Mandatory Helmet Legislation as a Policy Tool for Reducing Motorcycle Fatalities: Pinpointing the Efficacy of Universal Helmet Laws

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Abstract

This study uses repeated cross-sections of individual level crash data to study the effectiveness of motorcycle helmet legislation. Results suggest that motorcycle helmet laws reduce average individual fatality risks by 21.3%. Overall, the analysis suggests that mandatory helmet laws are an effective means of reducing state motorcycle fatalities and result in average annual state benefits that range from \$113 million to \$168 million. The effectiveness of helmet legislation can be attributed to the technological efficacy of helmets as well as enhancing behavior in the form of reduced risk taking among motorcyclists. Specifically, motorcyclists who use helmets in order to comply with mandatory helmet laws are 4.2 percentage points less likely to receive a traffic citation for risky driving behavior (speeding, alcohol, etc.), travel at a 6 mph lower average speed, and have a 30 percentage point reduction in the probability of "severely" damaging their motorcycle in a crash.

Keywords: motorcycle helmet legislation, offsetting behavior, nonlinear models with endogeneity

JEL Codes: K32, R41, I18

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1. Introduction

In 2010, motorcyclist fatalities accounted for 13.7% of all motor vehicle related fatalities in the U.S.; however, motorcycle registrations accounted for only 3.2% of the total vehicle registrations. The fatality rate (fatalities per registered vehicle) of motorcyclists is roughly six times the fatality rate of passenger car motorists, and using this criteria, motorcycles are consistently ranked as the most dangerous motor vehicles operated on roadways. As such, state legislatures have passed numerous legislative measures designed to improve motorcycle awareness, provide motorcycle training programs, and improve the safety of motorcyclists involved in crashes. Laws requiring motorcyclists to use protective helmets are generally considered to be a viable policy tool available to state legislatures to improve motorcyclist safety.

The history of state motorcycle helmet legislation in the U.S. has largely been influenced by federal regulation providing incentives for states to adopt mandatory helmet laws. There was a steady increase in the number of state laws requiring universal motorcycle helmet use from 1967 to 1975, and by the end of 1975 48 states implemented such laws. During this period the U.S. Highway Safety Act of 1966 was in operation, and the act required states to adopt universal helmet laws in order to avoid penalties of up to 10% reductions in their federal highway construction funds (Sass and Zimmerman, 2000). The helmet law incentives established in the 1966 Highway Safety Act remained in place until Congress passed the Federal-Aid Highway Act in May of 1976. The Federal-Aid Highway Act removed penalties for states without universal helmet laws provided the states maintained partial coverage levels that at minimum required helmet use for motorcyclists 18 years of age and younger (Ruschmann, 1977). As a result of the sanction removals 28 states repealed their universal helmet laws between 1976 and 1981. The majority of states that repealed their universal coverage laws replaced the laws with age-specific helmet laws designed to meet the requirements of the Federal-Aid Highway Act.

Congress once again attempted to influence state adoption of universal motorcycle helmet laws in 1991 with the passage of the Intermodal Surface Transportation Efficiency Act (ISTEA). ISTEA made provisions for states to receive federal grants upon passage of universal helmet laws and primary enforcement safety belt laws (Ulmer and Preusser, 2003). Furthermore, states that failed to enact such laws by October, 1993 faced sanctions in the form of up to 3% reallocation of their 1995 Federal-aid highway funds (Sass and Zimmerman, 2000). The proposed penalties were much less severe than those in the 1966 Highway Safety Act, and the penalties were not enforced because Congress repealed the reallocation provisions in 1995 with the passage of the National Highway System Designation Act (Ulmer and Preusser, 2003). As a result of the lack of enforcement and relatively smaller penalties, California and Maryland were the only states that passed universal helmet laws between 1991 and 1995.

Overall, universal helmet law adoption has remained fairly stable post 1981. From 1981 to 2012 eight states have repealed their universal helmet laws, and 6 states have enacted new universal helmet legislation.[2] Currently 19 U.S. states and the District of Columbia have mandatory motorcycle helmet laws requiring universal helmet use for all motorcyclists. Another 28 states have partial coverage helmet laws with age restrictions that stipulate helmets must be worn by minors. The remaining three states consisting of Iowa, Illinois, and New Hampshire have no helmet use requirements for motorcyclists.

Studies analyzing the effectiveness of helmets in preventing motorcyclist fatalities can largely be classified in two separate groups:

[2] Louisiana and Texas had multiple changes in their motorcycle helmet laws between 1981 and 2012. Louisiana readopted a universal law in 1982, repealed that law in 1999, and reinstated universal coverage in 2004. Texas reinstated universal coverage in 1989, and then repealed its universal helmet law in 1997.

1. Those analyzing the technological efficacy of motorcycle helmets (for a review, see Liu et al., 2008).
2. Studies addressing the effectiveness of motorcycle helmet legislation (summary provided in Table 1).

Estimates of technological efficacy employ individual level motorcycle crash data collected from police accident reports, and attempt to isolate the effects of helmet use on motorcyclists' likelihood of death given they are involved in a motorcycle crash. Peltzman (1975) suggests that automobile safety regulation may result in compensating behavior in the form of increased "driving intensity" and this behavior may offset some of the effectiveness of the safety regulation.[3] According to Peltzman's hypothesis, analysis of technological efficacy of motorcycle helmets is complicated by the fact that individuals' driving intensity is correlated with their decision to wear protective helmets. Stated alternatively, there is a simultaneity problem associated with the choice of helmet use and driving intensity as illustrated in the path analysis of Figure 1.

Researchers interested in analyzing the technological effects illustrated by the direct path from helmet use to injury severity have generally followed two types of estimation strategies. The first strategy attempts to directly control for confounding variables (i.e. crash characteristics and driving intensity) in order to isolate the direct effects of helmet usage on injury severity (see, for example, Goldstein, 1986, Hundley et al., 2004, Keng, 2005, Rowland et al., 1996, Sauter et al., 2005). This strategy is necessarily complicated by the fact that driving intensity is imperfectly measured (i.e., variables such as motorcyclist's travel speed must be proxied by posted speed-limits).

[3]Noland (2013) extends the theory of offsetting behavior to a more general concept of mobility that encompasses risky behavior as well as changes in vehicle utilization. In the analysis that follows the term driving intensity is used in the traditional sense posited by Peltzman to be synonymous with risk taking.

A more promising estimation strategy uses matched cohorts of drivers and passengers in which one of the matched individuals is helmeted and the other is not (see, for example, Anderson and Kraus, 1996, Dee, 2009, Evans and Frick, 1988, Norvell and Cummings, 2002). The matched pair cohort method necessarily controls for driving intensity by holding unobserved crash features constant for drivers and their matched passengers. Unfortunately, these studies may suffer from issues of external validity, because crashes involving motorcycles carrying passengers are a very small percentage of overall crashes and the characteristics of those crashes may not be representative of the population at large (Dee, 2009). In their meta-analysis, Liu, et al. (2008) estimate that studies of technological efficacy find helmets to be associated with an average 42% reduction in risk of death.

A second group of studies analyzing motorcycle helmet safety use state-level data to estimate the impact of mandatory motorcycle helmet laws on aggregate motorcycle fatalities. These studies use a variety of estimation approaches, and their main findings are summarized in Table 1. One key difference among the studies analyzing state motorcycle helmet law effectiveness is their choice of dependent variable. Specifically, the studies of helmet law efficacy generally choose between the following three alternative dependent variables: non-normalized fatality counts, fatalities per registered motorcycle, and fatalities per capita. As illustrated in Table 1, studies using non-normalized fatality counts and fatalities per capita generally estimate helmet laws to be more effective in preventing motorcycle fatalities in comparison to studies where the dependent variable is fatalities per registered motorcycle. On average across all the helmet law effectiveness studies reported in Table 1, motorcycle helmet laws are estimated to reduce motorcycle fatalities by 22.4%.

