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Bicyclist injury severities in bicycle–motor vehicle accidents

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Abstract

This research explores the factors contributing to the injury severity of bicyclists in bicycle–motor vehicle accidents using a multinomial logit model. The model predicts the probability of four injury severity outcomes: *fatal*, *incapacitating*, *non-incapacitating*, and *possible or no injury*. The analysis is based on police-reported accident data between 1997 and 2002 from North Carolina, USA. The results show several factors which more than double the probability of a bicyclist suffering a fatal injury in an accident, all other things being kept constant. Notably, inclement weather, darkness with no streetlights, a.m. peak (06:00 a.m. to 09:59 a.m.), head-on collision, speeding-involved, vehicle speeds above 48.3 km/h (30 mph), truck involved, intoxicated driver, bicyclist age 55 or over, and intoxicated bicyclist. The largest effect is caused when estimated vehicle speed prior to impact is greater than 80.5 km/h (50 mph), where the probability of fatal injury increases more than 16-fold. Speed also shows a threshold effect at 32.2 km/h (20 mph), which supports the commonly used 30 km/h speed limit in residential neighborhoods. The results also imply that bicyclist fault is more closely correlated with greater bicyclist injury severity than driver fault.

Keywords: Bicycle; Biking; Injury; Severity; Accident; Crash

1. Introduction

Bicycling is an often neglected transportation mode when it comes to analysis although it is used for both commuting and recreation. It is also an activity that carries some risk of serious injury (Schieber and Sacks, 2001) although there are positive trends towards greater safety. The number of bicyclist fatalities in the United States (US) has been decreasing, with 816 fatalities reported in 1993 and 622 fatalities reported in 2003, a decrease by 24%. An additional 46,000 bicyclists were injured in accidents in 2003 (NCSA, 2003).

Due to the still large number of injuries and deaths in bicycle accidents, research has investigated the characteristics of bicycle–motor vehicle accidents, for example: the influence of alcohol, head injuries, bicycle helmet usage, demographic and economic characteristics (age, gender, ethnicity, income, etc.), roadway characteristics (speed limit, type of roads, pavement, etc.), environmental factors (month, day, time, weather, road surface, etc.), collision types, party at fault, and locations (urban or rural areas, driveway, shoulder, bike lane, trail, etc.). However, existing studies have primarily investigated accident rates, or accident frequency associated with a certain type of injury, i.e. focused on risk, rather than investigate the factors associated with injury severity in individual accidents. Therefore, the main objective of this study is to develop a robust multivariate model of bicyclist injury severity in motor–vehicle accidents.

2. Literature review

There have been a number of studies on bicycle safety and they have identified various important individual, neighborhood, and roadway characteristics. Several studies investigated the relationship between alcohol and bicycle safety. Noland and Quddus (2004) found that alcohol expenditure per capita was significantly correlated with bicyclist casualties although it was not clear whether this was due to the intoxication of motorists or bicyclists. Some studies have found bicyclists under the influence of alcohol associated with a much greater risk of head

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or face injuries as compared with sober cyclists (Andersson and Bunketorp, 2002; Olkkonen and Honkanen, 1990). Interestingly, Olkkonen and Honkanen (1990) found in their study that bicyclist intoxication increased the risk of injury due to falling more so than injury due to motor vehicle collisions.

Research generally finds that most fatal and serious bicycle accident rates rise markedly with higher speed limits (Stone and Broughton, 2003; Garder, 1994). Therefore, bicyclist safety can be improved by reducing bicycle and vehicle speeds (Koike et al., 2003; Fernandez de Cieza et al., 1999; Garder et al., 1998). At higher approach speeds the driver's visual scanning pattern is modified, that is, high speed makes drivers pay attention to the most relevant direction and ignore the less relevant direction (Räsänen and Summala, 2000; Summala et al., 1996). This fits research results that indicate the most frequent type of bicycle–motor vehicle accidents are related to a driver turning right and a bicycle coming from the driver's right, e.g. the studies by Räsänen and Summala (1998) and Preusser et al. (1982).

In several studies, children and the old were the primary groups that suffered from bicycle-related injuries (Stone and Broughton, 2003; Rodgers, 2000; Rodgers, 1995, 1997; Eilert-Petersson and Schelp, 1997; Maring and van Schagen, 1990; Thompson et al., 1990a). Males, in Eilert-Petersson and Schelp's study (1997), were overrepresented in bicycle-related injuries compared to females at almost all ages. Maring and van Schagen (1990) pointed out that even though age by itself was not the causal factor, age was strongly associated with relevant variables such as perceptual-motor speed and cognitive development.

Numerous studies of bicycle accidents have focused on head injury and helmet usage. Generally, they found that head injuries were the most common type of bicycle-related injuries (Macpherson et al., 2004; Maki et al., 2003; Welander et al., 1999; Stutts and Hunter, 1999; Eilert-Petersson and Schelp, 1997). Helmets are protective against head injury and brain injury (Depreitere et al., 2004; Robinson, 2001; Schieber and Sacks, 2001; Povey et al., 1999; Thompson et al., 1996; Wasserman et al., 1988). Although helmets are effective for all bicyclists, regardless of age, helmets are not always properly used, e.g. worn in a poor position on the head, so helmet design can possibly be improved to reduce improper use (Curnow, 2003; Scuffham and Langley, 1997; Robinson, 2001; Ching et al., 1997). Helmet usage is related with other factors: for example, helmet usage rates were in one study found related with the time spent riding a bicycle each year (Rodgers, 2000), another study found those who wear helmets are more highly educated (Wasserman et al., 1988), and yet another study found helmet use in rural areas to be lower than in urban areas across all age groups and for both genders (Harlos et al., 1999).

Some research indicated that cycling on-road was safer than using off-road paths and sidewalks, in terms of the relative rates for falls and injuries (Forster, 2001; Aultman-Hall and Adams, 1998; Moritz, 1998; Rodgers, 1997). However, Smith and Walsh (1988) and Pucher (2001) argued that cycling was much safer where bicycle facilities such as bikeways and bike lanes were provided. This inconsistency shows that bicycle safety, in terms of risk of accidents, varies significantly and that there are safe and unsafe bike paths, just as there will be areas where on-road riding is relatively safe, e.g. wide lanes and a bicycle friendly environment, and areas where on-road riding is risky, e.g. narrow lanes with little or no shoulders. In a study by Thom and Clayton (1992), the most frequent contributing factor to bicycle–motorist accident risk for both bicyclists and drivers was the failure to yield right of way. Garder (1994) and Kim and Li (1996) observed that bicyclists were more likely than drivers to violate traffic laws.

Klop and Khattak (1999) observed that injury severity increased in fog, after dark on unlighted sections, with higher speed limit, on road sections with an up/downgrade, and decreased with increasing average annual daily traffic, street lighting, and an interaction of the shoulder-width and speed-limit. However, the study had a narrow scope as it focused on accidents on two-lane, undivided roadways. Other work, based on discussions with police and field observations, identified the main causes of bicycle-traffic accidents in San Juan, Puerto Rico (Fernandez de Cieza et al., 1999). The main causes identified were an excessive vehicle speed, lack of proper illumination during the afternoon peak period and at night, and poor roadway design.

Socioeconomic factors, particularly the percentage of poor households within a neighborhood, played an important role in the prediction of bicycle accident rates (Epperson, 1995). Pless et al. (1989) reported that family and neighborhood characteristics were stronger risk factors for bicycle injuries than children's personality and behavior; higher risk of injury was related to fewer years of parent education, a history of accidents in the family, an environment judged as unsafe, and poor parental supervision.

