An assessment of strategies to model opponent effects in crash severity analysis

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Abstract

Road accidents impose an important burden on health and the economy. Numerous efforts to understand the factors that affect road collisions have been undertaken. One stream of research focus on modelling the severity of crashes. Crash severity research is useful to clarify the way different factors can influence the outcome of the event. The objective of this paper is to assess different strategies to model the interactions between participants in a crash, in the context of crashes involving two parties. Towards this objective, a series of models are estimated using data from Canada's National Collision Database. Three levels of crash severity (no injury/injury/fatality) are analyzed using ordered logit models and covariates for the participants in the crash and the conditions of the crash. Modelling strategies include different ways of introducing the covariates (e.g., in a single-level or multi-level form), as well as by subsetting the dataset. The models are assessed using predicted shares and outcomes, and the results highlight the importance of considering opponent effects in crash severity analysis. On the other hand, the study suggests that hierarchical (i.e., multi-level) specifications and subsetting do not perform necessarily better than a relatively simple single-level model with opponent effects.

1. Introduction

Road safety continues to be a concern world-wide. According to a recent report from the World Health Organization (2019), road accidents are the 8th leading cause of death for all ages, and the number one cause of death for children and young people between the ages of 5 to 29. Of all leading causes of death, road accidents are the only cause of death unrelated to disease, disorder, or infection. Road accidents impose a heavy burden on individuals and society as a whole. Gobally, the rate of road collision-related deaths per 100,000 population and 100,000 vehicles have both fallen, even as the number of vehicles has grown (World Health Organization, 2019, Figs. 1 and 2). These gains, although they are to be celebrated, cannot distract from the crushing economic cost of premature death (e.g., Symons et al., 2019; Wijnen et al., 2019), not to mention the long-term consequences for survivors, measured in sometimes crippling emotional and physical pain (e.g., Merlin et al., 2007; Devlin et al., 2019; Pelissier et al., n.d.).

Evidence from across the world suggests that the burden of road accidents is not borne evenly. There are important disparities at the international level, where the odds of death due to road crashes are three times higher in low-income countries compared to high-income countries; in fact, no reductions in road accident-related fatalities were appreciated in low-income countries between 2013 and 2016 (World Health Organization, 2019). In the case of high-income countries, where substantial gains in road safety have been observed for years, said gains have also been unevenly distributed; thus, while fatal crashes involving older adults in the United States and Great Britain declined between 1997 and 2010 (despite the graying of the population), the trend remained stable or increased slightly in Australia in roughly the same period (Thompson et al., 2018). There are also systematic differences in the impact of road accidents. For example, in a study in the United States, Obeng (2011) reported that the impact of covariates of crash severity varied substantially in magnitude by gender. More recently, Regev et al. (2018) used adjusted crash risk to find that the risk of crashes in Great Britain peaked for people 21 to 29 years of age; on the other hand, the risk of fatal injuries for older drivers was constant, irrespective of the seriousness of the crash - which highlights the

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perils of accidents at older ages. Other studies have concentrated on the consequences of road accidents for the young (e.g., Peek-Asa et al., 2010), the old (e.g., Rakotonirainy et al., 2012), as well as pedestrians and cyclists (e.g., Hanson et al., 2013; McArthur et al., 2014).

Given the relevance and cost of this matter, as well as the important variations of the impacts among different population segments, numerous efforts efforts have been conducted to better understand the factors that affect road safety - including the probable consequences of crashes. Consequently, a stream of research in the analysis of road accidents is concerned with the severity of crashes. In particular, multivariate analysis of crash severity is a useful way to clarify the way various factors can affect the outcome of an incident, to discriminate between various levels of injury, from no injury (i.e., property damage only), to different degrees of injury up to and including fatality. This is an active area of research (e.g., Savolainen et al., 2011), and one where methodological developments have aimed at improving the reliability, accuracy, and precision of models.