The following analysis makes two key contributions to the literature on motorcycle helmet effectiveness. First, the results show that individual crash data (data typically used in technological effectiveness studies) can be used to estimate the effects of motorcycle helmet legislation on individual's probability of death. From a policy standpoint this is a useful measurement, because it captures the overall effect (direct effect + induced driving intensity effect) of helmet use on motorcyclists' probability of death for the individuals who are incentivized to wear a motorcycle helmet due to the passage of a mandatory helmet law. The results indicate that the adoption of a universal motorcycle helmet law is associated with a 21.3% reduction in motorcyclists' average probability of death given they are involved in a motorcycle crash. This estimated reduction in average fatality risk is remarkably similar to the average 22.4% estimated efficacy of helmet laws from the state-level studies reported in Table 1.

Second, the study builds upon the emerging literature using control functions in nonlinear models by employing novel control function and bivariate methods to correct for non-random selection of helmet use when examining the impact of helmets on fatality risks (see Blundell and Powell, 2004, Louviere et al., 2005, Petrin and Train, 2010, Villas-Boas and Winer, 1999, Wooldridge, 2014 for a review of control function methods).

The remainder of the analysis proceeds as follows. Section 2 presents an overview of the National Automotive Sampling System individual-level crash data used in the analysis. The empirical methodology and estimation results are given in section 3, and section 4 concludes the paper.

2. Data

The individual level data set used for estimating the effects of motorcycle helmet use on potential health outcomes for motorcyclists involved in crashes comes from the National Automotive Sampling System (NASS) General Estimates System (GES) for the years 2002-2008 (see, for example, Shelton, 1991, and US DOT, 2008 for details of the NASS GES data sampling design). The sampling structure for the GES data consists of a multistage procedure that first segments the entire United States into 1,195 primary sampling units (PSU). Sampled PSUs are chosen with different probabilities based on the number of fatal and injury crashes in each PSU. Within each PSU, police jurisdictions (PJ) are sampled using probability sampling based on the number of police accident reported (PAR) crashes within each PJ. PJs with a larger number of PAR crashes have a higher probability of being sampled. In the final sampling step, PARs are stratified into six different clusters based on injury outcome characteristics of the crash. Some of the clusters contain only a portion of the possible crash outcomes. Furthermore, the most serious outcome crashes are sampled at a higher frequency than their occurrence in the population. The sampling procedures are tantamount to choice-based sampling in discrete choice analysis. It is therefore important to control for sample design, because failure to do so will lead to biased coefficient estimates when the sample is clustered on the outcome variables of interest and sample selection frequency is not equivalent to population frequencies (Manski and Lerman, 1977).

Details of the variables used from the individual level NASS GES data set are summarized in Table 2. The key outcome of interest is injury severity as measured by three possible discrete crash outcomes: no injury, injury, and fatality. A binary indicator variable for state helmet legislation is used as an instrument for helmet use, and roughly 45% of the individual crash observations occur in states with universal helmet laws. These sampling percentages reflect the fact that approximately 41% of all U.S. states have universal motorcycle helmet legislation in place over time period from 2002 to 2008. Several individual factors that may affect injury severity are included as control variables in the analysis: sex of individual, age of individual, a binary indicator of whether the individual is a driver or passenger, and a binary indicator of individual helmet use. Importantly, over 90% of the individual observations are motorcycle drivers. This feature of the data highlights the considerable loss of information in a matched pair cohort study that uses less than 20% of the available observations.

Several variables measuring crash characteristics are also included in the analysis because they may affect the crash outcome. These variables include an indicator variable for whether the motorcycle caught on fire, indicator variables that control for collision with a moving vehicle, collision with animals, pedestrians, or bicyclists, and collision with a fixed object such as a tree or boulder. Finally, the crash characteristics also control for manner of collision measured by head on collisions, rear end collisions, angle collisions (a vehicle turning into another vehicle), and side swipe collisions.

A multinomial probit model is used to evaluate the effects of these characteristics on crash outcomes as measured by individual's injury severity. Multinomial probit was chosen as the preferred specification because likelihood ratio tests of an ordered outcome specification strongly reject the proportional odds assumption. Furthermore, Brant tests reveal that 12 out of the 21 individual explanatory variables violate the proportional odds assumption of ordered probit and ordered logit. Details of the empirical specification are given in the following section.

3. Empirical Model and Results

For individuals involved in a motorcycle crash their health status given crash involvement falls into one of three mutually exclusive and exhaustive categories: no injury (NI), injury (I), or fatality (F). Police accident reports are coded on the KABCO system based on the following distinctions: K is a fatal injury, A is an incapacitating injury, B is a non-incapacitating injury, C is a possible injury, and O means no injury. Farmer (2003) notes that police accident reports tend to do a good job of classifying fatal and non-injury crashes, but incapacitating injury crashes are misclassified approximately 49% of the time. Because injury severity is often misclassified, the incapacitating, non-incapacitating, and possible injury categories are grouped together into one injury category for the main analysis.

There is a continuous unobservable latent measure of injury outcome severity of a crash, $O_{n,j,t}$, that can be written as a function of the observable and unobservable individual and crash characteristics in the following manner:

$$O_{n,j,t} = V_{n,j,t} + \varepsilon_{n,j,t} = a_j + x_{n,t}\beta_j + c_{n,t}\gamma_j + \delta_j h_{n,t} + T_t + \varepsilon_{n,j,t},\ j \in [NI, I, F], \qquad (1)$$

where $V_{n,j,t}$ denotes the representative outcome as a function of an outcome specific constant, a_j, that captures the average effect of crash classification. Equation (1) includes year fixed effects, T_t, a vector of individual characteristics, $x_{n,t}$, that include the following variables: *Sex, Age, Age Squared*, and *Driver*.[4] Equation (1) also includes a vector of crash characteristics, $c_{n,t}$, that includes: *Fire, Major Moving Collision, Minor Moving Collision, Collision With Fixed Object, Rear End, Head On, Angle, Sideswipe Same Direction, Side Swipe Opposite Direction*, and *Speed Limit*. A dummy variable for helmet use, $h_{n,t}$, is included that is equal to 1 if the motorcyclist is wearing a helmet when they crash, and equal to zero otherwise. Finally, $\varepsilon_{n,j,t}$ is a

[4] Table 2 provides definitions for all the variables used in the analysis of individual crashes from PARs.

random error term with a density given by $f(\varepsilon_{n,j,t})$. The probability that individual n involved in a crash receives injury severity outcome j is given by:

$$P_{n,j,t} = \Pr(\varepsilon_{n,k,t} - \varepsilon_{n,j,t} < V_{n,j,t} - V_{n,k,t})\,\forall k \neq j. \tag{2}$$

Equation (2) is estimated using multinomial probit under the assumption that the error terms, ε_n, are normally distributed. Letting $E_{n,j,t}$ denote the set of all possible error terms, ε_n, that satisfy the inequality $\varepsilon_{n,k,t} - \varepsilon_{n,j,t} < V_{n,j,t} - V_{n,k,t}\ \forall k \neq j$, the probability of outcome j can be stated alternatively as the following:

$$P_{n,j,t} = \int_{\varepsilon_n \in E_{n,j,t}} \phi(\varepsilon_n) d\varepsilon_n\ , \tag{3}$$

where $\phi(\cdot)$ is the probability density function for the normal distribution. The multinomial probit model is estimated using maximum likelihood by finding the values of a_j, β_j, γ_j, and δ_j that maximize the simulated log-likelihood function given by the following:

$$LL(a_j, \beta_j, \gamma_j, \delta_j) = \sum_n \sum_j w_j d_{n,j,t} \ln(\hat{P}_{n,j,t})\,, \tag{4}$$

where $d_{n,j}$ is a dummy variable that is equal to 1 if individual n is observed in injury severity state j, and is equal to zero otherwise, and w_j is a weight for crashes of type j that is equal to the population shares of crashes of type j divided by the sample shares of crashes of the same type. The weighted exogenous sampling maximum likelihood estimator (WESMLE) developed by Manski and Lerman (1977) is employed in equation (4) to correct the aforementioned oversampling of severe crashes by the NASS GES survey. The predicted outcome probabilities, $\hat{P}_{n,j,t}$, are simulated using the Geweke Hajivassiliou Keane (GHK) simulator (see Hajivassiliou et al., 1996, for an overview of the performance of the GHK simulator) to evaluate the integral specified in equation (3).

