The Unintended Impact of Helmet Use on Bicyclists' Risk-taking Behaviors

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Abstract:

Bicycle helmet compensation effects suggest that bicyclists offset perceived gains in safety from wearing a helmet by behaving more aggressively. A better understanding of these compensation effects can be useful in assessing mandatory legislated helmet use laws. Using a sample of 131 bicyclists, this research studies how bicyclists respond with respect to risk-taking behaviors under various urban-street conditions, as a function of helmet use. Study participants are each shown 12 videos, shot in Berkeley, California, from the perspective of a bicyclist riding behind another bicyclist. A fractional factorial experiment design is used to systematically vary contextual attributes, such as speed, bike lane facilities, on-street parking, passing vehicles, etc., across the videos. After each video, participants are asked to indicate if they would overtake the bicyclist in the video. With the help of data adaptive estimation techniques, targeted maximum likelihood estimation (TMLE) is applied to estimate the average risk difference between helmet users and non-users, controlling for self-selection effects. Individual-based nonparametric bootstrap is performed to assess the uncertainty associated with the estimator. Our findings suggest, on average, helmet users are 15.6% more likely to overtake, and the effect is statistically significant using the non-parametric bootstrap sampling evaluation. This study serves as a cautionary warning that road safety programs may need to consider strategies in which unintended impact of bicycle helmet use can be mitigated.

Keywords:

Bicycle helmet; Compensation effects; Bicycle safety; Risk-taking Behavior; Targeted maximum likelihood estimation; Data adaptive estimation

1. Introduction

Bicycling is a world-wide activity and an important means of achieving sustainable transportation (Kang et al., 2013). However, as vulnerable road users sharing space with fast moving vehicles, bicyclists are also exposed to dangerous riding environment (Amoros et al., 2011; Kang and Fricker 2013). Many studies have shown the effectiveness of helmets in preventing head injuries among bicyclists and hence, legislated mandatory bicycle helmet use is required in several countries (Bambach et al., 2013; Thompson et al., 1989). Moreover, mandatory bicycle helmet laws have been found to increase helmet wearing rates internationally (Macpherson and Spinks, 2008). However, most countries haven't imposed such regulation on bicyclists and very few studies have investigated the compensation effects of wearing helmet. Hence, from policy makers' perspective, in order to capture the full spectrum of the impacts of helmet, studies examining the bicycle helmet compensation effects are needed for future policy making efforts, especially amid the emerging trend of using public bicycles (Jiang et al., 2010; Hsu et al., 2016; Wu et al., 2017).

In economic theory, the "risk compensation" hypothesis suggests that individuals offset perceived gains in safety by increasing their risk-taking behavior to maintain a stable or "homeostatic" level of risk. Many studies have tested this hypothesis in the context of motor vehicles, such as Cohen and Einav (2003), Winston et al. (2006), Lv et al. (2015), and Abay and Mannering (2016). For example, Winston et al. (2006) find that motorists drove faster when the vehicles were fitted with anti-lock brakes and airbags. By contrast, shared space, served as traffic calming strategy, is a highway design method which consciously aims to increase the level of perceived risk, thereby slowing traffic and reducing accidents (Department for Transport, 2011; Kang and Fricker, 2016).

In the context of bicycling, some studies have confirmed that helmet usage for bicyclists could reduce cases of severe injury (Rodgers, 2002; Thompson et al., 1989; Moore et al., 2011; Lee et al., 2005; Walter et al., 2011; Behnood and Mannering, 2017; Olofsson et al., 2017; Ohlin et al., 2017). However, other studies found different results of helmet use. Using the 2003-2008 General Estimates System databases, Kweon and Lee (2010) investigated the beneficial effect of bicycle helmet use. Helmet use was found to be statistically insignificant in 2003, 2005, 2006, and 2008 in terms of reducing bicyclists' injury severity. However, they claimed it might be due to a possible lack of representation of helmet use variable in above years. Based on a case-control study, Rivara et al. (1997) claimed that prevention of serious bicycle injuries cannot be accomplished solely by helmet use. Even though helmet use would help reduce bicyclists' injury severity, yet due to potential compensation effects of helmet use, in which bicyclists offset perceived gains in safety of wearing helmet by behaving more aggressively, the frequency of bicycle-related crashes might increase. However, it is difficult to analyze the effects of helmet policy in an aggregate level due to the difficulty of obtaining bicyclists' accurate exposure information (e.g. total bicycle-miles travelled). Without accurate estimate of bicycle exposure information, the estimated effect of helmet use might be biased and the corresponding policy implications might be misleading.

With the above discussion in mind, the intent of this study is to bridge the research gap by providing a rigorous statistical analysis of bicycle helmet compensation effects from a disaggregate perspective. By focusing on individual bicycling behaviors rather than aggregate level bicycle-related accident outcomes, no exposure information is needed. To this end, an online survey was conducted to collect stated behaviors of bicyclists under different scenarios. The objective of this study is to estimate the effect of helmet use on a bicyclist's risk taking behavior (specifically overtaking behavior) and test the compensation hypothesis of helmet use.

The remainder of the paper is organized as follows. Existing literature on two study streams on bicycle helmet effects will be reviewed in Section 2. Section 3 covers experiment design and data collection efforts. In Section 4, targeted maximum likelihood estimation (TMLE) approach is used to estimate the effect of helmet on bicyclists' risk taking behaviors. We target at the effect estimation of helmet so that policy implications can be drawn. Details regarding different estimators and model specification will be discussed in Section 4 and 5. Estimation results are presented in Section 6. Summary and conclusions are presented in Section 7.