Through reviewing the literature, we have gained insight into the factors affecting bicycle–motor vehicle accident risk but explorations of the factors affecting bicyclist injury severity in an accident are limited. This paper aims to contribute to filling that gap and develop a probabilistic model of bicyclist injury severity in bicycle–motor vehicle accidents which can be used for statistical hypothesis testing of variables thought to affect injury severity.

3. Methodology

The severity of bicyclist injury in bicycle–motor vehicle accidents is normally classified into discrete categories which describe the injury severity (usually from no injury to fatal injury with one or more categories in between). To develop a probabilistic model of discrete injury severities conditioned on an accident having occurred, we follow the work of Shankar et al. (1996) and Ulfarsson and Mannering (2004). The probability of cyclist n being injured with severity outcome i is written

$$P_{ni} = P(U_{ni} \geq U_{ni'}), \quad \forall i' \in I, \ \ i' \neq i, \tag{1}$$

where U_{ni} is a function determining the severity, and I is a set of I possible, mutually exclusive severity categories. It is assumed that a bicyclist experiences the injury severity with the largest U_{ni}. If we assume U_{ni} has a linear-in-parameters form it can be expressed

$$U_{ni} = \boldsymbol{\beta}_i \mathbf{x}_n + \varepsilon_{ni}, \tag{2}$$

where $\boldsymbol{\beta}_i$ is a vector of estimable coefficients for injury outcome i and $\mathbf{x}_n$ is a vector of exogenous variables for bicyclist n. ε_{ni} is a random component (an error term) that explains unobserved influences on injury severity. If we assume ε_{ni} is identically and independently distributed with a type 1 extreme value distribution this leads to the multinomial logit model (MNL) (McFadden, 1981):

$$P_{ni} = \frac{e^{\boldsymbol{\beta}_i \mathbf{x}_n}}{\sum_{\forall i' \in I} e^{\boldsymbol{\beta}_{i'} \mathbf{x}_n}}. \tag{3}$$

The coefficients $\boldsymbol{\beta}_i$ can be estimated by the method of maximum likelihood. While variables in ordered logit or probit models are constrained to give an effect in only one direction (either increase or decrease the injury severity level), in fact, it is also possible for a variable to have a U-shape (or its inverse) effect which pushes away from (towards) the middle injury severity levels and towards (away from) the high and low injury severity levels. Hence, the MNL model was applied in this study to allow that flexibility.

Additionally, in the MNL model, the coefficients on exogenous variables remain unbiased under choice-based sampling if the model includes a full set of $I-1$ alternative-specific constants, however, the alternative-specific constants become biased and the model will produce the sample shares, i.e. the probabilities of the alternatives will be biased (see proof in Manski and Lerman, 1977). This is important when using accident data due to the prevalence of underreporting for accidents with low severity or property damage only, which is essentially equivalent to choice-based sampling. This feature of MNL means that the estimated coefficients will remain unbiased on all variables unless the underreporting is a function of an included variable (e.g. age, gender, etc.).

Now note that $\mathbf{x}_n$ does not vary across injury severities, which leads to the log-odds ratio:

$$\ln\left(\frac{P_{ni}}{P_{nI}}\right) = \boldsymbol{\beta}_i \mathbf{x}_n - \boldsymbol{\beta}_I \mathbf{x}_n = (\boldsymbol{\beta}_i - \boldsymbol{\beta}_I)\mathbf{x}_n, \quad i = 1, \ldots, I-1. \tag{4}$$

Only the difference in coefficients can be identified and without loss of generality one injury severity is selected as a base case and its coefficients are set to 0.

In a logit model with three or more categories the coefficient and the odds ratio can yield misleading results about the actual effect of a variable on the probability of an injury severity category. A positive (negative) coefficient on a variable in an injury severity category cannot be freely interpreted as increasing (decreasing) the probability of that injury severity category. This is because the rate of change in probability is not a simple linear function of the coefficient in that injury severity category, but is also a function of its effect and the effects of all the other coefficients in all other injury severities. For a textbook proof see Greene (2003). Observing a positive coefficient (or odds ratio) and claiming this indicates the variable increases the probability can therefore be wrong.

To avoid this problem and properly explore marginal effects for binary indicator variables, we calculate the change in probability when each variable is altered. As seen when we explore the data later in this paper, the variables are not continuous. They are all coded as 0 and 1 indicator values. We therefore cannot differentiate the probability with respect to any of the observed variables to calculate a standard elasticity. In order to overcome this, the percentage change in probability when an indicator variable is changed from 0 to 1 (and 1 to 0) can be determined by

$$E_{x_{nk}}^{P_{ni}} = \frac{P_{ni}[\text{given } x_{nk}=1] - P_{ni}[\text{given } x_{nk}=0]}{P_{ni}[\text{given } x_{nk}=0]}. \tag{5}$$

This value is called the direct pseudo-elasticity of the probability, which captures the percentage change in probability when the kth indicator variable for bicyclist n, x_{nk}, is switched (0–1, 1–0). This method was for example applied in studies by Shankar and Mannering (1996) and Ulfarsson and Mannering (2004). By inserting (3) in (5) the direct pseudo-elasticity can be concisely written for the MNL as

$$E_{x_{nk}}^{P_{ni}} = \left(e^{\beta_{ik}} \frac{\sum e^{\boldsymbol{\beta}_{i'} \mathbf{x}_n}}{\sum e^{\Delta(\boldsymbol{\beta}_{i'} \mathbf{x}_n)}} - 1 \right) \times 100, \tag{6}$$

where $E_{x_{nk}}^{P_{ni}}$ is the direct pseudo-elasticity of the kth variable from the vector $\mathbf{x}_n$, I is the set of possible outcomes, $\Delta(\boldsymbol{\beta}_i \mathbf{x}_n)$ is the value with x_{nk} set to one, and $\boldsymbol{\beta}_i \mathbf{x}_n$ is the value with x_{nk} set to zero. Because the direct pseudo-elasticity is the percentage change in probability for each observation n, we summarize it by taking the average value for all observations.

Variables are selected to enter the model in a hypothesis-driven process, i.e. we select variables based on our hypothesis that they would be correlated with injury severity. Once the model is estimated with a full set of variables, we test the hypothesis of no significant difference from zero for each coefficient on each variable using an asymptotic t-test (Greene, 2003). To improve statistical efficiency, we restrict coefficients not found significantly different from zero at the 90% level to zero. Furthermore, we test differences between coefficients on one variable across injury severity categories, and when there are no statistically significant differences at the 95% level of significance as indicated by a likelihood ratio χ^2 test (Greene, 2003) the coefficients are constrained to be equal. This is done to avoid keeping artificial accuracy in the model.