This paper aspires to contribute to the literature on crash severity by assessing different modelling strategies useful to incorporate opponent effects in crash analysis, in the context of incidents involving two parties. The importance of these interactions has been recognized in the existing literature (e.g., Chiou et al., 2013; Lee and Li, 2014; Li et al., 2017; Tarrao et al., 2014), and a number of different modelling strategies have been proposed. In this paper we present a systematic assessment of several relevant modelling strategies, ranging from the way variables are defined in single-level models, in multi-level models (i.e., hierarchical models), as well as using data subsetting approaches. For the assessment we use data from Canada's National Collision Database, a database that collects all police-reported collisions in the country. Using the most recent version of the dataset (2017), three levels of crash severity (no injury/injury/fatality) are analyzed using ordered logit models and covariates for the participants in the crash and the conditions of the crash. For model assessment, we conduct an in-sample prediction exercise using the estimation sample (i.e., *nowcasting*), and also an out-of-sample prediction exercise using the dataset corresponding to 2016 (i.e., *backcasting*). The models are assessed using predicted shares and predicted individual outcomes using an extensive array of verification statistics. The results highlight the importance of considering opponent effects in crash severity analysis to improve the goodness-of-fit and predictive performance o. On the other hand, the study suggests that hierarchical variable specifications and subsetting do not perform necessarily better than a relatively simple single-level model with opponent effects.

The rest of this paper is structured as follows. In Section 2 we present a concise review of the methods used to analyze crash severity, with a particular focus on techniques that consider the interactions between participants in a crash. Section 3 describes the data requirements, data preprocessing, and the modelling strategy. Model estimation is presented in 4 and the assessment of models is in Section 5. We then present some additional thoughts about the applicability of this approach in Section 6 before offering some concluding remarks in Section 7.

2. Methodological approaches in crash severity analysis

Modelling the outcomes of crashes in terms of the severity of injuries to participants has been a preoccupation of transportation researchers, planners, auto insurance companies, governments and the public for decades. One of the earliests studies to investigate the severity of injuries conditional on an accident having occurred was by White and Clayton (1972). Kim et al. (1995) later stated that the "linkages between severity of injury and driver characteristics and behaviors have not been thoroughly investigated" (p. 470). Nowadays, there is a burgeoning literature on this subject, including methodological developments, case studies, and more niche research with a focus on particular situations (e.g., crashes at intersections, Mussone et al., 2017; crashes in rural roads, Gong and Fan, 2017) or special populations (e.g., crashes involving motorcyclists or active travelers; see Shaheed et al., 2013; Salon and McIntyre, 2018).

Crash severity is often modelled using models for discrete outcomes, including classification techniques from machine learning (e.g., Iranitalab and Khattak, 2017; Chang and Wang, 2006; Effati et al., 2015; Khan et al., 2015), Poisson models for counts (e.g., Ma et al., 2008), unordered logit/probit models [], as well as ordered logit/probit models (e.g., Rifaat and Chin, 2007), with numerous variants, such as random parameters/mixed logit (e.g., Aziz et al., 2013; Haleem and Gan, 2013), partial proportional odds models (e.g., Mooradian et al., 2013; Sasidharan and Menendez, 2014), and the use of copulas (e.g., Wang et al., 2015). Recent reviews of methods include Savolainen et al. (2011) and Shamsunnahar and Eluru (2013).

Table 1: Categories of variables used in the analysis of crash severity with examples

Category	Examples
Person-related	Attributes of participants in the crash, e.g., injury status, age, gender, licensing status, professional driver status
Traffic unit-related	Attributes of the traffic unit, e.g., type of traffic unit (car, motorcycle, etc.), maneouver, etc.
Crash-related	Attributes of the crash, e.g., location, weather conditions, light conditions, number of parties, etc.
Road-related	Attributes of the road, e.g., surface condition, grade, geometry, etc.

Shamsunnahar and Eluru (2013) in particular conducted an extensive comparison of models for discrete outcomes and found that while the difference between the performance of unordered models and ordered models was so small as to make not difference, ordered models are usually more parsimonious since only one latent functions needs to be estimated for all outcomes, as opposed to one for each outcome in unordered modelling mechanisms.

Irrespective of the modelling framework employed, models of crash severity often include variables in several categories, as shown with examples in Table 1 (also see Montella et al., 2013). Many crash databases (but not by any means all) also account for the multievent nature of many crashes. In this way, there are crashes that involve a single traffic unit (e.g., Kim et al., 2013; Gong and Fan, 2017), others that involve two traffic units (e.g., Tarrao et al., 2014; Wang et al., 2015), and more rarely there are multi-traffic unit crashes (e.g., Wu et al., 2014; Bogue et al., 2017). Likewise, each traffic unit can possibly involve more than one person (e.g., driver and passengers). Thus, depending on the incident, each record in a crash database may include unique identifier for the crash, as well as identifiers for the traffic units (or identifiers for dummy objects such as a light pole that was hit by a vehicle), and the people involved in the crash.