The results from the estimation of equation (1) are presented in columns 1 and 2 of Table 3 for injury and fatality outcomes, respectively. No injury is the omitted base category, so the estimates can be interpreted as measuring the impact of a variable on the likelihood of being observed in a fatal or injury outcome relative to the no injury outcome. In the multinomial probit specification, helmet use is associated with a negative impact on the probability of a fatal outcome and a positive impact on the probability of an injury outcome in comparison to the omitted no injury group. These estimated impacts of helmet use are, however, statistically insignificant at the 10% level.

One cause for concern with the multinomial estimates given in equation (1) is that motorcyclists are choosing whether or not to wear helmets and helmet use is likely correlated with the motorcyclists' unobserved driving intensity. The bias from such selection could be positive in the event of adverse selection in which individuals taking greater risks choose to wear helmets in order to reduce their potential losses. Alternatively, in the presence of advantageous selection individuals who are more risk averse are more likely to use helmets, and the multinomial probit estimates of changes in injury severity probability given in the last row of columns 1 and 2 of Table 3 are biased downward.

In order to correct for selection bias, state motorcycle helmet legislation is used as an instrument for individual helmet use by employing a control function (CF) multinomial probit estimator and an alternative bivariate (BV) multinomial probit estimator (see, for example, Petrin and Train (2010) for a general overview of the CF method in multinomial nonlinear models, and Roodman (2011) for a general overview of the techniques used for estimating limited information maximum likelihood models with joint normally distributed mixed processes). These models allow one to identify the overall effect of motorcycle helmets when states adopt universal helmet requirements. The overall effect of interest is illustrated by the path analysis from mandatory helmet laws to injury severity depicted in Figure 2, and it encompasses the technological efficacy of motorcycle helmets along with any behavioral adaptations induced by the mandatory helmet requirements. As such it should be directly comparable to the state-level estimates of helmet law efficacy summarized in Table I, and should also provide evidence on the direction of any behavioral adaptations when compared to studies of technological efficacy.

The basic premise of the CF and BV estimators is the same. There is a latent unobserved continuous probability of helmet use, $h^*_{n,t}$, that can be written as a function of all of the exogeneous instruments, $z_{n,t}$, that includes individual, $x_{n,t}$, and crash, $c_{n,t}$, characteristics along with other exogeneous predictors of helmet usage that are not directly correlated with injury outcome severity and driving intensity. Formally, the helmet use equation is specified as follows:

$$h^*_{n,t} = z_{n,t}'\varphi + \mu_{n,t}, \tag{5}$$

where $\mu_{n,t}$ is an unobserved error term that is presumed to be uncorrelated with $z_{n,t}$, but directly correlated with helmet use and therefore correlated with $\varepsilon_{n,j,t}$. Equation (5) can be estimated directly by OLS, or can be estimated in a latent variable framework using probit and logit. Using the error components from equation (5), crash outcome severity can now be specified as follows:

$$O_{n,j,t} = V_{n,j,t} + \varepsilon_{n,j,t} = a_j + x_{n,t}\beta_j + c_{n,t}\gamma_j + \delta_j h_{n,t} + T_t + CF(\mu_{n,t}) + \hat{\varepsilon}_{n,j,t},\ j \in [NI, I, F], \tag{6}$$

where $CF(\mu_{n,t})$ is a control function designed to purge the estimated coefficient on helmet use, δ_j , of any selection bias arising from the simultaneous determination of helmet use and unobserved driving intensity. Following the notation of equations (1) and (6), the error term from the outcome equation can be decomposed as follows:

$$\varepsilon_{n,j,t} = CF(\mu_{n,t}) + \hat{\varepsilon}_{n,j,t}\,, \tag{7}$$

where the error component $\hat{\varepsilon}_{n,j,t}$ is normally distributed mean zero and uncorrelated with the explanatory variables in the outcome equation. The choice of functional form for the control function can be linear (i.e. $CF(\mu_n) = \rho\mu_n$) or can be made more flexible with n-degree polynomial terms (Petrin and Train, 2010).

The endogeneity problem arising from unobserved driving intensity can be represented more explicitly by taking the expectation of crash outcomes from equation (1) with respect to helmet use:

$$E[O_{n,j,t} \mid h_{n,t} = 1) = a_j + x_{n,t}\beta_j + c_{n,t}\gamma_j + \delta_j + T_t + E[\varepsilon_{n,j,t} \mid h_{n,t} = 1], \tag{8}$$

$$E[O_{n,j,t} \mid h_{n,t} = 0) = a_j + x_{n,t}\beta_j + c_{n,t}\gamma_j + T_t + E[\varepsilon_{n,j,t} \mid h_{n,t} = 0], \tag{9}$$

The problem with estimation of equation (1) is that the last terms in equations (8) and (9) are not equal to zero due to unobserved driving intensity. In order to employ the control function approach to estimate unbiased coefficients for helmet use, it is necessary that the probability distributions, D, are such that $D(\varepsilon_{n,j,t}|h_{n,t})=D(\mu_{n,t})$. In the case of using a linear probability or logit model for first-stage estimation of helmet use, $D(\mu_{n,t})$ is non-normal, and therefore requires some unusual assumptions about the joint distribution for $\mu_{n,t}$ and $\hat{\varepsilon}_{n,j,t}$. However, if equation (5) is estimated using probit, $\mu_{n,t}$ is assumed to be normally distributed. Assuming a normal distribution for $\hat{\varepsilon}_{n,j,t}$ as well allows the following reformulation of the conditional expectation of the error terms in equations (8) and (9), respectively:

$$E[\varepsilon_{n,j,t} \mid h_{nt} = 1] = E[\varepsilon_{n,j,t} \mid \mu_{n,t} \geq -\varphi * z_{n,t})\,, \tag{10}$$

$$E[\varepsilon_{n,j,t} \mid h_{nt} = 0] = E[\varepsilon_{n,j,t} \mid \mu_{n,t} \leq -\varphi * z_{n,t})\,. \tag{11}$$

In the simplest case $\varepsilon_{n,j,t}$ is a linear function of the form:

$$\varepsilon_{n,j,t} = \rho \hat{\mu}_{n,t} + \hat{\varepsilon}_{n,j,t}, \tag{12}$$

where $\hat{\mu}_{n,t}$ is simply the predicted error term from equation (5) calculated as the inverse mills ratio that expresses $E(\mu_{n,t}|\mu_{n,t} \geq -\varphi^* z_{n,t})$ for helmeted riders and $E(\mu_{n,t}|\mu_{n,t} \leq -\varphi^* z_{n,t})$ for non-helmeted riders. Given that $\mu_{n,t}$ follows a normal distribution, the inverse mills ratio is expressed as follows:

$$\hat{\mu}_{n,t} = h_{n,t}\left(\frac{\phi(z_{n,t}'\varphi)}{\Phi(z_{n,t}'\varphi)}\right) - (1-h_{n,t})\left(\frac{\phi(z_{n,t}'\varphi)}{1-\Phi(z_{n,t}'\varphi)}\right). \tag{13}$$

In equation (12), ρ is the estimated covariance between the error terms $\mu_{n,t}$ and $\varepsilon_{j,n,t}$, and in equation (13) $\phi(\varphi^* z_{n,t})$ and $\Phi(\varphi^* z_{n,t})$ are the pdf and cdf for the normal distribution evaluated at the linear predictions of helmet use from equation (5), respectively. The inverse mills ratio given in equation (13) falls in the class of generalized residuals for nonlinear models developed in Gourieroux et al. (1987).