Since the estimated models are conditional on accident occurrence they do not have an accident-risk interpretation. Rather, the models show which explanatory factors are associated with increasing probability of particular injury severity categories given that an accident occurred. This approach avoids the need to know or measure exposure, a significant difficulty in bicycle accident studies. It yields a disaggregate view since we can use accident-specific information to test hypotheses about the importance of various covariates (characteristics of the bicyclist, driver, roadway, environment, etc.) on injury severity and most notably identify those factors associated with increased probability of a fatal injury given an accident. When interpreting coefficients we will for brevity say that a coefficient increases the probability of a particular injury severity category. Such statements should be taken in the conditional context of an accident having occurred, i.e. the coefficient on intoxicated driver does

Table 1
Descriptive statistics

Variables	Fatal injury	Incapacitating injury	Non-incapacitating injury	Possible/no injury	Total
Bicyclist characteristics					
Age					
<16	23 (2.4%)	128 (13.5%)	436 (45.9%)	363 (38.2%)	950 (32.4%)
16–24	16 (2.7%)	67 (11.3%)	255 (43.1%)	253 (42.8%)	591 (20.1%)
25–54	53 (4.3%)	153 (12.4%)	559 (45.2%)	472 (38.2%)	1237 (42.2%)
55+	12 (7.7%)	15 (9.6%)	73 (46.8%)	56 (35.9%)	156 (5.3%)
Gender					
Male	97 (3.8%)	322 (12.8%)	1124 (44.5%)	982 (38.9%)	2525 (86.1%)
Female	7 (1.7%)	41 (10.0%)	199 (48.7%)	162 (39.6%)	409 (13.9%)
Intoxicated					
Yes	22 (12.6%)	28 (16.1%)	75 (43.1%)	49 (28.2%)	174 (5.9%)
No	82 (3.0%)	335 (12.1%)	1248 (45.2%)	1095 (39.7%)	2760 (94.1%)
Helmet use					
Yes	6 (3.4%)	25 (14.2%)	97 (55.1%)	48 (27.3%)	176 (6.0%)
No	98 (3.6%)	338 (12.3%)	1226 (44.5%)	1096 (39.7%)	2758 (94.0%)
Driver characteristics					
Age					
<25	29 (4.1%)	93 (13.2%)	335 (47.6%)	247 (35.1%)	704 (24.0%)
25–54	61 (3.6%)	199 (11.8%)	741 (44.1%)	680 (40.5%)	1681 (57.3%)
55+	14 (2.6%)	71 (12.9%)	247 (45.0%)	217 (39.5%)	549 (18.7%)
Gender					
Male	75 (4.6%)	218 (13.3%)	735 (44.9%)	610 (37.2%)	1638 (55.8%)
Female	29 (2.2%)	145 (11.2%)	588 (45.4%)	534 (41.2%)	1296 (44.2%)
Intoxicated					
Yes	12 (17.9%)	15 (22.4%)	25 (37.3%)	15 (22.4%)	67 (2.3%)
No	92 (3.2%)	348 (12.1%)	1298 (45.3%)	1129 (39.4%)	2867 (97.7%)
Vehicle characteristics					
Estimated vehicle speed					
≤32.2 km/h (20 mph)	8 (0.6%)	89 (6.5%)	617 (44.7%)	665 (48.2%)	1379 (47.0%)
32.2–48.3 km/h (20–30 mph)	6 (1.4%)	70 (16.0%)	208 (47.6%)	153 (35.0%)	437 (14.9%)
48.3–64.4 km/h (30–40 mph)	18 (3.2%)	96 (17.3%)	268 (48.2%)	174 (31.3%)	556 (19.0%)
64.4–80.5 km/h (40–50 mph)	42 (11.2%)	64 (17.1%)	163 (43.6%)	105 (28.1%)	374 (12.8%)
80.5–96.6 km/h (50–60 mph)	27 (15.3%)	42 (23.7%)	64 (36.2%)	44 (24.9%)	177 (6.0%)
>96.6 km/h (60 mph)	3 (27.3%)	2 (18.2%)	3 (27.3%)	3 (27.3%)	11 (0.4%)
Vehicle type					
Car	62 (3.0%)	251 (12.0%)	939 (45.0%)	834 (40.0%)	2086 (71.1%)
Pickup	22 (5.3%)	59 (14.2%)	197 (47.4%)	138 (33.2%)	416 (14.2%)
Minivan	4 (5.8%)	7 (10.1%)	30 (43.5%)	28 (40.6%)	69 (2.4%)
SUV	2 (1.9%)	9 (8.4%)	46 (43.0%)	50 (46.7%)	107 (3.7%)
Van	5 (2.9%)	21 (12.4%)	77 (45.3%)	67 (39.4%)	170 (5.8%)
Bus	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Heavy truck	8 (15.1%)	12 (22.6%)	17 (32.1%)	16 (30.2%)	53 (1.8%)
Motorcycle	0 (0.0%)	1 (7.7%)	5 (38.5%)	7 (53.8%)	13 (0.4%)
Other type of vehicles	1 (5.0%)	3 (15.0%)	12 (60.0%)	4 (20.0%)	20 (0.7%)
Accident characteristics					
Bicycle direction					
Facing traffic	26 (2.9%)	77 (8.5%)	371 (40.9%)	433 (47.7%)	907 (30.9%)
With traffic	78 (3.8%)	286 (14.1%)	952 (47.0%)	711 (35.1%)	2027 (69.1%)
Type of accident					
Bicyclist turning/merging	36 (5.1%)	116 (16.5%)	331 (47.2%)	219 (31.2%)	702 (23.9%)
Motorist overtaking	33 (9.8%)	54 (16.0%)	139 (41.2%)	111 (32.9%)	337 (11.5%)
Motorist turning/merging	3 (1.0%)	26 (8.7%)	162 (54.0%)	109 (36.3%)	300 (10.2%)
Motorist backing	0 (0.0%)	1 (4.2%)	8 (33.3%)	15 (62.5%)	24 (0.8%)
Head-on collision	10 (10.3%)	16 (16.5%)	43 (44.3%)	28 (28.9%)	97 (3.3%)

Table 1 (*Continued*)