Interplay between participants:

Chiou et al. (2013)

Lee and Li (2014) consider effect on crash severity of interactions between different types of vehicles. This they do by subsetting the dataset and estimating independent models for each subset of data. Since they consider three types of vehicles, namely cars (C), light trucks (L), and heavy trucks (H), they work with nine datasets, for each type of interactions (i.e., C-C, C-L, C-H, and so on). Tarrao et al. (2014)

Mannering et al. (2016)

Li et al. (2017)

Salon and McIntyre (2018)

Chen et al. (2019)

Wu et al. (2014) two-vehicle crashes do not really consider the interactions.

Many models use a latent-variable approach, whereby the severity of the crash (observed) is linked to an underlying latent variable that is a function of the variables:

$$y^*_{ik} = \sum_{l=1} \beta_l p_{ikl} + \sum_{m=1} \gamma_m c_{km} + \epsilon_{ik}$$

The left-hand side of the expression above (y^*_{ik}) is a latent (unobservable) variable that is associated with the severity of crash k ($k = 1, \cdots, K$) for participant i ($i = 1, \cdots, n$). The right-hand side of the expression is split in three parts. The first part collects $l = 1, \cdots, L$ individual attributes p for participant i in crash k; these could relate to the person (e.g., age and gender) or be individual attributes of the traffic unit (e.g., maneuver or vehicle type). The second part collects $m = 1, \cdots, M$ attributes c related to the crash k, including crash-related and road-related data. The last part is a random term specific to participant i in crash k.

The latent variable is not observed directly, but it is possible to posit a probabilistic relationship with the outcome y_{ik} (the severity of crash k for participant i). Depending on the characteristics of the data and the assumptions made about the random component of the latent function different models can be obtained. For example, if crash severity is coded as a binary variable (e.g., non-fatal/fatal), we can relate the latent variable to the outcome as follows:

$$y_{ik} = \begin{cases} \text{fatal} & \text{if } y_{ik}^* > 0 \\ \text{non-fatal} & \text{if } y_{ik}^* \leq 0 \end{cases}$$

Due to the stochastic nature of the latent function, the outcome of the crash is not fully determined. However, we can make the following probability statement:

$$P(y_i = \text{fatal}) = P(y_i^* > 0)$$

In other words, the probability of a fatal accident equals the probability that the latent variable is greater than zero. This implies (see Maddala, 1986, p. 22):

$$\begin{aligned} P(y_i = \text{fatal}) \quad &= P(\textstyle\sum_{l=1} \beta_l p_{ikl} + \sum_{m=1} \gamma_m c_{km} + \epsilon_{ik} > 0) \\ &= P(\epsilon_{ik} > -\textstyle\sum_{l=1} \beta_l p_{ikl} - \sum_{m=1} \gamma_m c_{km}) \end{aligned}$$

It the random terms ϵ_i are assumed to follow the logistic distribution, the the binary logit model is obtained; if they are assumed to follow the normal distribution, the binary probit model is obtained.

More often, though, the outcome is recorded using more categories, for example property damage only (PDO)/injury/fatality. A similar approach can be adopted, with a latent variable that relates to the outcome as follows:

$$y_i = \begin{cases} \text{fatality} & \text{if } y_i^* > k_2 \\ \text{injury} & \text{if } k_1 < y_i^* < k_2 \\ \text{PDO} & \text{if } y_i^* < k_1 \end{cases}$$

where k_1 and k_2 are estimable thresholds. In this case, the associated probability statements are as follows:

$$\begin{aligned} P(y_{ik} = \text{PDO}) \quad &= \quad 1 - P(y_{ik} = \text{injury}) - P(y_{ik} = \text{fatality}) \\ P(y_{ik} = \text{injury}) \quad &= \quad P(k_1 - \textstyle\sum_{l=1} \beta_l p_{ikl} - \sum_{m=1} \gamma_m c_{km} < \epsilon_{ik} < k_2 - \sum_{l=1} \beta_l p_{ikl} - \sum_{m=1} \gamma_m c_{km}) \\ P(y_{ik} = \text{fatality}) \quad &= \quad P(\epsilon_{ik} < k_1 - \textstyle\sum_{l=1} \beta_l p_{ikl} - \sum_{m=1} \gamma_m c_{km}) \end{aligned}$$

If the random terms are assumed to follow the logistic distribution, the ordered logit model is obtained; if the normal distribution, then the ordered probit model. Estimation methods for these models are very well-established (e.g., Maddala, 1986; Train, 2009)

There are numerous variations of the basic modelling framework above, including hierarchical models, bivariate models, multinomial models, and Bayesian models, among others (see Savolainen et al., 2011 for a review of methods).