2. Literature Review

In this section, we focus on reviewing existing literature on two study streams with regard to bicycle helmet effects in terms of study scope: population level and individual level. This provides us a starting point for study design and illustrates the significance of the proposed disaggregate (individual-level) based method.

The analyses of mandatory bicycle helmet legislation are usually based on actual accident data or hospital injury report to assess its impacts. For example, based on hospital admission data from New South Wales, Australia, Walter et al. (2011) found a drop in head injury rate of bicyclists at the time when the legislation was enacted and they claimed that there was a positive effect on bicyclist head injuries. Macpherson et al. (2002) found the bicycle-related head injury rate for children declined significantly (45% reduction) in provinces where legislation had been adopted, compared with provinces and territories that did not adopt the legislation (27% reduction). Based on the information of 22,814 bicyclists involved in traffic crashes in Spain, Lardelli-Claret et al. (2003) applied a linear logistic model (accounting for cyclist and crash related variables) in which helmet use and four types of infraction were set as dependent variables. Adjusted odds ratios were computed to assess the relation between committing a traffic violation and using a helmet. Their results suggested that committing a traffic violation was associated with a lower frequency of helmet use and did not support the existence of a strong risk compensation mechanism among helmeted bicyclists. Many other studies have also confirmed the effectiveness of the compulsory helmet law in reducing head injuries (Rivara et al., 1994; Povey et al., 1999; Scuffham et al., 2000; Ji et al., 2006). A more comprehensive review of the impacts of compulsory helmet law could be found in Macpherson and Spinks (2008). Besides legislation studies, Moore et al (2011) found that helmet use would significantly decrease the injury severity of bicyclists in bicycle-vehicle crashes. Most population level studies focus on accident data. Despite the merits of using such population level accident data, this type of study has several limitations. First, the conclusions of many previous studies were only built on summary statistics without accounting for control factors. It is possible that the decline in head injury rate is the result of other laws or events. Second, due to the lack of reliable bicycle exposure information, most crash frequency analysis results could be questioned in terms of the accuracy of their estimation results and corresponding policy implications. Third, and perhaps most importantly, even if overall crash rates are observed to decline, that doesn't mean that there isn't a compensation effect. If we can identify the compensation effect and develop programs and rules to control for that, we can achieve even better bicycle safety performance.

Different from population level studies, individual level studies could provide more psychological and behavioral explanations with regard to bicycle helmet's effects on bicyclists. By asking 35 bicyclists to cycle 0.4 km downhill, once with and once without a helmet, Phillips et al. (2011) found routine helmet users reported experiencing higher risk and cycled slower when they did not wear their helmet in the experiment than when they did. On the contrary, those who use helmets routinely perceived reduced risk when wearing a helmet, and compensated by cycling faster. Gamble and Walker (2016) conducted a lab-based experiment measuring risk-taking of those either wearing a bicycle helmet, finding higher levels of risk-taking and sensation seeking in the helmet condition. According to a study based on school-age children, Morrongiello et al. (2007) found children went more quickly and behaved more recklessly in running an obstacle course when wearing safety gear than when not wearing gear, providing evidence of risk compensation. However, other studies find no evidence supporting the existence of helmet compensation effect. Fyhri et al. (2012) used structural equation model to analyze whether the lack of effect of helmet wearing laws was due to risk compensation or population shifts (discouraging some bicyclists to bike). Their results suggest that fast bicycling behavior is less likely to be the result of compensating for a safety device. Instead, safest bicyclists would be somewhat discouraged from bicycling by introducing helmet law. In the same vein, by interviewing 394 injured children (aged 8 to 18) from Montreal Children's Hospital emergency department, and comparing protective equipment users and non-equipment users, Pless et al. (2006) also found little support for risk compensation behavior among their study age group.

However, these studies rely heavily on parametric models (e.g. linear regressions) to control for possible confounders in which estimation results of helmet effects might be biased. Nevertheless, the existence of helmet compensation effect is still an open question. Thus, in vein of the individual level study stream, by designing an experiment capturing individual bicyclist behaviors and employing a more sophisticated modeling framework (e.g.TMLE) and data-driven or machine learning estimation techniques, we hope to provide new insights that will inspire future work in furthering our understanding of the impact of bicycle helmet.

In the next section, we will describe an experiment design and discuss how individual level data was collected in our study.

3. Experiment Design and Data Collection

To assess the effect of helmet use, stated preference surveys were conducted using Qualtrics, an online survey system. The survey consists of three sections. The first section is a questionnaire that gathers socioeconomic information including gender, age, income, daily travel mode, etc.

This section also establishes whether the bicyclist is a helmet user. A bicyclist is identified as a helmet-user if their self-reported helmet usage frequency is 'always', 'often', or 'sometimes'. If the frequency is stated as 'seldom' or 'never', then they are defined as a non-user. Detailed description regarding each variable and summary statistics can be found in Table 1.