Variables	Fatal injury	Incapacitating injury	Non-incapacitating injury	Possible/no injury	Total
Party at fault					
Both driver and bicyclist	17 (3.2%)	31 (5.8%)	205 (38.5%)	280 (52.5%)	533 (18.2%)
Driver	22 (3.4%)	75 (11.5%)	317 (48.7%)	237 (36.4%)	651 (22.2%)
Bicyclist	61 (3.7%)	250 (15.4%)	749 (46.0%)	567 (34.8%)	1627 (55.5%)
None or it cannot be determined	4 (3.3%)	7 (5.7%)	52 (42.3%)	60 (48.8%)	123 (4.2%)
Speeding-involved					
Yes	8 (24.2%)	7 (21.2%)	9 (27.3%)	9 (27.3%)	33 (1.1%)
No	96 (3.3%)	356 (12.3%)	1314 (45.3%)	1135 (39.1%)	2901 (98.9%)
Road defects-involved					
Yes	2 (3.7%)	8 (14.8%)	25 (46.3%)	19 (35.2%)	54 (1.8%)
No	102 (3.5%)	355 (12.3%)	1298 (45.1%)	1125 (39.1%)	2880 (98.2%)
Accident location					
Shared travel lane on a street	90 (3.8%)	323 (13.5%)	1083 (45.1%)	903 (37.6%)	2399 (81.8%)
Bicycle lane or paved shoulder on a street	10 (7.7%)	17 (13.1%)	56 (43.1%)	47 (36.2%)	130 (4.4%)
Sidewalk/crosswalk/driveway crossing	1 (0.3%)	17 (5.1%)	143 (42.8%)	173 (51.8%)	334 (11.4%)
Separate bicycle path	0 (0.0%)	1 (7.1%)	8 (57.1%)	5 (35.7%)	14 (0.5%)
Driveway or alley	1 (8.3%)	1 (8.3%)	4 (33.3%)	6 (50.0%)	12 (0.4%)
Other place	2 (4.4%)	4 (8.9%)	29 (64.4%)	10 (22.2%)	45 (1.5%)
Control characteristics					
No traffic control present	87 (5.2%)	237 (14.3%)	738 (44.4%)	599 (36.1%)	1661 (56.6%)
Stop/go signal or flashing signal	6 (1.6%)	32 (8.4%)	174 (45.7%)	169 (44.4%)	381 (13.0%)
Stop/yield/warning sign	11 (1.3%)	91 (10.4%)	407 (46.3%)	370 (42.1%)	879 (30.0%)
Other sign (railroad gate/flash, human control, etc.)	0 (0.0%)	3 (23.1%)	4 (30.8%)	6 (46.2%)	13 (0.4%)
Geometry characteristics					
Intersection					
Yes	21 (1.4%)	157 (10.6%)	680 (45.7%)	630 (42.3%)	1488 (50.7%)
No	83 (5.7%)	206 (14.3%)	643 (44.5%)	514 (35.6%)	1446 (49.3%)
Asphalt road					
Yes	99 (3.5%)	357 (12.5%)	1290 (45.0%)	1120 (39.1%)	2866 (97.7%)
No	5 (7.4%)	6 (8.8%)	33 (48.5%)	24 (35.3%)	68 (2.3%)
Posted speed limit[a]	47.14 (9.87)	41.43 (10.59)	38.69 (10.00)	37.63 (9.78)	38.92 (10.17)
Road class type					
Freeway or US route	18 (8.4%)	36 (16.8%)	96 (44.9%)	64 (29.9%)	214 (7.3%)
North Carolina primary state route	19 (8.4%)	40 (17.8%)	101 (44.9%)	65 (28.9%)	225 (7.7%)
North Carolina secondary state route	42 (6.4%)	112 (17.0%)	286 (43.3%)	220 (33.3%)	660 (22.5%)
North Carolina state route	61 (6.9%)	152 (17.2%)	387 (43.7%)	285 (32.2%)	885 (30.2%)
Local city street	24 (1.3%)	169 (9.5%)	818 (45.9%)	772 (43.3%)	1783 (60.8%)
Public vehicular area (parking, etc.) or private property	1 (1.9%)	6 (11.5%)	22 (42.3%)	23 (44.2%)	52 (1.8%)
Road geometry					
Curved road	19 (7.8%)	51 (20.9%)	91 (37.3%)	83 (34.0%)	244 (8.3%)
Straight level	65 (3.3%)	224 (11.3%)	899 (45.2%)	802 (40.3%)	1990 (67.8%)
Straight grade	20 (2.9%)	88 (12.6%)	333 (47.6%)	259 (37.0%)	700 (23.9%)
Road type					
One-way	2 (2.0%)	10 (10.1%)	37 (37.4%)	50 (50.5%)	99 (3.4%)
Two-way not divided	89 (3.6%)	321 (12.9%)	1115 (44.8%)	962 (38.7%)	2487 (84.8%)
Two-way divided	13 (3.7%)	32 (9.2%)	171 (49.1%)	132 (37.9%)	348 (11.9%)
No. of traffic lanes					
1	4 (9.1%)	4 (9.1%)	21 (47.7%)	15 (34.1%)	44 (1.5%)
2	75 (3.8%)	272 (13.7%)	888 (44.7%)	750 (37.8%)	1985 (67.7%)
3	1 (0.6%)	18 (10.5%)	82 (48.0%)	70 (40.9%)	171 (5.8%)
4	12 (2.9%)	39 (9.4%)	194 (46.5%)	172 (41.2%)	417 (14.2%)
5	8 (3.8%)	22 (10.6%)	90 (43.3%)	88 (42.3%)	208 (7.1%)
6	2 (3.9%)	4 (7.8%)	25 (49.0%)	20 (39.2%)	51 (1.7%)
7+	2 (3.4%)	4 (6.9%)	23 (39.7%)	29 (50.0%)	58 (2.0%)

Table 1 (*Continued*)

Variables	Fatal injury	Incapacitating injury	Non-incapacitating injury	Possible/no injury	Total
Land characteristics					
Urban area					
Yes	30 (1.7%)	171 (9.6%)	806 (45.4%)	769 (43.3%)	1776 (60.5%)
No	74 (6.4%)	192 (16.6%)	517 (44.6%)	375 (32.4%)	1158 (39.5%)
Development					
Less than 30% developed	48 (8.4%)	94 (16.5%)	249 (43.6%)	180 (31.5%)	571 (19.5%)
30–70% developed	21 (4.7%)	75 (16.8%)	201 (45.1%)	149 (33.4%)	446 (15.2%)
More than 70% developed	35 (1.8%)	194 (10.1%)	873 (45.5%)	815 (42.5%)	1917 (65.3%)
Land use					
Farm/woods/pasture	42 (8.8%)	82 (17.2%)	202 (42.4%)	150 (31.5%)	476 (16.2%)
Residential area	41 (2.9%)	177 (12.5%)	662 (46.8%)	534 (37.8%)	1414 (48.2%)
Commercial area	21 (2.1%)	95 (9.6%)	435 (44.0%)	438 (44.3%)	989 (33.7%)
Institutional area	0 (0.0%)	8 (17.8%)	18 (40.0%)	19 (42.2%)	45 (1.5%)
Industrial area	0 (0.0%)	1 (10.0%)	6 (60.0%)	3 (30.0%)	10 (0.3%)
Temporal characteristics					
Weekend					
Yes	36 (4.7%)	109 (14.3%)	371 (48.8%)	244 (32.1%)	760 (25.9%)
No	68 (3.1%)	254 (11.7%)	952 (43.8%)	900 (41.4%)	2174 (74.1%)
Time					
00:00 a.m. to 05:59 a.m.	7 (9.9%)	17 (23.9%)	25 (35.2%)	22 (31.0%)	71 (2.4%)
06:00 a.m. to 09:59 a.m.	11 (4.0%)	32 (11.8%)	127 (46.7%)	102 (37.5%)	272 (9.3%)
10:00 a.m. to 02:59 p.m.	13 (1.7%)	77 (10.2%)	347 (46.0%)	318 (42.1%)	755 (25.7%)
03:00 p.m. to 05:59 p.m.	26 (2.7%)	119 (12.3%)	439 (45.3%)	385 (39.7%)	969 (33.0%)
06:00 p.m. to 11:59 p.m.	47 (5.4%)	118 (13.6%)	385 (44.4%)	317 (36.6%)	867 (29.6%)
Environmental characteristics					
Weather					
Clear	72 (3.0%)	289 (12.1%)	1082 (45.2%)	949 (39.7%)	2392 (81.5%)
Cloudy	23 (5.5%)	60 (14.4%)	185 (44.4%)	149 (35.7%)	417 (14.2%)
Fog	1 (20.0%)	0 (0.0%)	4 (80.0%)	0 (0.0%)	5 (0.2%)
Rain	8 (6.8%)	14 (12.0%)	51 (43.6%)	44 (37.6%)	117 (4.0%)
Snow	0 (0.0%)	0 (0.0%)	0 (0.0%)	1 (100.0%)	1 (0.0%)
Other weather	0 (0.0%)	0 (0.0%)	1 (50.0%)	1 (50.0%)	2 (0.1%)
Light					
Daylight	51 (2.3%)	252 (11.3%)	1035 (46.4%)	891 (40.0%)	2229 (76.0%)
Dawn or dusk	2 (1.5%)	15 (11.4%)	58 (43.9%)	57 (43.2%)	132 (4.5%)
Dark—streetlights	8 (2.9%)	35 (12.5%)	125 (44.8%)	111 (39.8%)	279 (9.5%)
Dark—no streetlights	43 (14.6%)	61 (20.7%)	105 (35.7%)	85 (28.9%)	294 (10.0%)
Road surface					
Dry	93 (3.4%)	335 (12.3%)	1228 (45.1%)	1065 (39.1%)	2721 (92.9%)
Wet	10 (4.9%)	27 (13.3%)	94 (46.3%)	72 (35.5%)	203 (6.9%)
Iced or snowed	0 (0.0%)	0 (0.0%)	0 (0.0%)	4 (100.0%)	4 (0.1%)
Muddy	0 (0.0%)	0 (0.0%)	1 (50.0%)	1 (50.0%)	2 (0.1%)

Percentages are in parentheses. Percentages are calculated across severities for the injury severity categories (first four columns), and across categories of each variable (e.g. two rows for no–yes variables) for the total frequency.