3. Methods

3.1. Data considerations

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Montella et al. (2013)

3.2. Model specification

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4. Application

> **Note:** that this paper presents reproducible research. The source file is an R Markdown document. All code and data necessary to reproduce the analysis are available from the following anonymous Drive folder:
>
> https://drive.google.com/open?id=12aJtVBaQ4Zj0xa7mtfqxh0E48hKCb_XV
>
> The source files, code, and data will be publicly available in a GitHub repository upon acceptance of the paper for publication

4.1. Data for the application

To assess the performance of the modelling strategies discussed in Section 3, we use data from Canada's National Collision Database (NCDB). This is database contains all motor vehicle collisions on public roads in Canada as reported by a police service. Data are collected by provinces and territories, and shared with the federal government, where data are combined, tracked, and analyzed for reporting of deaths, injuries, and collisions in Canada at the national level. The NCDB is provided by Transport Canada, the agency of the federal government of Canada in charge of transportation policies and programs, under the Open Government License - Canada version 2.0 [https://open.canada.ca/en/open-government-licence-canada].

The NCDB is available from 1999. For the purpose of this paper, we use the most recent year available as of this writing (2017). Furthermore, for assessment we also use the data corresponding to 2016. Similar to databases in other jurisdictions [see @], the NCDB contains information pertaining to the collision, the traffic unit, and the person(s) involved.

Variable	Details
Age	Details

Note:
NCDB available from https://open.canada.ca/data/en/dataset/1eb9eba7-71d1-4b30-9fb1-30cbdab7e63a

4.2. Model estimation

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Model specification. See Table:

Variable	Notes	Model 1	Model 2	Model 3	Model 4
Individual-level variables					
Age	In decades	✓	✓	✓	✓
Age Squared		✓	✓	✓	✓
Sex	Reference: Female	✓	✓	✓	✓
Use of Safety Devices	7 levels; Reference: No Safety Device	✓	✓	✓	✓
Traffic unit-level variables					
Passenger	Reference: Driver	✓	✓		✓
Pedestrian	Reference: Driver	✓	✓		✓
Bicyclist	Reference: Driver	✓	✓		✓
Motorcyclist	Reference: Driver	✓	✓		✓
Light Truck	Reference: Light Duty Vehicle	✓	✓		✓
Heavy Vehicle	Reference: Light Duty Vehicle	✓	✓		✓
Opponent variables)					
Age of Opponent	In decades		✓	✓	
Age of Opponent Squared			✓	✓	
Sex of Opponent	Reference: Female		✓	✓	
Opponent: Light Duty Vehicle	Reference: Pedestrian/Bicyclist/Motorcyclist		✓	✓	✓
Opponent: Light Truck	Reference: Pedestrian/Bicyclist/Motorcyclist		✓	✓	✓
Opponent: Heavy Vehicle	Reference: Pedestrian/Bicyclist/Motorcyclist		✓	✓	✓
Hierarchical traffic unit variables)					
Age:Light Truck Driver				✓	
Age Squared:Light Truck Driver				✓	
Age:Heavy Vehicle Driver				✓	
Age Squared:Heavy Vehicle Driver				✓	
Age:Light Truck Passenger				✓	
Age Squared:Light Truck Passenger				✓	
Age:Heavy Vehicle Passenger				✓	
Age Squared:Heavy Vehicle Passenger				✓	
Age:Pedestrian				✓	
Age Squared:Pedestrian				✓	
Age:Bicyclist				✓	
Age Squared:Bicyclist				✓	
Age:Motorcyclist				✓	
Age Squared:Motorcyclist				✓	
Hierarchical opponent variables)					
Age:Age of Opponent					✓
Age:Age of Female Opponent					✓
Age:Age of Male Opponent Squared					✓
Age:Age of Female Opponent Squared					✓
Age Squared:Age of Male Opponent					✓
Age Squared:Age of Female Opponent					✓
Case-level variables)					
Crash Configuration	19 levels; Reference: Hit a Moving Object	✓	✓	✓	✓
Road Configuration	12 levels; Reference: Non-Intersection	✓	✓	✓	✓
Weather	9 levels; Reference: Clear and Sunny	✓	✓	✓	✓
Surface	11 levels; Reference: Dry	✓	✓	✓	✓
Road Alignment	8 levels; Reference: Straight and Level	✓	✓	✓	✓
Traffic Controls	19 levels; Reference: Operational Traffic Signals	✓	✓	✓	✓
Month	12 levels; Reference: January	✓	✓	✓	✓

Notice how there are zero cases of user: BYCICLIST - opponent: Heavy Vehicle.
Re-estimate model after subsetting by USER Type of person 1. LDxLD:
Summary of models. See Table 2.