As such, the only differences between the CF and BV multinomial probit estimators are the methods employed to estimate the unknown parameter ρ in equation (12). In the CF approach, the generalized residuals estimated in equation (13) are included as an additional regressor in the second stage outcome equation as follows:

$$O_{n,j,t} = V_{n,j,t} + \varepsilon_{n,j,t} = a_j + x_{n,t}\beta_j + c_{n,t}\gamma_j + \delta_j h_{n,t} + T_t + \rho_j * \hat{\mu}_{n,t} + \hat{\varepsilon}_{n,j,t},\ j \in [NI, I, F]. \tag{14}$$

where all the variables are defined as in equations (1) and (13), and the values of a_j, β_j, γ_j, δ_j, and ρ_j are estimated to maximize the multinomial probit log-likelihood function. The BV multinomial probit estimator chooses the values of a_j, β_j, γ_j, δ_j, ρ_j, and φ to simultaneously solve equations (1) and (5) by maximizing the joint log-likelihood function given by the following:

$$LL(a_j, \beta_j, \gamma_j, \delta_j, \rho_j, \varphi) = \sum_n \sum_j w_j \begin{bmatrix} d_{n,j,t} h_{n,t} \ln\left(\Pr\{\varepsilon_{n,k,t} - \varepsilon_{n,j,t} < V_{n,j,t} - V_{n,k,t}, -\mu_{nt} < -\varphi^* z_{n,t}\}\right) \\ + d_{n,j,t}(1-h_{n,t}) \ln\left(\Pr\{\varepsilon_{n,k,t} - \varepsilon_{n,j,t} < V_{n,j,t} - V_{n,k,t}, -\mu_{nt} > -\varphi^* z_{n,t}\}\right) \end{bmatrix}, \tag{15}$$

where $\begin{pmatrix} \varepsilon_{n,j,t} \\ \mu_{n,t} \end{pmatrix} \sim N\begin{pmatrix} 0, & 1 & \rho_j \\ & \rho_j & 1 \end{pmatrix}$. As such, the covariance between the error terms, ρ_j, are free parameters in the BV approach, and their estimation does not require assumptions regarding the functional form for the correlation of error components.

Appendix Table A1 gives the results for the CF first stage estimation of individual helmet use using a linear probability model and probit model as specified in equation (5). The results are very similar in terms of predicted sign and strength of the regressors. Motorcycle drivers are more likely to wear helmets than passengers, and riders who have been drinking are less likely to wear helmets than sober motorcyclists. In both models, universal helmet laws are positively correlated with the probability of helmet use. The last row in Table A1 provides estimates of the average posterior probabilities of helmet use between states with universal helmet laws and states without such laws. Average probability of helmet use is between 87.6% and 88.0% for motorcyclists riding in states with universal helmet laws, and the average posterior probabilities are roughly 41 percentage points lower in states without universal helmet laws.

The t-statistics on the estimated coefficients for the universal helmet law variable in the first-stage models presented in Table A1 are extremely high suggesting that universal helmet laws meet the necessary requirements for a strong instrument. Table A1 also reports F-statistics and χ^2-statistics that are calculated by comparing the unrestricted models reported in Table A1 with restricted versions that omit the universal helmet law indicator. Staiger and Stock (1997) and Bound et al. (1995) suggest a rule of thumb F-statistic threshold of ten or more for determining a strong instrument in OLS models. The F-statistic reported with the linear probability model of helmet use is 1,027.45, which provides further evidence that motorcycle helmet legislation is a strong instrument for helmet use.

The results from the second stage CF and BV multinomial probit models developed above are presented in columns 3 through 6 of Table 3. Overall the estimation results using the CF and BV approach to correct for selection bias are quite similar in terms of sign, significance, and magnitude. Focusing on the results from the preferred single-step Bivariate Multinomial Probit model in the last two columns of Table 3, the average partial effects suggest helmet use is associated with a 5.8 percentage point reduction in risk of injury and 2.4 percentage point reduction in fatality risk, and the results are significant at the 5% level and 1% level, respectively. The average partial effects are calculated as the difference in predicted posterior probabilities when everyone in the sample is treated as if they were wearing a motorcycle helmet versus their predicted posterior probability without a protective helmet.

Table 4 presents estimates of the conditional effects of helmet use on motorcyclists' crash outcomes in percentage change terms based on the same BV multinomial probit specification. The first set of results presented in panel A of Table 4 provide a measure of the technological efficacy of motorcycle helmets in reducing fatality risks. The 5.8 percentage point reduction in risk of injury is associated with a 6.9% reduction in the average probability of injury, and the 2.4 percentage point reduction in fatality risk is associated with a 53.9% reduction in the average probability of death conditional on being involved in a motorcycle crash. In the absence of regulatory induced changes in driving intensity following passage of universal helmet laws, the aforementioned estimates provide an unbiased measure of the technological efficacy of motorcycle helmet use for those riders who are incentivized to wear helmets in order to comply with mandatory helmet laws. It is worth noting that the estimated 53.9% reduction in fatal outcome probability is within the range of technological efficacy estimates in the literature and slightly larger than the 42% average fatality risk reductions calculated in the technological efficacy meta-analysis by Liu, et al. (2008).

Panel B of Table 4 compares the mean of the posterior probabilities of outcomes in states with helmet laws and states without helmet laws in order to estimate the average effectiveness of mandatory helmet laws in reducing fatalities and injuries of motorcyclists involved in crashes. Effectiveness of helmet laws is measured as the percentage change in average posterior means between universal helmet law states and states without universal helmet laws using the following formula:

$$\%\Delta\overline{P}_j = \frac{\frac{1}{N_{HL}}\sum_{i=1}^{N_{HL}} P_{i,j} - \frac{1}{N_{NL}}\sum_{k=1}^{N_{NL}} P_{k,j}}{\frac{1}{N_{NL}}\sum_{k=1}^{N_{NL}} P_{k,j}}, \tag{16}$$

where the percentage change in average probability of outcome j following the adoption of a universal helmet law, $\%\Delta\overline{P}_j$, is calculated as the percentage difference in average posterior probabilities between helmet law states and states without helmet laws. As such, N_{HL} is the total number of sampled individuals involved in motorcycle crashes in helmet law states, and N_{NL} is the total number of sampled individuals involved in motorcycle crashes in states without helmet laws. Estimates of equation (16) reveal that states adopting universal motorcycle helmet laws have a 21.3% lower average probability of death, and a 4.1% lower average probability of injury for motorcyclist involved in crashes in comparison to states without universal helmet requirements. Lee (2015) provides the only state-level estimates of helmet law efficacy for which these results are directly comparable. When measuring risk exposure in terms of the number of motorcycle crashes, Lee (2015) estimates that universal helmet laws are associated with a 16% to 26% reduction in motorcycle fatalities, and the estimate of 21.3% provided herein falls within this range.

It is worth noting that in the presence of local average treatment effects (LATEs) the estimated treatment effect of helmet law adoption using the approach outlined above is only applicable to those individuals that choose to wear helmets in order to comply with mandatory state helmet laws. From a policy standpoint, however, the LATE for complying individuals is precisely the parameter of interest, because it allows policy makers to estimate the expected reduction in fatal motorcycle crashes associated with universal helmet law adoption.