[a] Posted speed limit displays mean (S.D.) in stead of frequency (percentage).

not predict the probability of encountering a drunk driver but the probability of suffering a particular injury severity category given an accident involving a drunk driver.

4. Data description

This study uses police-reported accident data from the State of North Carolina for the years 1997–2002. The University of North Carolina Highway Safety Research Center has a Pedestrian and Bicycle Information Center which has received U.S. federal funds to prepare and maintain what is likely the most comprehensive bicycle accident database in the U.S. Bicycle data is often lacking in statewide accident databases since such accidents occur mainly on local streets and are not always well reported or collected at the state level.

A general limitation of police reported data is underreporting; people do not always report minor or non-injury accidents to the police. As discussed in the methodology this biases the alternative-specific constants and the probabilities in an MNL model but does not bias the estimated coefficients on the variables, allowing useful hypothesis testing. However, if the accident reporting rate is a function of an included variable, such as age, this will bias the coefficient on that variable. Despite this limitation, police records are the best for this type of analysis due to the richness of the collected data. Other data have other limitations, e.g. hospital records do not generally contain enough information for bicycle accidents (Stutts et al., 1988), e.g. roadway, driver, and environmental characteristics, and survey data is limited since it is subject to recall and response bias among respondents (e.g. Doherty et al., 2000).

For the analysis of bicyclist injury severity, we use only bicycle accidents that involve a single motorist and a bicyclist. This results in 2934 bicycle accidents available for study. Table 1 shows the descriptive statistics for the variables tested in this study, broken down by bicyclist injury severity and with a totals column. The dependent variable in the study, the bicyclist injury severity category, is classified as one of four categories in this data: "fatal injury", "incapacitating injury", "non-incapacitating injury", and "possible or no injury". Incapacitating injury is a level of injury which can be termed disabling or severe injury. Table 1 shows the percentage distribution across the injury severity categories, and in the totals column, Table 1 shows the percentage distribution across categories of each variable (e.g. the distribution between males and females).

Regarding bicyclist characteristics, children younger than 16 accounted for about 32.4% of the accidents and the age group from 25 to 54 were in 42.2% of the accidents. Most accidents were observed for male bicyclists (86.1%). Intoxicated bicyclists accounted for 5.9% of the accidents and a significant number of bicyclists in the data did not wear a helmet (94.0%).

In the case of drivers, the distributions of age, gender, and intoxication were different from the bicyclist distributions. Vehicle drivers aged 25–54 accounted for 57.3% of the accidents. There was a smaller difference in the gender distribution for the drivers, about 55.8% were male and about 44.2% were female. The percentage of intoxicated drivers (2.3%) involved in accidents was smaller than that of intoxicated bicyclists.

In about half of the accidents, the estimated vehicle speed prior to impact was less than or equal to 32.2 km/h (20 mph). A passenger car was the vehicle type most often involved in bicycle related accidents (71.1%), followed by pickup trucks (14.2%). Although heavy trucks accounted for only 1.8% of the accidents, if a heavy truck was involved, the percentage of fatal injury was 15.1%; on the other hand, in the cases of a passenger car or a pickup truck the percentages of fatal injury were 3.0% and 5.3%, respectively.

About 69.1% of vehicle related bicycle accidents occurred when the bicyclist was biking with traffic, and 30.9% when the bicyclist was facing traffic. Concerning the type of accident, bicyclist turning or merging accounted for 23.9% of the accidents; following were motorist overtaking (11.5%) and motorist turning or merging (10.2%). Bicyclists were found solely at fault in 55.5% of the accidents and drivers were found solely at fault in 22.2% of the accidents; in the remaining accidents either both were found at fault or fault could not be determined. Speeding was a factor in 1.1% of the accidents, and road defects were involved in 1.8% of the accidents. The accidents occurred most commonly in a shared travel lane on a street (81.8%), with a roughly equal split between intersections and mid-block areas. The most common road class type and road surface type were local streets (60.8%) and asphalt roads (97.7%). The majority of the accidents occurred on local streets (60.8%) with two traffic lanes (67.7%). More than 80% of the accidents occurred in residential and commercial areas.

The distribution between weekdays and weekend shows 25.9% of the accidents occurring on weekends. About one-third of the accidents occurred during the afternoon-peak hours and most of the accidents occurred on a clear day, in daylight, and on dry road surfaces (81.5%, 76.0%, and 92.9%, respectively).

5. Results

We present the estimated bicyclist injury severity model in Table 2, which shows the coefficient estimates and standard errors, as found by the method of maximum likelihood for each injury severity category. As discussed in the methodology, one category is selected as a base case; in this paper it is the possible or no injury category. The estimated coefficients therefore show a difference (or log odds ratio) compared to this base case (see Eq. (4)).

The ρ^2 in this paper compares the log-likelihood of a model with only constants to the log-likelihood at convergence for the full specification. This means the presented model is being compared to a naïve model that assigns each severity a probability equal to its share in the estimation data set.

Interpreting the coefficients in Table 2 can occasionally be misleading (e.g. since a positive coefficient can reduce the probability as explained in Section 3). Therefore, we also present Table 3, which indicates the average direct pseudo-elasticity for each variable (all are 0/1 indicator variables) in the model, which is simply the average percentage change in probability of an injury severity category when a variable switches (from 0 to 1 or 1 to 0) for all observations.

Table 4 follows a design by Holdridge et al. (2005) and summarizes factors that have a large effect on the probability of at least one injury severity category. A large effect is defined here as an average direct pseudo-elasticity larger than a 100% which means at least a doubling of the probability of the injury severity category (this category is shaded). The arrow indicates whether the probability is increased (up arrow) or decreased (down arrow) by that variable for each injury severity outcome.