5. Model assessment

5.1. Outcome shares based on probabilities

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The datasets are used to predict the probabilities of the outcomes:
The results of calculating the Average Prediction Error appear in Table 3.

Table 2: Summary of model estimation results

Model	Number of observations	Number of coefficients	AIC
Full sample models			
Model 1	164,511	100	195,215
Model 2	164,511	106	178,943
Model 3	164,511	116	181,333
Model 4	164,511	109	179,018
Model 1 Ensemble (sample subsets by user type vs opponent)			
Light duty vehicle vs light duty vehicle	114,841	95	145,396
Light duty vehicle vs light truck	3,237	95	3,979
Light duty vehicle vs heavy vehicle	5,013	95	5,913
Light truck vs light duty vehicle	3,121	95	3,921
Light truck vs light truck	809	95	1,230
Light truck vs heavy vehicle	198	95	354
Heavy vehicle vs light duty vehicle	4,763	95	4,362
Heavy vehicle vs light truck	180	95	291
Heavy vehicle vs heavy vehicle	779	95	1,193
Pedestrian vs light duty vehicle	7,176	94	2,842
Pedestrian vs light truck	328	94	270
Pedestrian vs heavy vehicle	376	94	473
Bicyclist vs light duty vehicle	3,521	94	686
Bicyclist vs light truck	148	94	192
Bicyclist vs heavy vehicle	NA	NA	NA
Motorcyclist vs light duty vehicle	2,298	94	1,403
Motorcyclist vs light truck	127	94	233
Motorcyclist vs heavy vehicle	73	94	204
Model 2 Ensemble (sample subsets by user type vs opponent)			
Light duty vehicle vs light duty vehicle	114,841	98	143,909
Light duty vehicle vs light truck	3,237	98	3,963
Light duty vehicle vs heavy vehicle	5,013	98	5,896
Light truck vs light duty vehicle	3,121	98	3,913
Light truck vs light truck	809	98	1,216
Light truck vs heavy vehicle	198	98	347
Heavy vehicle vs light duty vehicle	4,763	98	4,315
Heavy vehicle vs light truck	180	98	275
Heavy vehicle vs heavy vehicle	779	98	1,182
Pedestrian vs light duty vehicle	7,176	98	2,839
Pedestrian vs light truck	328	98	270
Pedestrian vs heavy vehicle	376	98	476
Bicyclist vs light duty vehicle	3,521	98	693
Bicyclist vs light truck	148	98	200
Bicyclist vs heavy vehicle	NA	NA	NA
Motorcyclist vs light duty vehicle	2,298	98	1,411
Motorcyclist vs light truck	127	98	235
Motorcyclist vs heavy vehicle	73	98	201

Note:
There are zero cases of BICYCLIST vs HV in the sample

Table 3: Predicted shares and average prediction errors (APE) by model (percentages)

	No Injury			Injury			Fatality			
Model	Observed	Predicted	APE	Observed	Predicted	APE	Observed	Predicted	APE	WAPE
In-sample (nowcasting using 2017 dataset, i.e., estimation dataset)										
Model 1	78886	79029.00	0.18	84675	84533.74	0.17	950	948.26	0.18	0.17
Model 1 Ensemble	62449	62439.99	0.01	83606	83614.28	0.01	933	933.73	0.08	0.01
Model 2	78886	78928.98	0.05	84675	84641.94	0.04	950	940.08	1.04	0.05
Model 2 Ensemble	62449	62438.99	0.02	83606	83615.22	0.01	933	933.80	0.09	0.01
Model 3	78886	79027.29	0.18	84675	84512.50	0.19	950	971.21	2.23	0.20
Model 4	78886	78939.18	0.07	84675	84622.54	0.06	950	949.28	0.08	0.06
Out-of-sample (backcasting using 2016 dataset)										
Model 1	82812	82574.35	0.29	88586	88737.88	0.17	935	1020.77	9.17	0.28
Model 1 Ensemble	64469	64525.65	0.09	87476	87291.39	0.21	909	1036.96	14.08	0.24
Model 2	82812	82900.86	0.11	88586	88432.82	0.17	935	999.32	6.88	0.18
Model 2 Ensemble	64469	64541.74	0.11	87476	87261.66	0.25	909	1050.60	15.58	0.28
Model 3	82812	82948.83	0.17	88586	88340.07	0.28	935	1044.10	11.67	0.29
Model 4	82812	82878.68	0.08	88586	88446.37	0.16	935	1007.94	7.80	0.16