Finally, panel C in Table 4, calculates the average of the individual posterior means for motorcyclists in states without universal helmet laws under two scenarios. In the first scenario, non-helmeted motorcyclists are given helmets in order to calculate the average of their counterfactual conditional probabilities, and helmeted riders remain unchanged. In the second scenario, helmeted motorcyclists remain helmeted and non-helmeted motorcyclists remain without helmets in order to calculate the average of their indicative conditional probabilities. The results are intended to mimic universal helmet law adoption assuming 100% compliance with the law. As expected, the third set of results in Table 4 lie between the first and second set of results from Panels A and B that measured technological effectiveness and universal helmet law effectiveness, respectively. The estimates with 100% compliance are closest in magnitude to the universal helmet law results from Panel B, which is not surprising given the fact that the first stage estimates from Table A1 in the appendix suggest that universal helmet laws result in roughly 88.0% compliance rates with helmet mandates. The subsection that follows tests for the presence of any regulatory induced driving behavior changes among motorcyclists in order to gauge how such changes bias the technological efficacy estimates presented in Panel A of Table 4.

3A. Estimating the Direction of Induced Changes in Motorcycle Driving Intensity

In order to more directly test for the presence of regulatory induced changes in driving behavior associated with motorcycle helmet laws this sub-section analyzes whether helmeted motorcyclists are more/less likely to receive citations for the following risky driving behaviors: alcohol or drugs, speeding, reckless driving, failure to yield a right of way, and running a traffic signal or stop sign. Specifically, the following equation is estimated using OLS:

$$Citation_{n,t} = a + x_{n,t} * \beta + c_{n,t} * \gamma + \theta * h_{n,t} + T_t + \varepsilon_{n,t}, \tag{17}$$

where all variables are defined as in equation (1), and $Citation_{n,t}$ is an indicator variable equal to one if the individual received a ticket for risky driving behavior and equal to zero otherwise. As such, the estimated coefficient on helmet use, Θ, is the key coefficient of interest, because it provides an estimate of the degree to which the probability of receiving a ticket citation is reduced due to enhancing behavior, or increased in the presence of offsetting behavior.

The first column in Table 5 presents the OLS estimates of equation (17). Helmeted motorcyclists have a 2.5 percentage point lower probability of receiving a risky driving citation in comparison to motorcyclists that choose not to wear helmets, and the difference is significant at the 1% level. Probit estimates accounting for the latent nature of citation probability yield similar estimates to OLS. Column 2 of Table 5 presents the results of the probit analogue to equation (17) where helmet use is estimated to reduce the probability of ticket citation by 2.6 percentage points. The OLS and Probit estimates in columns 1 and 2 of Table 5 are subject to the same selection bias as the multinomial probit esitmates of injury severity given in equation (1).

In order to correct for potential selection bias an instrumental variable estimator (IV) is used to estimate the following system of equations:

$$h_{n,t} = \partial + x_{n,t}\varphi + c_{n,t}\eta + \phi * hl_{n,t} + T_t + \mu_{n,t}\,, \tag{18}$$

$$Citation_{n,t} = a + x_{n,t} * \beta + c_{n,t} * \gamma + \theta * \hat{h}_{n,t} + T_t + \varepsilon_{n,t}\,, \tag{19}$$

where mandatory motorcycle helmet laws, $hl_{n,t}$, serve as an instrument for helmet use in equation (18), and the predicted helmet use from equation (18) is used as an explanatory variable, $\hat{h}_{n,t}$, in equation (19).

Estimates of the IV structural equation (19) are given in column 3 of Table 5. The estimated coefficient on helmet use, Θ, now measures the change in citation probability for individuals in mandatory helmet law states divided by the change in probability of helmet use for individuals in mandatory helmet law states. As such, Θ, measures the local average treatment effect of helmet use on risk of traffic citations for individuals who are incentivized to wear helmets in order to comply with mandatory helmet laws. This is precisely the coefficient of interest when attempting to test for behavioral adaptations to mandatory helmet laws because it is void of any advantageous or adverse selection effects. The IV results from column 3 of Table 5 suggest helmet use is associated with a 4.8 percentage point reduction in probability of traffic citation, and the results are significant at the 5% level. The F-statistic testing the significance of the first stage coefficient on helmet laws is equal to 1,029.97 suggesting once again that helmet laws are a strong instrument for helmet use.

The last two columns of Table 5 present the two alternative CF and BV probit estimators for citation probability that are analgous to the CF and BV multinomial probit estimators for injury severity presented in equations (5) – (15). These estimators are capable of correcting for selection bias similar to the IV estimator given in equations (18) and (19), and account for the discrete nature of the citation indicator variable.

In general, the CF Probit and BV Probit estimates are similar to the results from the IV model. Helmet use is associated with a 4.2 to 4.3 percentage point reduction in the posterior predicted probability of receiving a traffic citation using the BV Probit and CF Probit estimators, respectively. Stated alternatively, individuals who are incentivized to wear motorcycle helmets in order to comply with state helmet laws have a 4.2 to 4.3 percentage point lower risk of receiving a traffic citation for risky driving behavior.

Appendix Tables A2 and A3 present similar analyses of the impact of helmet laws on alternative measures of motorcyclists' driving intensity, and the results are all consistent with the theory of enhancing behavior. In Table A2, helmeted motorcyclists' estimated traveling speed is roughly 6 mph lower on average in comparison to their non-helmeted counterparts, and the effect is statistically significant at the 1% level. Similarly in Table A3 individuals wearing helmets in order to comply with universal helmet laws have a reduced probability of being involved in a moderate or severe vehicle damage crash relative to the minor damage reference category. On average, motorcyclists wearing helmets are estimated to have a 30 to 35 percentage point (statistically significant at the 1% level) reduced posterior probability of "severely" damaging their motorcycle in a crash.

Overall, the findings from the IV, CF, and BV estimators are consistent with the presence of enhancing behavior resulting from motorcycle helmet laws as opposed to offsetting behavior. Lee (2015) also finds evidence of enhancing behavior following helmet law adoption using state-level motorcycle crash data. Given that the results herein suggest the presence of enhancing behavior with regards to motorcycle helmet laws, the efficacy estimates presented in Panel A of Table 4 are likely to be an upper bound in absolute terms for technological effectiveness of motorcycle helmets. The results from Panel B of Table 4, however, remain an unbiased estimate of the overall effect of helmet laws on motorcycle fatalities and injuries holding the number of state motorcycle crashes constant.

3.B. Robustness Checks

The empirical results for the CF multinomial probit model presented above rely on probit models in the first and second stages when estimating the effectiveness of universal helmet laws for reducing motorcycle crash victim's risk of injury and death. A probit model was chosen in both stages in order to avoid unrealistic assumptions on the distribution of the error terms $\varepsilon_{n,j}$ in equation (1). Table A4 in the appendix reports results from several specifications that relax the first stage probit model choice when estimating the outcome equation specified in equation (14). For sake of clarity, the first model presented in Table A4 repeats the probit-probit results from the CF model from Table 3. The second model presents the results from a logit-probit specification where the first stage estimates of helmet use are estimated using logit. The generalized residuals from the first stage logit model are calculated as follows:

$$\hat{\mu}_{n,t} = h_{n,t}\left(1 - \frac{1}{1+e^{(-\hat{h}_{n,t})}}\right) - (1-h_{n,t})\left(\frac{1}{1+e^{(-\hat{h}_{n,t})}}\right) \qquad (20)$$

Finally, the third model in Table A4 presents the results from a linear probability-probit model where the generalized residuals in the second stage probit estimation are simply the residuals from the first stage OLS estimates of equation (5).

Overall the results from all CF models using probit in the second stage are very similar suggesting that the distributional assumptions of the error terms, $\varepsilon_{n,j}$, are of little consequence to the second stage estimates of the effects of helmet use on risk of injury and death when using the CF multinomial probit estimator in this application. The last three rows of Table A4 present the conditional effects of helmet use that can be compared to the results presented in Table 3. The estimated average risk reductions are all within 1.4 percentage points of the probit-probit model, and therefore provide further evidence that the distributional assumptions of the error term do not have a strong influence on the predicted safety effectiveness of motorcycle helmets.