5.1. Bicyclist characteristics

Bicyclists aged 55 and over are more likely to be fatally injured when they are in bicycle–motor vehicle accidents than younger age groups. This result fits other studies that older adults are more likely to suffer fatal injuries in bicycle accidents (Rodgers, 1995; Eilert-Petersson and Schelp, 1997; Stone and Broughton, 2003). As reasoned by Maring and van Schagen (1990), age itself is not a causal factor but rather factors correlated with age. For example, a person's increased perception

Table 2
Multinomial logit bicyclist injury severity model estimation results

Variables	Fatal injury	Incapacitating injury	Non-incapacitating injury
Alternative specific constant	−4.991 (0.304)**	−2.765 (0.200)**	−0.375 (0.110)**
Bicyclist characteristics			
Bicyclist age 55+	0.773 (0.387)*		
Bicyclist is intoxicated	1.057 (0.309)**		
Bicyclist used a helmet		0.451 (0.175)**	0.451 (0.175)**
Driver characteristics			
Driver is intoxicated	1.506 (0.400)**	0.840 (0.325)**	
Vehicle characteristics			
Estimated vehicle speed			
32.2–48.3 km/h	0.808 (0.171)**	0.808 (0.171)**	
48.3–64.4 km/h	1.756 (0.382)**	1.054 (0.176)**	0.294 (0.112)**
64.4–80.5 km/h	2.984 (0.352)**	1.056 (0.204)**	0.270 (0.138)*
>80.5 km/h	3.254 (0.375)**	1.330 (0.220)**	
Pickup	0.252 (0.115)*	0.252 (0.115)*	0.252 (0.115)*
Heavy truck	1.833 (0.493)**	0.965 (0.357)**	
Accident characteristics			
Bicycle direction, facing traffic		−0.257 (0.091)**	−0.257 (0.091)**
Motorist turning or merging			0.331 (0.133)*
Head-on collision	0.731 (0.400)		
Driver at fault		0.683 (0.225)**	0.294 (0.130)*
Bicyclist at fault		0.985 (0.196)**	0.468 (0.105)**
Speeding-involved accident	1.469 (0.462)**		
Geometry characteristics			
Curved road	0.639 (0.163)**	0.639 (0.163)**	
Two-way divided			0.241 (0.118)*
Land characteristics			
Institutional area		1.052 (0.410)**	
Temporal characteristics			
Weekend	0.333 (0.091)**	0.333 (0.091)**	0.333 (0.091)**
a.m. peak (06:00 a.m. to 09:59 a.m.)	0.645 (0.354)		
Environmental characteristics			
Inclement weather (fog, rain, snow, etc.)	0.867 (0.409)*		
Darkness with no streetlights	0.851 (0.257)**	0.513 (0.172)**	
No. of observations	2934		
Log-likelihood for constants only	−3237		
Log-likelihood at convergence	−2992		
ρ^2	0.076		

Standard errors are in parentheses. Level of significance: all greater than 90%, *>95%, and **>99%. Coefficients that were not significant at the 90% level were restricted to zero and omitted from the table. Possible or no injury is the base case with coefficients restricted at zero.

and reaction times, which likely affect the probability of being in an accident although this is not being modeled, may impact the severity of an accident as well, since if people respond slowly they can be hit harder than if they react quickly and possibly change a direct blow to a glancing blow. Additionally, greater fragility due to age and various medical conditions (including osteoporosis and atherosclerosis) more common in older adults will increase the probability of fatal and severe injuries in older adult bicyclists in an accident.

Bicyclist intoxication increases the probability of the bicyclist suffering a fatal injury in an accident involving a vehicle. Previous research has found that intoxicated cyclists have a greater risk of head injury (Olkkonen and Honkanen, 1990; Andersson and Bunketorp, 2002) and that the intoxicated cyclist's ability to react may be impaired (Andersson and Bunketorp, 2002) which will affect probability of an accident (not considered in our study) and which may affect the severity of the accident due to lesser evasive reaction. Li and Baker (1994) noted that intoxicated bicyclists may be less likely to wear helmets (the helmet effect is controlled for in our model as discussed below). In our study, only one bicyclist, among 174 intoxicated bicyclists in the data, wore a helmet. Intoxication is likely to lead to more careless behavior which appears to lead to more severe injuries if an accident occurs.

Helmets decrease the probability of fatal injury and possible or no injury. As found in previous studies, helmets can protect against serious injuries, head injury and brain injury

Table 3
Average direct pseudo-elasticity of variables

Variables	Fatal injury	Incapacitating injury	Non-incapacitating injury	Possible/No injury
Bicyclist characteristics				
Bicyclist age 55+	109.3%*	−3.4%	−3.4%	−3.4%
Bicyclist is intoxicated	173.9%*	−4.8%	−4.8%	−4.8%
Bicyclist used a helmet	−24.3%	18.8%	18.8%	−24.3%
Driver characteristics				
Driver is intoxicated	265.2%*	87.7%	−19.0%	−19.0%
Vehicle characteristics				
Estimated vehicle speed, 32.2–48.3 km/h	92.5%	92.5%	−14.2%	−14.2%
Estimated vehicle speed, 48.3–64.4 km/h	302.7%*	99.6%	−6.7%	−30.4%
Estimated vehicle speed, 64.4–80.5 km/h	1 159.1%*	83.2%	−16.6%	−36.3%
Estimated vehicle speed, >80.5 km/h	1 503.9%*	134.2%*	−38.0%	−38.0%
Pickup	9.8%	9.8%	9.8%	−14.7%
Heavy truck	380.9%*	101.8%*	−23.1%	−23.1%
Accident characteristics				
Bicycle direction, facing traffic	15.6%	−10.6	−10.6	15.6%
Motorist turning or merging	−14.8%	−14.8%	18.7%	−14.8%
Head-on collision	101.2%*	−3.1%	−3.1%	−3.1%
Driver at fault	−20.6%	57.3%	6.6%	−20.6%
Bicyclist at fault	−27.6.%	94.0%	15.7%	−27.6%
Speeding-involved accident	300.1%*	−7.9%	−7.9%	−7.9%
Geometry characteristics				
Curved road	68.1%	68.1%	−11.3%	−11.3%
Two-way divided	−10.7%	−10.7%	13.5%	−10.7%
Land characteristics				
Institutional area	−17.6%	136.1%*	−17.6%	−17.6%
Temporal characteristics				
Weekend	13.2%	13.2%	13.2%	−18.8%
AM peak (06:00 a.m.–09:59 a.m.)	85.4%	−2.7%	−2.7%	−2.7%
Environmental characteristics				
Inclement weather (fog, rain, snow etc.)	128.8%*	−3.9%	−3.9%	−3.9%
Darkness with no streetlights	110.9%*	50.4%	−10.0%	−10.0%
Mean probability	0.035 (0.073)	0.124 (0.075)	0.451 (0.084)	0.390 (0.115)

The elasticity of number of traffic lanes is discrete elasticity. Standard deviations for probabilities are in parentheses.
* Shading indicates increase greater than 100%.

(Wasserman et al., 1988; Thompson et al., 1990b; Povey et al., 1999; Robinson, 2001; Schieber and Sacks, 2001; Depreitere et al., 2004) and as a result, the probability of fatal injury decreases (−24.3% in Table 3). Possible or no injury accidents involving bicyclists with helmets may be less likely to be reported than similar accidents for bicyclists without helmets, since the lack of a helmet may cause greater concern for possible unobserved injury. This can explain why helmets are not positively correlated with possible or no injury in the study. When considering only injury accidents, it is clear that the results indicate that bicycle helmets reduce probability of fatal injury and thereby increase the probability of the other categories. It can be questioned why helmets do not also reduce incapacitating injuries. This can be in part because the helmet has reduced the severity of serious accidents which would have lead to a fatality to incapacitating injury. There may also be a remaining correlation with trip purpose and the environment. Bicyclists may be more likely to wear helmets when they know the ride will expose them to greater risk of accidents, e.g. while riding in heavy traffic.

5.2. Driver characteristics

When the vehicle driver is intoxicated, the probabilities of bicyclist fatal injury and incapacitating injury, particularly fatal injury, increase by a large margin. A similar result is found by Noland and Quddus (2004) who reported that alcohol consumption had a significant effect on accident severity although they could not distinguish whether this was caused by the intoxication of drivers or cyclists. Note that a driver's intoxication has a stronger effect on the probability of fatal injury than a bicyclist's intoxication: the average direct pseudo-elasticities for a driver's intoxication and a bicyclist's intoxication are 265.2% and 173.9%, respectively. In either case, intoxication is shown to be correlated with serious or fatal bicyclist injury in bicycle–motor vehicle accidents.