5.2. Predicted outcomes

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Verification statistics used are summarized in Table 4.

Table 4: Verification statistics

Statistic	Description	Notes
Percent Correct (PC)	Total hits and correct rejections divided by number of cases	Strongly influenced by most common category
Percent Correct by Class (PC_c)	Same as Percent Correct but by category	Strongly influenced by most common category
Bias (B)	Total predicted by category, divided by total observed by category	$B > 1$: class is overpredicted; $B < 1$: class is underpredicted
Critical Success Index (CSI)	Total hits divided by total hits + false alarms + misses	$CSI = 1$: perfect score; $CSI = 0$: no skill
Probability of False Detection (F)	Proportion of no events forecast as yes; sensitive to false alarms but ignores misses	$F = 0$: perfect score
Probability of Detection (POD)	Total hits divided by total observed by class	$POD = 1$: perfect score
False Alarm Ratio (FAR)	Total false alarms divided by total forecast yes by class; measures fraction of predicted yes that did not occur	$FAR = 0$: perfect score
Heidke Skill Score (HSS)	Fraction of correct predictions after removing predictions attributable to chance; measures fractional improvement over random; tends to reward conservative forecasts	$HSS = 1$: perfect score; $HSS = 0$: no skill; $HSS < 0$: random is better
Peirce Skill Score (PSS)	Combines POD and F; measures ability to separate yes events from no events; tends to reward conservative forecasts	$PSS = 1$: perfect score; $PSS = 0$: no skill
Gerrity Score (GS)	Measures accuracy of predicting the correct category, relative to random; tends to reward correct forecasts of less likely category	$GS = 1$: perfect score; $GS = 0$: no skill

We next evaluate the outcomes of the nowcast using an array of verification statistics. See Table 6.
We next evaluate the outcomes of the nowcast using an array of verification statistics. See Table 6.

6. Further considerations

Here I plan to discuss the applicability of the modelling strategy to advanced modelling techniques (partial proportional odds, heterogeneity, hierarchical models, etc.)

7. Concluding remarks

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Table 5: Assessment of in-sample outcomes (nowcasting using 2017 dataset, i.e., estimation dataset)

Observed	Predicted Outcome			Verification Statistics									
Outcome	No Injury	Injury	Fatality	Percent Correct	Percent Correct by Class	Bias[1]	Critical Success Index[2]	Probability of False Detection[3]	Probability of Detection[4]	False Alarm Ratio[5]	Heidke Skill Score[6]	Peirce Skill Score[7]	Gerrity Score[8]
Model 1													
No Injury	50652	22504	150		69.067	0.929	0.499	0.265	0.642	0.309			
Injury	28232	62120	797	68.552	68.644	1.076	0.546	0.364	0.734	0.318	0.372	0.370	0.190
Fatality	2	51	3		99.392	0.059	0.003	0.000	0.003	0.946			
Model 1 Ensemble													
No Injury	34711	16429	63		69.909	0.820	0.440	0.195	0.556	0.322			
Injury	27738	67167	830	69.338	69.380	1.145	0.599	0.451	0.803	0.298	0.363	0.353	0.202
Fatality	0	10	40		99.386	0.054	0.042	0.000	0.043	0.200			
Model 2													
No Injury	51530	17136	85		72.903	0.872	0.536	0.201	0.653	0.250			
Injury	27356	67515	864	72.364	72.415	1.131	0.598	0.353	0.797	0.295	0.447	0.443	0.227
Fatality	0	24	1		99.409	0.026	0.001	0.000	0.001	0.960			
Model 2 Ensemble													
No Injury	35473	16147	60		70.621	0.828	0.451	0.192	0.568	0.314			
Injury	26976	67446	829	70.049	70.089	1.139	0.605	0.439	0.807	0.292	0.379	0.368	0.212
Fatality	0	13	44		99.386	0.061	0.047	0.000	0.047	0.228			
Model 3													
No Injury	51102	17297	79		72.549	0.868	0.531	0.203	0.648	0.254			
Injury	27784	67337	868	71.996	72.044	1.134	0.594	0.359	0.795	0.298	0.440	0.436	0.224
Fatality	0	41	3		99.399	0.046	0.003	0.000	0.003	0.932			
Model 4													
No Injury	51574	17317	84		72.821	0.874	0.536	0.203	0.654	0.252			
Injury	27312	67335	863	72.282	72.333	1.128	0.597	0.353	0.795	0.295	0.446	0.441	0.227
Fatality	0	23	3		99.410	0.027	0.003	0.000	0.003	0.885			