Table 1 Socio-demographic Information

Variable	Description and Summary Statistics
Gender	Male (71%); Female (29%)
Marital Status	Married (37%); Single (63%)
Age	Continuous (Mean 34, Max 67, Min 19)
The highest degree or level of education you have completed	High school (8%); Technical college degree (2%); Bachelor's degree (31%); Master's degree (41%); Doctorate Degree (18%)
Are you currently a student?	Yes (28%); No (72%)
What is your annual income ($)?	0--40,000 (26%); 40,001--60,000 (8%); 60,001--80,000 (11%); 80,001--100,000 (11%); 100,001--120,000 (12%); 120,001--140,000 (11%); 140,001--160,000 (10%); 160,001--180,000 (5%); 180,001--200,000 (2%); Above 200,000 (2%)
Including yourself, what is your household size?	1 (25%); 2 (29%); 3 (18%); More than 3 (28%)
Including yourself, how many people in your household are currently employed?	1 (35%); 2 (39%); 3 (13%); More than 3 (13%)
How many bicycles do you own?	0 (6%); 1 (50%); 2 (30%); 3 (5%); More than 3 (9%)
How many automobiles do you own?	0 (23%); 1 (42%); 2 (24%); 3 (9%); More than 3 (2%)
On average, how many days do you ride a bicycle per week?	1 (20%); 2 (17%); 3 (19%); 4 (17%); 5 (9%); 6 (5%); 7 (13%)
On average, how long does your biking trip take?	Less than 10 minutes (6%); Between 10 and 20 minutes (27%); Between 20 and 30 minutes (19%); Between 30 and 40 minutes (17%); Between 40 and 50 minutes (15%); Above 50 minutes (15%)
How often do you use your helmet?	Always (38%); Often (21%); Sometimes (7%); Seldom (21%); Never (13%)

The second section is a video clip survey which is designed to elicit a bicyclist's actual risk-taking decisions under different real world bicycling situations. Twelve 20-second video clips were shot from various streets in the city of Berkeley from the perspective of a bicyclist riding behind another bicyclist. Each of these videos was presented to each survey participant in a random order[1] for them to envision themselves as the bicyclist traveling behind the one seen in the video. After watching each video clip, respondents made decisions on whether or not they would overtake the bicyclist in front of them. See Figure 1 for screenshots of selected scenarios. For instance, in the last picture of Figure 1 (located at the lower right corner), it represents the situation of no vehicle or parking or bicycle lane presence and 2 lanes. For this case, the question for the respondents is: "*You are biking for recreation and you are behind a bicyclist traveling at 10 mph (38kph), would you overtake the bicyclist in the video?*" The overtaking action is defined as risk-taking behavior, because in our designed scenarios, one can only overtake from the left leading to potential higher risk of interacting with passing vehicles.

Six design factors - street parking, vehicle presence, number of lanes, bicycle lane availability, bicyclist speed and trip purpose - were selected to capture common bicycling environment. The goal of presenting real-world videos is to mimic actual bicycling situations for survey participants and help reveal their true bicycling behavior. Since it is impossible to develop all possible scenarios, twelve scenarios were developed using a fractional factorial design based on the following factors.

- **Trip Purpose**: Commuters may experience sensitivity to time greater than recreational bicyclists. All scenarios that were developed were either for commuting or recreational purposes.
- **Parking**: Bicyclists are aware of parked vehicles and the possibility of vehicle doors opening or vehicles pulling out of their parking locations. There are two levels of this factor: with parking and without parking.
- **Vehicle Presence**: Passing vehicles pressure bicyclists to ride close to the curb or street parked vehicles. Similar to parking indicator, this factor also has two levels: vehicle presence and no vehicles.
- **Number of Vehicular Lanes**: Bicyclists may feel more comfortable on streets with one travel lane in each direction than 2 lanes. This is because vehicular presence and vehicular speeds may not be as high. Two design levels are used: one travel lane and two travel lanes.

[1] Due to survey setting adjustment, some participants were presented with ten randomly selected video clips instead of twelve.

- **Bike Lane Availability**: Bicycle lane may increase a bicyclist's sense of safety while there is a bike lane. Bike lane availability also has two levels.
- **Bicyclist Speed**: High bicyclist speed is often associated with risk taking behavior. Three speeds were used in the scenarios. 10-mph bicyclist speed, 15-mph bicyclist speed, and 20-mph bicyclist speed.

The third section is a questionnaire of Likert-scale questions that intends to capture bicycling habits and preferences, such as whether or not they feel comfortable riding close to moving vehicles, the frequency of using hand signals, etc. Responses to these questions will serve as another set of confounders which we need to control for. Detailed scores can be found in Table 2.

This video-based online survey was sent to graduate students in the Department of Civil and Environmental Engineering at UC Berkeley and members of San Francisco Bay Area Bicycle Coalition. At this point, there is no mandatory helmet use law in the Bay Area, allowing us to observe responses from both helmet users and non-users. In the invitation email, we have screening questions to make sure survey participants are bicyclists. We have gathered responses from 131 survey participants, 86 of whom are found to be helmet-users. After removing 33 missing responses, we end up with 1355 observations (where we have a maximum of 12 observations for any one participant).

Notably, due to limited sample size (only 131 participants), we only apply a binary split of survey participants. In this paper, we treat a bicyclist as a helmet user if her/his self-reported helmet usage frequency is 'always', 'often', or 'sometimes'. However, the 'sometimes' category might be an important third group - perhaps including those who wear a helmet when mountain biking or racing, but not when commuting at relatively slow speed. This could be analyzed when more data becomes available.

Figure 2 presents the results of individual overtake rate (defined as total number of overtakes per individual divided by total number of evaluated video clips per individual) across different helmet use frequency categories. The figure suggests that individuals who always or often use helmets tend to have higher overtake rate. However, this rough comparison might not provide us with a statistically valid helmet effect estimation result. In the following sections, we will introduce statistical models that can give us more reliable helmet effect estimates.