5.3. Vehicle characteristics

As shown in several previous studies, fatality rates are directly related to vehicle speed (Garder, 1994; Garder et al., 1998;

Table 4
Selected variable effects on the probability of bicyclist injury severity

Variables	Fatal Injury	Incapacitating Injury	Non-Incapacitating Injury	Possible / No Injury
Bicyclist Characteristics				
Bicyclist age 55+	**↑**	↓	↓	↓
Bicyclist is intoxicated	**↑**	↓	↓	↓
Bicyclist used a helmet	↓	↑	↑	↓
Driver Characteristics				
Driver is intoxicated	**↑**	↑	↓	↓
Vehicle Characteristics				
Estimated vehicle speed, 32.2–48.3 km/h	↑	↑	↓	↓
Estimated vehicle speed, 48.3–64.4 km/h	**↑**	↑	↓	↓
Estimated vehicle speed, 64.4–80.5 km/h	**↑**	↑	↓	↓
Estimated vehicle speed, > 80.5 km/h	**↑**	**↑**	↓	↓
Heavy Truck	**↑**	**↑**	↓	↓
Accident Characteristics				
Bicycle direction, facing traffic	↑	↓	↓	↑
Head-on collision	**↑**	↓	↓	↓
Speeding-involved accident	**↑**	↓	↓	↓
Geometry Characteristics				
Curved Road	↑	↑	↓	↓
Temporal Characteristics				
AM Peak (06:00 AM − 09:59 AM)	↑	↓	↓	↓
Environmental Characteristics				
Increment weather (fog, rain, snow, etc.)	**↑**	↓	↓	↓
Darkness with no streetlights	**↑**	↑	↓	↓

Arrows show increase (up) or decrease (down) in elasticity and shading indicates change greater than 100%.

Fernandez de Cieza et al., 1999; Stone and Broughton, 2003). Speed may be associated with other factors such as roadway curves, driver age, and sobriety. In this study, we control for several such factors which isolates the effects of speed. The police on the scene estimate vehicle speed prior to impact, however the methodology will vary based on conditions at each accident.

The estimated vehicle speed has an important effect in the model. It shows that both probabilities of fatal injury and incapacitating injury increase with increasing vehicle speed prior to impact, which is logical and as expected given the increasing kinetic energy and greater impact at higher speeds. The coefficients of estimated vehicle speed for non-incapacitating injury are positive but smaller than those for fatal injury and incapacitating injury (Table 2), thereby showing an increasing effect on probability of more severe injuries. It is also notable that as estimated vehicle speed prior to impact increases beyond 32.2 km/h (20 mph) there is a threshold effect, which greatly increases the probability of injury or fatality in an accident. This supports a 30 km/h speed limit inside residential neighborhoods with bicycle traffic. As speeds pass 64.4 km/h (40 mph) the change in probability of fatal injury in an accident exceeds 1 000% (see Table 3), indicating a more than 11-fold increase in the probability of fatal injury in high-speed accidents.

The coefficients of pickup trucks are not significantly different for fatal injury, incapacitating injury, and non-incapacitating injury, and are therefore constrained to be equal. They show a simple increase in the probability of all injury severities compared to other types of vehicles, except heavy trucks (Table 3). There were not many minivans and sport utility vehicles in the database, causing lack of significance of those vehicle types, although such vehicles could be expected to cause greater injury than passenger cars, just as pickup trucks.

Heavy trucks are linked with an increase in the probabilities of both fatal injury and incapacitating injury in accidents. When a bicycle collides with a heavy truck, the bicyclist is more likely to suffer a fatal injury: an average direct pseudo-elasticity for the heavy truck indicator is 380.9% for fatal injury and is 101.8% for incapacitating injury (Table 3). This finding is an injury severity result which is consistent with McCarthy and Gilbert's (1996) study that heavy goods vehicles were more frequently involved in fatal bicycle accidents. The effects of heavier vehicles, pickup trucks, and heavy trucks towards increasing probability of more severe injuries is logical and as expected, since heavier vehicles have greater momentum at a particular speed than passenger cars. Also, it has been shown that vehicles with a higher hood, i.e. where the grill section hits the middle or upper body, rather than the feet, cause greater injuries (e.g. Maki et al., 2003; who explored minivans).

5.4. Accident characteristics

Wachtel and Lewiston (1994) showed that biking against the direction of traffic flow at intersections increased accident risk. In this study we tested the effect on injury severity and it was found that biking against the traffic flow had a weak U-shape distribution: the probabilities of fatal injury and possible or no injury increase, while those of incapacitating injury and non-incapacitating injury decrease, keeping other things constant (see Table 3). Table 1 shows that there are indeed more no injury and possibly injury accidents when facing traffic and it shows that all the injury categories have lower shares when facing traffic. This explains the up-tick for possible and no injury. However, the model was unable to estimate a significant coefficient for fatal injury, thereby creating the up-tick for fatal injury, despite there being a smaller share for fatal injuries when facing traffic (see Table 1). The interpretation is that although the share is smaller for fatal injuries when facing traffic, it is not statistically significantly smaller in this data. The share is only significantly smaller for the incapacitating and non-incapacitating injury categories. These results may possibly be explained by that both drivers and bicyclists see each other which allows both biker and driver to react and thereby increase the probability of the no injury or possible injury, and conversely reduce the shares of the injury categories. Note the confounding effect with the accident type "head-on" which will be discussed shortly. Its significance towards fatal injury may contribute to the lack of significance of facing traffic towards fatal injury.

Head-on collisions increase the probability of fatal injury (101.2% in Table 3) in accidents, while decreasing the probabilities of the other categories (−3.1% in Table 3). Multicollinearity was suspected between head-on collisions and biking while facing traffic. However, the correlation between these variables turned out to be relatively low (0.24), so both variables were included in the model. There are other accident types that can occur when facing traffic, e.g. sideswipes. The head-on accident type nonetheless may contribute to the lack of significance of the coefficient towards fatal injury for biking while facing traffic.

When considering fault, we note from Table 1 that in possible or no injury collisions both driver and bicyclist are being found jointly at fault most of the time but in injury collisions there is a stronger tendency to assign fault to either party. In terms of the frequency distribution, there is little difference between the fault classifications for fatal accidents and this is borne out by the model in Table 2 which shows no significant difference between driver found at fault, bicyclist found at fault, both at fault, or none at fault. The model results, and the percentage changes in probability from Table 3, indicate that bicyclist found solely at fault is associated more strongly with incapacitating injury than driver solely at fault, implying that bicyclist fault is more closely correlated with greater bicyclist injury severity than driver fault.

When speeding is involved in bicycle–motor vehicle collisions, the probability of fatal injury noticeably increases by 300% (Table 3). This is reasonable since speeding, driving above the speed limit and quite possibly above the design speed of the roadway, is an indication of more aggressive driving. This finding is interesting since we separately control for the effect of speed itself (as discussed in Section 5.3).

5.5. Geometry characteristics

A curved road was found to significantly increase the probability of fatal injury and incapacitating injury in the observed bicycle–motor vehicle accidents; that is, a curve increases the injury severity. This result can be reasoned by that curves decrease the visibility and maneuverability for both driver and cyclist and can affect injury severity because of less efficient evasive maneuvers.