Notes:
[1] $B > 1$: class is overpredicted; $B < 1$: class is underpredicted;
[2] $CSI = 1$: perfect score; $CSI = 0$: no skill;
[3] $F = 0$: perfect score;
[4] $POD = 1$: perfect score;
[5] $FAR = 0$: perfect score;
[6] $HSS = 1$: perfect score; $HSS = 0$: no skill; $HSS < 0$: random is better;
[7] $PSS = 1$: perfect score; $PSS = 0$: no skill;
[8] $GS = 1$: perfect score; $GS = 0$: no skill.

Table 6: Assessment of in-sample outcomes (nowcasting using 2017 dataset, i.e., estimation dataset)

Observed	Predicted Outcome			Verification Statistics									
Outcome	No Injury	Injury	Fatality	Percent Correct	Percent Correct by Class	Bias[1]	Critical Success Index[2]	Probability of False Detection[3]	Probability of Detection[4]	False Alarm Ratio[5]	Heidke Skill Score[6]	Peirce Skill Score[7]	Gerrity Score[8]
Model 1													
No Injury	53167	23097	145		69.311	0.923	0.501	0.260	0.642	0.304			
Injury	29642	65455	788	68.834	68.920	1.082	0.550	0.363	0.739	0.317	0.378	0.375	0.192
Fatality	3	34	2		99.437	0.042	0.002	0.000	0.002	0.949			
Model 1 Ensemble													
No Injury	35564	16930	71		69.967	0.815	0.437	0.192	0.552	0.323			
Injury	28891	70451	822	69.368	69.423	1.145	0.601	0.454	0.805	0.297	0.362	0.351	0.188
Fatality	14	95	16		99.344	0.138	0.016	0.001	0.018	0.872			
Model 2													
No Injury	54430	17615	81		73.262	0.871	0.542	0.198	0.657	0.245			
Injury	28382	70954	850	72.759	72.806	1.131	0.602	0.349	0.801	0.292	0.455	0.451	0.232
Fatality	0	17	4		99.450	0.022	0.004	0.000	0.004	0.810			
Model 2 Ensemble													
No Injury	36234	16840	73		70.463	0.824	0.445	0.191	0.562	0.318			
Injury	28216	70527	819	69.856	69.916	1.138	0.605	0.444	0.806	0.292	0.373	0.362	0.194
Fatality	19	109	17		99.333	0.160	0.016	0.001	0.019	0.883			
Model 3													
No Injury	53985	17731	83		72.936	0.867	0.536	0.199	0.652	0.248			
Injury	28827	70819	849	72.422	72.470	1.134	0.599	0.354	0.799	0.295	0.448	0.444	0.228
Fatality	0	36	3		99.438	0.042	0.003	0.000	0.003	0.923			
Model 4													
No Injury	54493	17843	79		73.168	0.874	0.541	0.200	0.658	0.247			
Injury	28318	70725	852	72.663	72.709	1.128	0.601	0.348	0.798	0.292	0.453	0.449	0.231
Fatality	1	18	4		99.449	0.025	0.004	0.000	0.004	0.826			

Notes:
[1] $B > 1$: class is overpredicted; $B < 1$: class is underpredicted;
[2] $CSI = 1$: perfect score; $CSI = 0$: no skill;
[3] $F = 0$: perfect score;
[4] $POD = 1$: perfect score;
[5] $FAR = 0$: perfect score;
[6] $HSS = 1$: perfect score; $HSS = 0$: no skill; $HSS < 0$: random is better;
[7] $PSS = 1$: perfect score; $PSS = 0$: no skill;
[8] $GS = 1$: perfect score; $GS = 0$: no skill.

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