Figure 1 Screen Shot of Selected Scenarios where Design Factors Vary Systematically

Table 2 Liker-scale Statement Questions (1-Strongly disagree, 7-Strongly agree)

Statement	Mean	Standard Deviation
I like to ride fast	4.5	1.7
I often try to ride faster than other bicyclists and overtake them on the road	4.0	1.7
I do not like it when other bicyclists are faster than me	3.9	1.6
I usually detour to a longer and safer route to avoid a dangerous but shorter route	4.0	1.6
I prefer to ride on the sidewalk to avoid interaction with vehicles	3.8	1.8
I always make a full stop at a four-way-stop intersection	4.2	1.7
I always feel comfortable riding close to moving vehicles	3.0	1.7
I always feel comfortable riding close to parked vehicles	3.1	1.7
I always move to the front of queued vehicles when I arrive at signalized intersections	4.5	1.7
I feel that my bicycling environment is generally safe	4.0	1.8
I always feel safe when bicycling on a street without a bicycle lane	3.3	1.7
I always step off the bicycle when I am about to cross at a crosswalk	3.6	1.8
I always ride against red lights when there is no crossing traffic	3.0	1.6
I feel comfortable riding in the opposite direction on a one-way street	2.6	1.5
I am always aware that a vehicle is approaching me from behind	4.8	1.5
I always use hand signals when I need to make turns at intersections	4.9	1.5
I always slow down when I see a parallel parked vehicle pulling out of their spot.	5.5	1.3

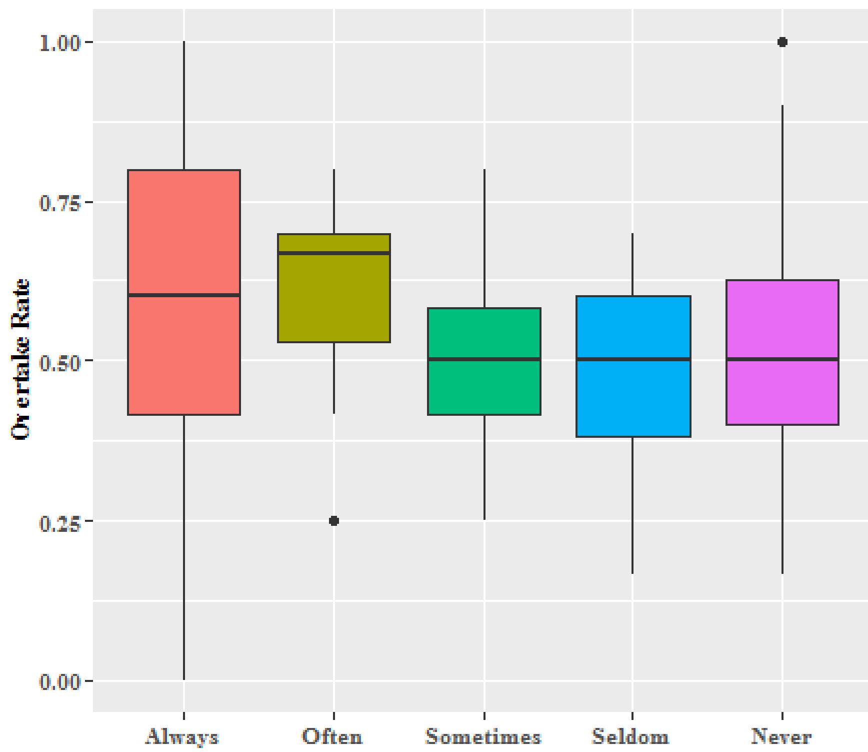

Figure 2 Overtake Rate Across Different Helmet Use Categories

4. Estimators for the Average Treatment Effect

We are interested in measuring the causal effect of treatment A (1-helmet user, 0-otherwise) on outcome Y (1-overtake, 0-otherwise). Following the Neyman–Rubin causal model framework (Sekhon, 2007), we can define the potential outcome or counterfactuals of interests as Y_A: $A = \{1,0\}$, the overtaking decision under helmet use ($A = 1$) or non-helmet use ($A = 0$). Then the treatment effect for a single observation is defined as $Y_1 - Y_0$. However, it is impossible to observe both Y_1 and Y_0 for the same observation at the same time; hence we can only identify the treatment effect on expectation by

$$\tau = E[Y_1 - Y_0] = E[Y_1] - E[Y_0] \tag{1}$$

This is called the average treatment effect (ATE), which can be interpreted as the average causal risk difference between helmet use ($A = 1$) and non-helmet use ($A = 0$). In a randomized experiment where individuals can be randomly assigned to helmet use group and non-helmet use group, we can simply take the empirical difference of overtaking rates between treatment group and control group to obtain an unbiased estimate of the ATE.

However, in our setting, we cannot manipulate helmet use (treatment) assignment, as survey participants self-select into the treatment and control groups, based on whether they do or don't wear helmets while bicycling. In order to control for self-selection in estimating ATE, we can condition on covariates X and Z, such that X denotes video-specific covariates (related to the six design factors) and can be treated as sampling from real world bicycling situations, and Z denotes both individual-specific demographic characteristics (e.g. age and gender) and individual-specific attitudinal characteristics (responses to statements in Table 2). We can represent the relationship between A, Y, X and Z as follows:

$$A = f_A(Z,\varepsilon_A) \tag{2}$$

$$Y = f_Y(X,Z,A,\varepsilon_Y) \tag{3}$$

where ε_A and ε_Y are error terms; and f_A and f_Y denote data generating process for A and Y, respectively. We implicitly assume that helmet use depends solely on individual-specific demographic and attitudinal characteristics; and overtaking decisions depend on video-specific design factors, individual-specific demographic and attitudinal characteristics, and helmet use. For identification purpose, we assume further that:

$$\varepsilon_A \perp \varepsilon_Y | \, Z \tag{4}$$

This assumption implies that after conditioning on the individual-specific demographic and attitudinal characteristics, any observed association between helmet use and overtaking behavior is due to the effect of the former on the latter. Put another way, treatment A can be viewed as good as randomly assigned after conditioning on Z.

