence survivability, independently from the type of collision or the characteristics of the cyclist. These findings suggest that there might be opportunities to better protect cyclists involved in certain types of collisions or look for ways to prevent these collisions in the first place.

Since collision survivability appears to improve for younger cyclists up to age 21, peaks between age 21 and 34, and then decreases after age 35, there might be opportunities to sensitize cyclists in different age groups about the risks they are exposed to. These results also show that it is useful to control for the size of each age group when analyzing aggregate, population-level trends around cyclist fatality rates.

CONFLICT OF INTEREST DISCLOSURES

A version of this paper was submitted to and accepted by the 2018 Conference of the Canadian Association of Road Safety Professionals (CARSP). It will be presented at the Conference in Victoria, BC in June 2018, and is expected to eventually appear in the Conference Proceedings. These Conference Proceedings will be accessible only to CARSP members, through the secure CARSP website. The author states that there are no conflicts of interest.

AUTHOR AFFILIATIONS

*Planning, Research & Audit Section, Vancouver Police Department, Vancouver, BC, Canada.

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