Table A5 in the appendix completely relaxes the probit model choice and replicates the results from the CF estimator using a multinomial logit estimation strategy. The CF multinomial logit results are not directly comparable to the CF multinomial probit estimates presented in Table 3 in terms of magnitude, but the sign and significance of the estimated coefficients are similar across both models. The last row of Table A5 also presents the conditional effects of helmet use using a logit first and second stage specification, and these effects are directly comparable to the CF multinomial probit estimates presented in Table 3. The conditional effects results from Table A5 are all within 0.08 percentage points of the results from the CF multinomial probit models from columns 3 and 4 of Table 3. Overall, the results appear robust to choice of first and second stage estimation strategy.

4. Conclusion

Using individual level crash data, this study finds evidence that motorcycle helmets are technologically effective in preventing motorcyclist fatalities and injuries. Once the selection bias of helmet use is controlled for, results indicate that motorcycle helmets reduce the average probability of death and injury for crash victims by 53.9% and 6.9%, respectively. These findings are much higher than those reported by previous authors such as Goldstein (1986) who do not control for selection effects and as a result find no statistically significant impact of helmet usage on the probability of death. The estimates are likely an upper bound in absolute terms of the true technological efficacy of motorcycle helmets because analysis of traffic citations, motorcycle damage, and police estimated travel speed are all consistent with motorcyclists reducing their risky driving behavior when forced to wear helmets in order to comply with mandatory helmet laws.

In terms of universal helmet law efficacy, the results suggest that mandatory helmet laws reduce motorcyclists' fatality risks by 21.3%. The economic benefits of lives saved from mandatory helmet laws is calculated as the value of a statistical life (VSL) multiplied by the average number of state motorcycle fatalities and the 21.3% estimated fatality reduction associated with helmet laws. Using the U.S. Department of Transportation's current $9.0 million estimate of the VSL, and the average state-level 87.6 annual motorcycle fatalities over the 2002 to 2008 time period results in estimated economic benefits of motorcyclists lives saved of $167.9 million following adoption of a universal helmet law. Dickert-Conlin et al. (2011) estimate that each motorcycle fatality saves the life of up to 0.33 organ transplant recipients. In order to account for fewer organ donations following universal helmet law adoption the estimated economic benefits are multiplied by 0.67, and the estimated donor-adjusted benefits are $112.5 million.

The results presented herein suggest that universal helmet laws are an effective means for reducing state motorcycle fatalities. In addition to fatalities, motorcycle helmet laws are estimated to reduce motorcyclists' risk of injury by 4.3%. Helmet law effectiveness is due to a combination of the technological effectiveness of motorcycle helmets and regulatory induced enhancing behavior in the form of less risk taking among motorcyclists who are forced to wear helmets in order to comply with mandatory helmet laws. Unfortunately the estimation strategy presented herein cannot disentangle the behavioral and technological effects of helmet laws. Matched pair cohort studies are likely a better means of isolating the technological efficacy, but the approach highlighted herein is more useful for policy analysis where both technological and behavioral effects are of interest.

Finally, it is worth noting that the results do not provide estimates of the economic costs of helmet laws measuring the explicit costs of helmets as well as the implicit costs associated with motorcyclists' disutility of helmet use. If motorcyclists are making well informed decisions regarding the risks associated with not using helmets, then the economic costs of helmet laws are likely to outweigh benefits. Teresi (1999), however, notes that motorcycle rights groups often claim that helmets are ineffective in preventing fatalities and increase the risk of serious neck injury. In the presence of such misinformation regarding helmet efficacy, helmet laws may actually generate positive net economic benefits by encouraging helmet use among riders who would choose to wear helmets of their own volition if they were well informed regarding fatality and injury risks.

Table 1. Research Examining State Motorcycle Helmet Law Effectiveness.

Study	**Estimation Method**	**Years Studied**	**Fatality Reduction**
Panel A: Dependent Variable is ln(Fatalities), Exposure variable is ln(Registered Motorcycles)			
Watson et al. (1980)	Poisson with square root link	1975-1978	38.7%
Hartunian et al. (1983)	Poisson with log link	1976-1980	24.2%
Houston (2007)[a]	Negative Binomial Fixed Effects	1975-2004	31.4%
Dee (2009)	Two-way fixed effects	1988-2005	25.8%-32.5%
Graham and Lee (1986)	Two-way fixed effects	1975-1984	19.7%
Lee (2015)	Two-way fixed effects	1975-2007	24.8%-33.9%
Panel B: Dependent Variable is ln(Fatalities/Registered Motorcycles)			
Branas and Knudson (2001)	Random effects	1994-1996	3.6%[b]
Morris (2006)	Poisson with log link	1993-2002	12.1%
Houston and Richardson Jr (2007)[c]	Two-way fixed effects	1975-2004	11.1%-22.3%
Houston and Richardson (2008)	Two-way fixed effects	1975-2004	14.6% – 21.7%
Graham and Lee (1986)	Two-way fixed effects	1975-1984	11.3% – 13.1%
Panel C: Dependent Variable is ln(Fatalities/Capita)			
Sass and Leigh (1991)	Selection Model	1976-1980	0.4% - 14.3%
Sass and Zimmerman (2000)	Two-way fixed effects	1976-1997	28.9%-33.3%
Houston and Richardson (2008)	Two-way fixed effects	1975-2004	28.9%-33.1%
Dickert-Conlin, et al. (2011)[c]	Two-way fixed effects	1994-2007	38.8%
Panel D: Dependent Variable is ln(Fatalities), Exposure variable is ln(Crashes)			
Lee (2015)	Two-way fixed effects	1975-2007	16.0% - 26.0%

[a]Estimated fatality differential is for young motorcyclists age 15-20 yrs.
[b]Estimated fatality differential is statistically insignificant.
[c]Dependent variable is in levels rather than logs

Table 2. Data Appendix – Individual Motorcycle Crash Data[a]

Variable Name	**Sample Mean (Std. Dev.)**	**Variable Definition**
Injury Severity	1.984 (0.277)	Discrete variable characterizing crash outcome. 1=No Injury, 2=Injury, 3=Fatality
Universal Helmet Law[b]	0.448 (0.497)	Dummy Variable =1 if state has a Universal Helmet Law. Equal to 0 otherwise.
Helmet	0.649 (0.477)	Dummy variable=1 if motorcyclist is wearing a helmet, and equal to zero otherwise.
Sex	0.862 (0.345)	Dummy Variable=1 if person is male, and equal to 0 otherwise.
Age	36.81 (13.89)	Age of person.
Driver	0.908 (0.289)	Dummy Variable=1 if person is driver of motorcycle, and equal to 0 otherwise.
Fire	0.003 (0.054)	Dummy Variable=1 if vehicle caught on fire, and equal to 0 otherwise.
Alcohol Involved	0.078 (0.269)	Dummy Variable =1 if driver was drinking, and equal to 0 otherwise.
Major Moving Collision	0.394 (0.489)	Dummy Variable=1 if motorcyclist collided with a moving train or car, and equal to zero otherwise.
Minor Moving Collision	0.024 (0.153)	Dummy Variable=1 if motorcyclist collided with a dog, person or cyclist, and equal to zero otherwise.
Collision With Fixed Object	0.098 (0.297)	Dummy Variable=1 if motorcyclist collided with a fixed object, and equal to zero otherwise.
Rear End	0.119 (0.324)	Dummy Variable=1 if collision was rear end collision, and equal to zero otherwise.
Head On	0.025 (0.157)	Dummy Variable=1 if collision was a head on collision, and equal to zero otherwise.
Angle	0.226 (0.418)	Dummy variable=1 if collision was an angle collision, and equal to zero otherwise.
Side Swipe Same Direction	0.055 (0.227)	Dummy variable=1 if collision was a sideswipe involving two vehicles traveling in the same direction, and equal to zero otherwise.
Side Swipe Opposite Direction	0.008 (0.092)	Dummy variable=1 if collision was a sideswipe involving two vehicles traveling in opposite directions, and equal to zero otherwise.
Speed Limit	41.73 (12.19)	Posted speed limit at accident location.