Under this assumption, ATE can be estimated in one of three approaches using the G-computation estimator, the inverse probability of treatment weighted (IPTW) estimator, or the targeted maximum likelihood estimator (TMLE). Over subsequent subsections, we describe each of these estimators in greater detail.

4.1 The G-computation estimator

The traditional approach to estimating the ATE is based on the G-computation estimator proposed by Robins (1986):

$$\tau = E_{X,Z}[E[Y|A = 1,X,Z] - E[Y|A = 0,X,Z]] \tag{5}$$

where $E[Y|A,X,Z]$ is the conditional expectation of the response function f_Y over the error term ε_Y, given A, X and Z. The reader should note that in our case, the following holds true:

$$E[Y|A,X,Z] = P(Y = 1|A, X,Z) \tag{6}$$

where $P(Y = 1|A, X,Z)$ denotes the probability that Y equals 1, conditional on the random variables A, X and Z. Let $\hat{P}(Y = 1|A, X,Z)$ denote an estimate of the same. In the next section, we will describe how $P(Y|A, X,Z)$ may be estimated in practice, using nonparametric procedures for model estimation.

Once we have good estimates for $P(Y|A, X,Z)$, we can plug in $A = 1$ and $A = 0$ to generate predicted probabilities of overtaking for each observation for each individual. The mean difference between corresponding counterfactuals, marginalized over all individuals and observations, yields an estimate for ATE:

$$\hat{\tau}_{GC} = \frac{1}{N}\sum_{n=1}^{N}\frac{1}{T_n}\sum_{t=1}^{T}\hat{P}(Y = 1|A = 1, X = x_{nt},Z = z_n) - \hat{P}(Y = 1|A = 0, X = x_{nt},Z = z_n) \tag{7}$$

where N denotes the number of individuals in the sample; T_n denotes the number of observations for individual n; x_{nt} denotes the video-specific covariates for observation t corresponding to individual n; and z_n denotes the individual-specific covariates for individual n. In this way, we can mimic the conditions where each individual received and did not receive the treatment A. If the model $P(Y|A, X,Z)$ is correctly specified, the G-computation estimator for ATE is consistent.

4.2 The inverse probability of treatment weighted (IPTW) estimator

The IPTW estimator of the ATE does not require assuming a model for $P(Y|A, X,Z)$, but relies instead on a model for $P(A|Z)$, i.e. probability of self-selecting into the treatment or control group, given the individual-specific covariates Z. Let $\hat{P}(A|Z)$ denote an estimate of the same. Then, the IPTW estimator is given by:

$$\hat{\tau}_{IPTW} = \frac{1}{N}\sum_{n=1}^{N}\frac{1}{T_n}\sum_{t=1}^{T}w_n y_{nt} \tag{8}$$

$$w_n = \frac{I[a_n = 1]}{\hat{P}(A = 1|Z = z_n)} - \frac{I[a_n = 0]}{\hat{P}(A = 0|Z = z_n)} \quad (9)$$

where w_n is a weighting factor for individual n; y_{nt} equals one if individual n during observation t indicated that they would overtake, and zero otherwise; and I is an indicator function that equals one if the condition within the bracket is satisfied, and zero otherwise.

By reweighting each observed individual in the sample by the inverse of the probability of treatment A, the IPTW estimator creates a pseudo population where treatment A is no longer confounded with the observed covariates Z (Robins, 2000). Conditional on Z, assignment to treatment or control group is effectively random, and the difference between mean outcomes between the weighted treatment and control groups yields an estimate for ATE. Consequently, the IPTW estimator does not require the estimation of the model $P(Y|A, X,Z)$. If the model $P(A|Z)$ is correctly specified, the IPTW estimator for ATE is consistent (Neugebauer and van der Laan, 2005).

4.3 The targeted maximum likelihood estimator (TMLE)

The Targeted Maximum Likelihood Estimator (TMLE) has been proposed as a viable alternative that combines the G-computation and IPTW estimators. For a comprehensive discussion about TMLE, the reader is referred to van der Laan and Rubin (2006), Gruber and van der Laan (2009), and van der Laan and Rose (2011).

In our case, the TMLE can be implemented in six steps. First, we estimate a model of how individuals self-select into the treatment or control group, denoted $P(A|Z)$ as before. Second, we use predicted probabilities from this model to create a new "clever covariate", denoted $H(A, Z)$, similar to the weights used by the IPTW estimator (van der Laan and Rose, 2011):

$$H(A = a_n, Z = z_n) = \frac{I[a_n = 1]}{\hat{P}(A = 1|Z = z_n)} - \frac{I[a_n = 0]}{\hat{P}(A = 0|Z = z_n)} \quad (10)$$