Two-way divided roadways have one positive coefficient, for non-incapacitating injury. This result indicates that two-way divided roadways decrease the injury severity. This may be due to a confounding effect, e.g. bicyclists are less likely to ride against traffic on divided roads which leads to fewer head-on collisions. Also, divided roads are normally wider, which gives bicyclists and drivers more room, and this can mean more accidents are glancing blows, i.e. lower severity.

5.6. Land characteristics

There were largely no significant differences between the different land development characteristics which caused them to be restricted out of the model. However, one factor remained significant. Institutional areas (e.g., school) increase the probability of incapacitating injury and decrease the other injury severities, compared to other areas. In future research into the interplay between the built environment and bicycle–motor vehicle accidents, development characteristics need to be available with much greater detail than is available in this dataset.

5.7. Temporal characteristics

When bicycle–motor vehicle collisions occur on a weekend, bicyclists are more likely to get injured than on weekdays (coefficients are constraint to be same across weekdays in Table 2). Table 3 shows that in accidents occurring between 06:00 and

09:59 a.m. the probability of fatal injury increases. These results are reasonable. As shown in studies by Eilert-Petersson and Schelp (1997) and Rodgers (1995), these effects may be caused by driver behavior and the type of activities. Both motorists and bicyclists tend to drive and bike more aggressively during the busy morning commute and such behavior can increase bicyclist injury severity. Eilert-Petersson and Schelp (1997) reported that leisure activities were the predominant type of bicyclist activities in injury events (most biking on weekends might be leisure activities instead of transport).

5.8. Environmental characteristics

While most bicycle–motor vehicle accidents occurred on clear days (81.5% in Table 1), inclement weather conditions (rain, snow, fog, etc.) were significantly associated with bicyclist injury severity. In Klop and Khattak's (1999) study, fog increased injury severity. Table 3 shows that inclement weather conditions increase the probability of fatal injury in an accident by 128.8% on average, as compared to clear and cloudy weather. It can be noted that inclement weather may have a confounding effect with omitted variables because it can be related with both driver and bicyclist behavior, e.g. people that ride bicycles in inclement weather may be more experienced riders who ride regularly and do not let weather affect their decision to use the bicycle. However, in our opinion, the effect of inclement weather on injury severity is likely caused because of reductions in visibility and/or traction. Reduced visibility due to inclement weather can lead to a more severe accident since it can distract and/or reduce perception of both bicyclist and driver which reduces their ability to respond, i.e. brake or take an evasive maneuver. Also, inclement weather makes roads and trails more slippery which can also lead to more severe injury since braking and steering are suboptimal, leading to greater impact speeds and possibly worse impact angles. Additionally, inclement weather affects the risk of an accident occurring but since our model is conditional on an accident having happened we only measure its effect on injury severity in accidents.

Darkness without streetlights increases the probability of fatal injury by 110.9% in accidents compared to accidents occurring in daylight or darkness with streetlights. Rodgers (1995) reported that about 35.2% of deaths in bicycle accidents occurred after dark and another 5.5% occurred at dawn or dusk, although exposure is lesser at night. Certainly lighting condition is directly related with visibility which primarily affects the risk of accidents, but also affects severity due to lack of evasive action (e.g. driver did not see bicyclist) which leads to greater impact and thus severity. In this study, only lighting on streets was considered. To thoroughly uncover the effects of lighting, it would also be necessary to consider the illumination equipment of bicycles.

6. Conclusion

This study examines factors associated with injury severity of bicyclists in bicycle–motor vehicle accidents from the following groups of characteristics: bicyclist, driver, vehicle, accident, geometry, land, temporal, and environmental. A multinomial logit model predicting injury severity conditional on accident occurrence was estimated with the method of maximum likelihood. The analysis was based on police-reported collision data from 1997 through 2002 from the State of North Carolina.

The estimation results show there are important factors that significantly increase the probability of fatal injury for bicyclists: greater vehicle speeds prior to impact, truck involved accidents, speeding-involved accidents, intoxicated driver or bicyclist, bicyclist aged 55 and over, inclement weather, darkness without streetlights, head-on collision.

Although biking facing traffic was found partly associated with non-injury, head-on collisions greatly increase the probability of fatal injury (101.2% in Table 3). The frequency of speeding involved bicycle–motor vehicle accidents is low but speeding involved significantly increases fatal injury (300.1% in Table 3) in accidents. This variable can be an indicator of aggressive driving which leads to more serious injuries in case of an accident, even when controlling for estimated vehicle speed. The estimated vehicle speed causes a dramatic increase in the probability of fatal injury, the increase in the probability of fatal injury is 92.5% for 32.2–48.3 km/h (20–30 mph), 302.7% for 48.3–64.4 km/h (30–40 mph), 1 159.1% for 64.4–80.5 km/h (40–50 mph), and 1 503.9% for over 80.5 km/h (50 mph), all compared to speeds less than 32.3 km/h (20 mph). These findings suggest the importance of separating bicycling from high-speed traffic, for example separate bicycle paths on roadways that have a speed limit of 50 km/h or over, and lends support to a 30 km/h speed limit in residential neighborhoods with significant pedestrian and bicycle traffic.

Fatal injury is, as expected, more likely to occur in heavy truck involved accidents; therefore, we need to take special precautions in the design of bicycle facilities, or when selecting arterials for bicycle lanes, to decrease the chance of conflicts with heavy vehicles.

Inclement weather increases the probability of fatal injury by 128.8%. Although this variable may capture the confounding effects of driver and bicyclist behavior we believe this effect is largely due to increased slipperiness which reduces both the vehicle's and bicycle's maneuverability and can lead to a more severe accident than if braking and maneuvering were optimal. Reduced visibility can affect perception times which can lead to a more severe accident since drivers and bicyclists have less time to maneuver and thereby possibly reduce the force of the crash.

Intoxication, by either driver or bicyclist, is linked with a large increase in the probability of the bicyclist suffering a fatal injury in an accident (265.2% and 173.9%, respectively). Bicyclists aged 55 and over are more subject to fatal injury in accidents (109.3% increase in the probability) than the younger age groups. Older adult bicyclists need to be particularly careful because they are more vulnerable to severe injury when bicycle–motor vehicle accidents occur. Certain progressive illnesses, such as osteoporosis, atherosclerosis, Alzheimer's disease (AD) and macular degeneration, eventually cause physical fragility. Informing older adult bicyclists of the greater fragility related to particular medical conditions may prove beneficial since it allows older adults to adjust their biking behavior to reduce their probability of more severe injury if they happen to be in an accident.

In this study, numerous observable factors (behavioral, engineering, and environmental) are controlled simultaneously to uncover the isolated effect of each variable. The study indicates that modified bicyclist and driver behavior (e.g. intoxication, helmet usage, speeding, biking during the a.m. peak or in inclement weather, street lighting, special caution by bicyclists suffering from increased fragility due to medical conditions or age), engineering (e.g. conflicts with oncoming traffic and heavy vehicles) and policy (e.g. speed limits), can reduce injury severities.

Further study needs to explore detailed road and bicycle lane geometry to assist in developing more specific engineering solutions to reduce injury severity in bicycle–motor vehicle accidents. Lastly, the descriptive statistics (Table 1) indicate that there are links between land characteristics and bicyclist injury severity but those effects (except institutional area) were not found significant in the model. Further study needs to develop a more detailed picture of land use and the built environment around accident sites to facilitate design and policy solutions that may affect bicyclist injury severities.

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