[a]Data available from the National Automotive Sampling System General Estimates System (NASS GES) unless otherwise noted. The datasets are available as downloadable files from: ftp://ftp.nhtsa.dot.gov/NASS/ (last accessed February, 2013)
[b]Data available from the National Highway Traffic Safety Administration. Available online: http://www-fars.nhtsa.dot.gov/States/StatesLaws.aspx (last accessed February, 2013)

Table 3. Multinomial Probit Models Using the No Injury Group as the Comparison Group.[a]

Variable Name	Multinomial Probit Estimated Coefficient (Std. Error)		CF[b] Estimated Coefficient (Std. Error)		BV Estimated Coefficient (Std. Error)	
Group:	**Injury**	**Fatality**	**Injury**	**Fatality**	**Injury**	**Fatality**
Helmet	0.003	-0.181	-0.487**	-0.923***	-0.496**	-0.879***
	(0.090)	(0.112)	(0.218)	(0.261)	(0.201)	(0.229)
Sex	-0.332*	-0.262	-0.346*	-0.283	-0.337*	-0.268
	(0.200)	(0.223)	(0.202)	(0.230)	(0.198)	(0.219)
Age	-0.010	-0.015	-0.012	-0.017	-0.012	-0.017
	(0.016)	(0.019)	(0.016)	(0.020)	(0.015)	(0.019)
Age Squared	0.00004	0.0002	0.00006	0.0002	0.00006	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Driver	-0.058	0.001	0.026	0.128	0.031	0.124
	(0.229)	(0.261)	(0.236)	(0.272)	(0.226)	(0.257)
Fire	-0.137	0.796	-0.179	0.760	-0.187	0.747
	(0.866)	(0.867)	(1.127)	(1.568)	(0.817)	(0.817)
Alcohol Involved	0.197	0.649***	0.070	0.452*	0.060	0.446**
	(0.187)	(0.214)	(0.198)	(0.232)	(0.193)	(0.219)
Major Moving	-0.652***	-0.306	-0.652***	-0.301	-0.640***	-0.285
Collision	(0.181)	(0.233)	(0.185)	(0.241)	(0.178)	(0.229)
Minor Moving	-0.817***	-1.517***	-0.788***	-1.478**	-0.768***	-1.446***
Collision	(0.236)	(0.395)	(0.251)	(0.648)	(0.232)	(0.390)
Collision With	-0.033	0.646***	-0.021	0.660***	-0.021	0.651***
Fixed Object	(0.181)	(0.199)	(0.184)	(0.203)	(0.178)	(0.195)
Rear End	-0.464**	-0.669***	-0.468**	-0.681***	-0.457**	-0.663***
	(0.198)	(0.254)	(0.201)	(0.253)	(0.194)	(0.249)
Head On	0.430	1.067***	0.402	1.012***	0.389	0.989***
	(0.338)	(0.364)	(0.350)	(0.382)	(0.336)	(0.361)
Angle	0.234	0.435*	0.218	0.396	0.212	0.385
	(0.198)	(0.251)	(0.200)	(0.255)	(0.196)	(0.247)
Side Swipe Same	-0.535**	-1.504***	-0.532**	-1.502***	-0.519**	-1.471***
Direction	(0.222)	(0.365)	(0.223)	(0.416)	(0.218)	(0.356)
Side Swipe Opp.	-0.773**	0.168	-0.773**	0.163	-0.762**	0.173
Direction	(0.321)	(0.438)	(0.341)	(1.095)	(0.322)	(0.420)
Speed limit	0.003	0.0406***	0.005	0.043***	0.005	0.042***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)
Err. Correlation	----	----	0.360***	0.542***	0.270***	0.381***
Coeff.	----	----	(0.136)	(0.171)	(0.099)	(0.120)
Constant	2.478***	-2.019***	2.704***	-1.690***	2.660***	-1.715***
	(0.381)	(0.452)	(0.390)	(0.469)	(0.374)	(0.460)
Number of obs.	13,610	13,610	13,610	13,610	13,610	13,610
ΔPredicted Risk Prob. for Helmeted Motorcyclists:	0.007	-0.008	-0.053**	-0.026***	-0.058**	-0.024***

[b]Standard errors for the two-step control function estimator were calculated using bootstrapping with 2,000 reps.

Table 4. Motorcycle Helmet Effectiveness Using Bivariate Multinomial Probit Specification.

	Number of obs.	Predicted Mean Probability of Injury	Predicted Mean Probability of Death
Panel A: Technological Effectiveness:			
Universal Helmet Use	13,610	0.788	0.020
No Helmet Use	13,610	0.846	0.044
Percentage change in mean predicted probabilities with helmet use		-6.88%	-53.91%
Panel B: Helmet Law Effectiveness:			
States with a Universal Helmet Law	6,099	0.790	0.024
States without Universal Helmet Laws	7,511	0.824	0.031
Percentage Change in Mean probabilities from Adopting a Universal Helmet Law		-4.12%	-21.30%
Panel C: 100% Compliance Helmet Law Effectiveness:			
Universal Helmet Use in Non-helmet Law States	7,511	0.793	0.019
States without Universal Helmet Laws	7,511	0.824	0.031
Percentage Change in Mean Probabilities from Adopting a Universal Helmet Law with 100% compliance		-3.84%	-38.34%

Table 5. Estimates Predicting Individual Motorcyclists' Ticket Citations.[a]

	Model Choice:				
	OLS	Probit	IV	CF Probit[b]	Bivariate Probit
Variable Name	**Estimated Coefficient (Std. Error)**	**Estimated Coefficient (Std. Error)**	**Estimated Coefficient (Std. Error)**	**Estimated Coefficient (Std. Error)**	**Estimated Coefficient (Std. Error)**
Helmet	-0.025***	-0.140***	-0.048**	-0.225*	-0.220*
	(0.010)	(0.051)	(0.022)	(0.128)	(0.122)
Sex	0.050***	0.312***	0.049***	0.308***	0.308***
	(0.013)	(0.091)	(0.013)	(0.091)	(0.090)
Age	0.0002	0.002	0.0001	0.001	0.001
	(0.002)	(0.010)	(0.002)	(0.010)	(0.010)
Age Squared	-0.00001	-0.00008	-0.00001	-0.00007	-0.00007
	(0.00002)	(0.0001)	(0.00002)	(0.0001)	(0.0001)
Driver	-0.019	-0.130	-0.015	-0.116	-0.117
	(0.017)	(0.105)	(0.017)	(0.108)	(0.106)
Fire	0.016	0.080	0.015	0.076	0.076
	(0.083)	(0.372)	(0.083)	(0.435)	(0.373)
Major Moving Collision	0.014	0.092	0.014	0.095	0.094
	(0.015)	(0.096)	(0.014)	(0.097)	(0.095)
Minor Moving Collision	-0.093***	-0.690***	-0.091***	-0.681***	-0.681***
	(0.015)	(0.176)	(0.015)	(0.190)	(0.176)
Collision With Fixed Object	0.029*	0.121*	0.030*	0.123*	0.123*
	(0.017)	(0.073)	(0.017)	(0.072)	(0.073)
Rear End	-0.046**	-0.264**	-0.046***	-0.265**	-0.265**
	(0.018)	(0.109)	(0.018)	(0.112)	(0.108)
Head On	-0.096***	-0.605***	-0.098***	-0.611***	-0.610***
	(0.027)	(0.218)	(0.027)	(0.224)	(0.220)
Angle	-0.071***	-0.415***	-0.072***	-0.418***	-0.417***
	(0.016)	(0.106)	(0.016)	(0.109)	(0.106)
Side Swipe Same Direction	-0.091***	-0.582***	-0.090***	-0.582***	-0.582***
	(0.019)	(0.156)	(0.020)	(0.156)	(0.156)
Side Swipe Opposite Direction	-0.064*	-0.377	-0.063*	-0.376	-0.376
	(0.034)	(0.236)	(0.034)	(0.254)	(0.236)
Speed limit	-0.0003	-0.002	-0.0002	-0.001	-0.001
	(0.0003)	(0.002)	(0.0004)	(0.002)	(0.002)
Generalized Residual	----		----	0.061	
				(0.089)	
Constant	0.152***	-1.028***	0.162***	-0.993***	-0.994***
	(0.039)	(0.226)	(0.041)	(0.238)	(0.237)
R-squared	0.020	----	0.019	----	----
Number of obs.	13,610	13,610	13,610	13,610	13,610
F-Statistic (p-value)	----	----	1,029.97	----	----
			(0.000)		
χ^2-Statistic (p-value)	----	----	----	724.18	724.59
				(0.000)	(0.000)
ΔPredicted Citation Probability for Helmeted Motorcyclists:	-.025***	-.026***	-0.048**	-0.043*	-0.042*