Third, we estimate a separate model of overtaking behavior, denoted $P(Y|A, X,Z)$ as before. Let $\hat{P}(Y|A, X,Z)$ denote an estimate of the same, as before. Fourth, we run a logistic regression of the actual overtaking outcome on the clever covariate $H(A, Z)$ calculated in the second step, using the predicted overtaking probabilities from the model estimated in the third step as offsets:

$$\begin{aligned}\text{logit}\left[P^{'}(Y = y_{nt}|A = a_n, X = x_{nt}, Z = z_n)\right] \\ = \text{logit}\left[\hat{P}(Y = y_{nt}|A = a_n, X = x_{nt}, Z = z_n)\right] + \gamma H(A = a_n, Z = z_n)\end{aligned} \tag{11}$$

where logit denotes the logit function, i.e. the inverse of the logistic function; $P^{'}(Y|A, X,Z)$ is an update to the initial model of overtaking behavior; and γ is a parameter to be estimated, typically using maximum likelihood estimation, such that $\hat{\gamma}$ is an estimate of the same. Fifth, we update our initial estimate of $\hat{P}(Y|A, X,Z)$, denoted $\hat{P}^{'}(Y|A, X,Z)$, using the parameter estimate $\hat{\gamma}$:

$$\begin{aligned}\hat{P}^{'}(Y = 1|A = a_n, X = x_{nt}, Z = z_n) \\ = \exp\left\{\text{logit}\left[\hat{P}(Y = 1|A = a_n, X = x_{nt}, Z = z_n)\right]\right\} + \hat{\gamma} H(A = a_n, Z = z_n)\end{aligned} \tag{12}$$

As in the case of the G-computation estimator, we can plug in $A = 1$ and $A = 0$ to generate predicted probabilities of overtaking for each observation for each individual. And finally, the mean difference between corresponding counterfactuals, marginalized over all individuals and observations, yields an estimate for ATE:

$$\hat{\tau}_{TMLE} = \frac{1}{N}\sum_{n=1}^{N}\frac{1}{T_n}\sum_{t=1}^{T}\left[\hat{P}^{'}(Y = 1|A = 1, X = x_{nt}, Z = z_n) - \hat{P}^{'}(Y = 1|A = 0, X = x_{nt}, Z = z_n)\right] \tag{13}$$

What is the logic behind the TMLE? Our initial outcome probability function $P(Y|A, X,Z)$ is typically estimated through procedures such as maximum likelihood estimation or cross entropy minimization that aim at achieving optimal bias-variance tradeoff for the full conditional expectation function $E[Y|A,X,Z]$. However, we are not interested in estimating the full conditional expectation; we wish to estimate the ATE of A on Y. Achieving the optimal bias-variance tradeoff for the full conditional expectation function may not produce the optimal bias-variance tradeoff for the ATE.

The TMLE corrects the wrong bias-variance tradeoff used in estimating $P(Y|A,X,Z)$ by leveraging the estimate of $P(A|Z)$ in a way that targets the maximum likelihood estimate of the ATE. If $P(Y|A,X,Z)$ is correctly specified, the estimate $\hat{\gamma}$ should be zero, and our estimate for ATE should be consistent. If $P(Y|A,X,Z)$ is *not* correctly specified, but $P(A|Z)$ *is* correctly specified, the targeting step given by equations (10)-(13) reduces bias for ATE, the target parameter of interest (van der Laan, 2010). In this way, the TMLE is doubly robust: if either the model $P(A|Z)$ or the model $P(Y|A,X,Z)$ is correctly specified, the TMLE for ATE is consistent (van der Laan and Rubin, 2006).

5 Model Specification

Having discussed different estimators for ATE, we now need to specify functional forms for the models $P(A|Z)$ and $P(Y|A,X,Z)$, and estimate them using the observed data. Most existing studies on helmet effects analysis have used parametric models. For instance, both $P(A|Z)$ and $P(Y|A,X,Z)$ are typically specified as logistic regression models. However, parametric models may be too restrictive in that we only search in a limited function space and bet on the first-order approximation. If the models are incorrectly specified, our ATE estimators may be biased.

An increasingly popular alternative is to use nonparametric models, such as the Super Learner (van der Laan et al., 2007). Nonparametric models do not have well-defined functional forms with a fixed number of parameters. Rather, they are data-adaptive models, such that the number of parameters increases and the functional form grows in complexity as more data become available. Nonparametric models can asymptotically mimic any parametric model.

We specify a parametric model for $P(A|Z)$. In particular, we use a logistic regression, where helmet use A is modeled as a function of individual-specific characteristics Z. We only have 131 individuals in the dataset, and the estimation of more complex nonparametric models of self-selection was deemed infeasible. However, we have 1355 observations of overtaking behavior for these individuals, and are able to specify a semi(non)parametric model for $P(Y|A,X,Z)$. In particular, we use Super Learner, described in more detail over subsequent paragraphs.

Super Learner, or stacking method, is an ensemble learning technique introduced by Wolpert (1992) and extended to a regression framework by Breiman (1996). Van der Laan et al. (2007) provide the theory for stacking and have shown that Super Learner performs asymptotically as well as best possible weighted combination of the base learners. Base learners refer to any possible parametric or non-parametric functions that we use to fit $P(Y|A, X,Z)$, such as a logistic regression or a decision tree. The Super Learner seeks to find the optimal linear combination of multiple base learners. By leveraging the strengths of different base learners, one can achieve improvement in prediction accuracy.

The idea is to perform k-fold cross-validation on the original dataset (a.k.a. level zero data) using each base learner, then stack the cross-validated predictions from each learner to form a new set of features (a.k.a. level one data) and perform another layer of training based on level one data. Take the estimation of $P(Y|A, X,Z)$ as an example. Suppose we have selected L base learners $P_1(Y|A, X,Z)$,...,$P_L(Y|A, X,Z)$. Instead of following a winner-takes-all strategy by selecting the learner based on lowest cross validation error (e.g. cross-entropy error), we can stack the predicted outcome probabilities from different learners to form a new design matrix and combine them in the following form (Wolpert 1992; Brieman 1996b):

$$P(Y=1|A, X,Z) = \frac{1}{1+\exp\left\{-\sum_{l=1}^{L}\alpha_l \text{logit}\left[\hat{P}_l(Y=1|A, X,Z)\right]\right\}} \tag{14}$$

where α_l are the weights associated with each base learner, such that $\alpha_l \geq 0$ and $\sum_{l=1}^{L}\alpha_l = 1$; and $\hat{P}_l(Y=1|A, X,Z)$ denotes cross-validated predicted outcome probabilities from base leaner l. The α_l are chosen to minimize the cross entropy loss between observed outcomes and predicted outcome probabilities.

In terms of base learners, we want a library that covers the function space well in places where they are needed, and are sufficiently different from each other for the meta-learning to be effective (Hastie et al., 2009). In this case, five categories of base learners are considered to find the best estimates of the outcome model $P(Y|A, X,Z)$: multivariate adaptive polynomial spline regression (MARS), decision tree, Lasso (L2 regularization), Ridge (L1 regularization), and standard linear logistic regression with main effects. Each base learner is trained based on minimizing cross-entropy loss using 5-fold cross validation. Super Learner is used to find the best linear combination of these five base learners.

By using data-adaptive estimation procedures such as Super Learner to estimate the outcome model $P(Y|A, X,Z)$, we can improve prediction accuracy and decrease the likelihood of incorrect model specification. However, we may lose in terms of model interpretability. There is a general debate between complex machine learning algorithms (black box) and simple interpretable models like linear regression. For example, we are unable to estimate the effects of the six design factors on overtaking decisions using the TMLE framework because those covariates enter $P(Y|A, X,Z)$ in a highly non-linear manner. Nevertheless, since our goal is to estimate the causal effect of helmet use on overtaking decisions, we are willing to sacrifice interpretability of other covariates.

Besides point estimation of ATE, we also need to make statistical inference. To do so, we use bootstrap technique to estimate standard errors for our estimate of ATE. However, there are some caveats about the bootstrap implementation. Observations generated by the same individuals are likely to be correlated, violating the independence assumption. To account for this potential correlation, we use individual-based nonparametric bootstrap instead of observation-based nonparametric bootstrap. Specifically, we randomly sample individuals from our sample population, such that all observations generated by an individual appear in a bootstrap sample if that individual is selected. In this way, correlation among observations generated by the same individual is preserved.

6 Estimation Results

The Super Learner estimation results of outcome mechanism $P(Y|A, X,Z)$ are presented in Table 3. It is found that the weighted combination of decision tree, MARS, and Ridge produce the best estimation of $P(Y|A, X,Z)$. The ATE based on TMLE using the Super Learner is estimated to be 0.156 which indicates that, on average, the likelihood of overtaking is 15.6% higher for helmet users than non-helmet users. This estimate is in line with the information presented in Figure 2, which suggests the existence of helmet compensation effects in our study sample. For comparison purpose, we also include the results from the following estimators: G-computation based on linear logistic regression, G-computation based on Super Learner, and IPTW. The results are shown Table 4. All four estimators yield consistent results in the mean estimation.

Regarding ATE estimates, IPTW is almost four times larger than G-computation estimate. TMLE leverages both treatment mechanism and outcome mechanism estimation to achieve bias reduction compared to G-computation estimate. This explains why TMLE ATE estimate lies in between G-computation and IPTW estimates.

We also quantify the uncertainty associated with these estimators using nonparametric bootstrap. As mentioned before, due to repeated measurements from a same survey participant, independence assumption might no longer hold. Therefore, instead of resampling observations, we resample individuals. 500 bootstrap samples were generated and each bootstrap sample yields a point estimation result. As shown in Table 4, 95% confidence intervals are constructed using quantiles of the empirical distribution of the estimates. Empirical distributions of bootstrap estimates are presented in Figure 3. IPTW is found to have the highest variance across four estimators. G-computation estimates (based on linear logistic regression and Super Learner) are found to have lower variance. However, the ATE estimate from linear logistic regression is found to be statistically insignificant based on nonparametric bootstrap, whereas the rest three estimators are found to produce statistically significant results. This suggests the widely used linear model may be biased and results in "no effect" being identified. To this end, TMLE is preferable due to its desirable theoretical properties (double robust and bias reduction than G-computation) and good finite sample performance (smaller variance than IPTW).

Table 3 Super Learner Estimation of Overtake Decisions

$P(Y\|A, X,Z)$	5-fold CV cross-entropy loss	Weights
Decision tree with depth 5	0.494	0.357
MARS	0.510	0.135
Ridge regression with regularization parameter equals to 100	0.474	0.508

Note: to save space, algorithms with a zero weight are not presented.

Table 4 Estimation Results

	G-computation (linear regression)	G-computation (Super Learner)	IPTW (Super Learner)	TMLE (Super Learner)
Average treatment effects	0.086	0.062	0.222	0.156
Bootstrap based standard deviation	0.057	0.024	0.078	0.058
Bootstrap based 95% confidence interval	[-0.024, 0.203]	[0.020, 0.104]	[0.093, 0.450]	[0.066, 0.281]

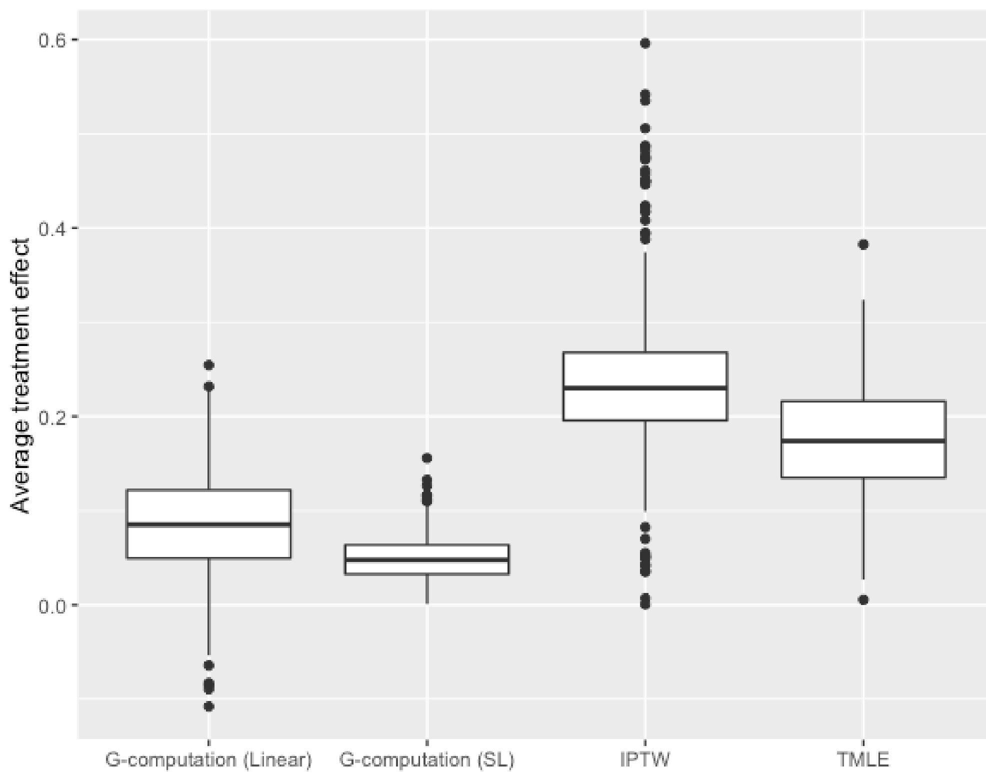

Figure 3 Bootstrap Results of Four Estimators

7. Conclusions and Future Research

In this study, we investigated the compensation effect of helmet use on a bicyclist's risk-taking behavior. Our hypothesis is that helmet users will be more likely to engage in risk-taking behavior due to helmet compensation effect. Based on 131 survey participants, a significant positive compensation effect has been identified using the TMLE estimator and the size of effect is estimated to be about 15.6%. Due to the ethical and practical impossibility of randomizing helmet use in our survey, the estimated effect obtained can at best be considered a biased assessment of the helmet effect. Yet the hope is that our video-based experiment design will serve as a pilot study in this new perspective and inspire further exploration on better understand of the response of bicyclists as a result of mandatory bicycle helmet laws.

Our findings should be of importance to policy makers who might be interested in imposing mandatory bicycle helmet laws to increase road safety. Our analysis suggests that the benefits from any such policy could potentially be weakened by helmet compensation effects. To this regard, it might be beneficial to initiate road safety programs that could mitigate these unintended compensation effects. For instance, traffic calming measures (e.g. roundabouts, curb bulb-outs, speed humps, and shared space) may help reduce the speed of vehicles and bicyclists by increasing the perceived risk for both parties, resulting in slow traffic and thereby reducing the number of seriousness of injuries.

Some studies have also recommended using cost-benefit analysis to determine if mandatory bicycle helmet use laws are worthwhile (Robinson 2007). It has been suggested that helmet legislation should be evaluated in terms of the effect on bicycle-use, injury rates per km cycled, and changes in percentages of hospitalized bicyclists with head and brain injuries. By identifying helmet compensation effects, our study also adds another important dimension in the cost-benefit framework of evaluating helmet law.

There are two major limitations of this study. The first limitation is the use of a small and potentially biased sample. It is hard to generalize the results based on only 131 individuals. In order to obtain a full spectrum of helmet effect on bicyclists, we need to increase our sample size and incorporate more representative individuals.

Second, it is possible that there might be unobserved confounders influencing both helmet use and overtaking behavior that violate the identification assumption we mentioned above, hence resulting in self-selection bias. For instance, bicycling culture of a community may influence a bicyclist's attitudes toward both helmet use and bicycling behavior. The hope is that by controlling for observed sociodemographic characteristics and personal attributes, we can balance out the differences other than helmet use itself between helmet users and non-users, hence be able to identify the causal effects of helmet use. To this end, more aggregate level sociodemographic characteristics such as city-level median income and city-level trip frequency should be collected as additional controls. It is also noted that the most commonly used econometric approach of adding control variables to account for self-selectivity is to apply linear regression with observable explanatory variables as covariates. However, this approach might be too simplistic and sometimes problematic (Mannering, 2018). Therefore, in this paper, we use data-driven or machine learning techniques to account for observable explanatory variables in two layers: layer one is helmet use prediction and layer two is overtaking decisions prediction. Then by applying TMLE framework, we then combine both prediction models to control for self-selection in a more robust manner.

Acknowledgements

The authors wish to acknowledge the contribution of Professor Joan Walker from the University of California, Berkeley, for her support and valuable comments on experiment design. Also the authors would like to express the sincere thanks for those respondents involved in this project. The authors greatly appreciate the helpful comments from Professor Maya Peterson and Professor Haiyan Huang from the University of California, Berkeley, and Professor Fred Mannering from the University of South Florida.

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