[a] Statistical Significance at the 1 percent, 5 percent, and 10 percent level are represented by ***,**,and *. Although not reported each model also includes a full set of year fixed effects as specified in equation (13).

[b]Standard errors for the two-step control function estimator were calculated using bootstrapping with 2,000 reps.

Figure 1. Path Analysis Diagram for Helmet Use and Injury Severity.

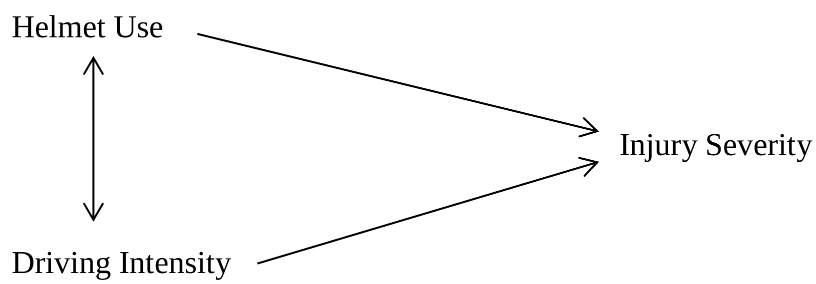
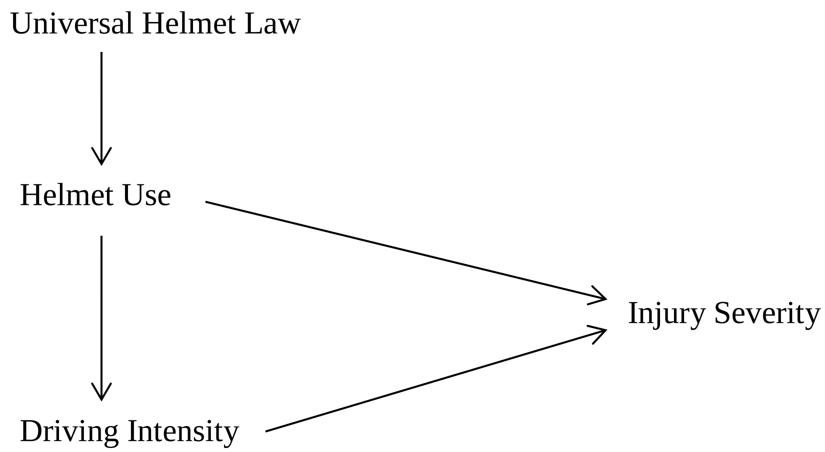


Figure 2. Path Analysis Diagram for Universal Helmet Laws and Injury Severity.



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Appendix

Table A1. First Stage Estimates of Motorcycle Helmet Use.[a]

	First Stage Model Choice:	
	Linear Probability	Probit
Variable Name	Estimated Coefficient (Std. Error)	Estimated Coefficient (Std. Error)
Universal Helmet Law	0.403***	1.275***
	(0.013)	(0.047)
Sex	-0.038	-0.103
	(0.027)	(0.087)
Age	-0.005**	-0.014*
	(0.002)	(0.008)
Age Squared	0.00007**	0.0002**
	(0.00003)	(0.0001)
Driver	0.146***	0.427***
	(0.032)	(0.098)
Fire	0.034	0.099
	(0.108)	(0.315)
Alcohol Involved	-0.256***	-0.796***
	(0.021)	(0.068)
Major Moving Collision	-0.017	-0.071
	(0.023)	(0.075)
Minor Moving Collision	0.002	-0.0008
	(0.045)	(0.165)
Collision With Fixed Object	-0.007	-0.023
	(0.021)	(0.068)
Rear End	-0.046*	-0.123
	(0.027)	(0.088)
Head On	-0.100**	-0.308**
	(0.046)	(0.141)
Angle	-0.045*	-0.128
	(0.026)	(0.082)
Side Swipe Same Direction	-0.043	-0.101
	(0.033)	(0.114)
Side Swipe Opposite Direction	0.048	0.174
	(0.063)	(0.202)
Speed limit	0.004***	0.013***
	(0.001)	(0.002)
Constant	0.368***	-0.468***
	(0.055)	(0.175)
R-squared	0.208	----
Pseudo R-squared	----	0.176
Number of obs.	13,610	13,610
F-Statistic (p-value)	1,027.45 (0.000)	----
χ^2-Statistic (p-value)	----	720.33 (0.000)
Predicted Helmet Use:		
Helmet Law States	88.0%	87.6%
States w/o Helmet Law	47.1%	47.1%

[a] Statistical Significance at the 1 percent, 5 percent, and 10 percent level are represented by ***,**,and *, respectively.

Table A2: Impact of Helmet Use on Motorcyclists' Estimated Travel Speed.[a]

	First Stage Model Choice:	
	OLS	IV
Variable Name	**Estimated Coefficient (Std. Error)**	**Estimated Coefficient (Std. Error)**
Helmet	0.260	-6.133***
	(0.697)	(1.955)
Sex	3.942***	3.891***
	(1.173)	(1.253)
Age	-0.231*	-0.287**
	(0.131)	(0.134)
Age Squared	0.0002	0.0007
	(0.002)	(0.002)
Driver	-2.462*	-1.301
	(1.417)	(1.532)
Fire	16.026***	15.177***
	(4.793)	(5.696)
Alcohol Involved	4.025***	2.220
	(1.262)	(1.374)
Major Moving Collision	-3.284**	-3.285***
	(1.282)	(1.260)
Minor Moving Collision	2.334**	2.331**
	(0.968)	(1.036)
Collision With Fixed Object	3.510***	3.412***
	(1.039)	(1.044)
Rear End	-14.607***	-14.944***
	(1.606)	(1.570)
Head On	-1.189	-1.285
	(2.154)	(2.234)
Angle	-2.619**	-3.332**
	(1.316)	(1.334)
Side Swipe Same Direction	-8.796***	-8.855***
	(1.726)	(1.787)
Side Swipe Opposite Direction	-1.409	-1.713
	(2.540)	(2.424)
Speed limit	0.691***	0.727***
	(0.030)	(0.033)
Constant	14.689***	17.752***
	(2.791)	(2.920)
R-squared	0.343	0.319
Number of obs.	6,924	6,924

[a] Statistical Significance at the 1 percent, 5 percent, and 10 percent level are represented by ***,**,and *, respectively.

Table A3: Multinomial Probit Models Using Minor Vehicle Damage as the Comparison Group.[a]

	Multinomial Probit		CF Multinomial Probit[b]		Bivariate Multinomial Probit	
Variable Name	**Estimated Coefficient (Std. Error)**		**Estimated Coefficient (Std. Error)**		**Estimated Coefficient (Std. Error)**	
Group:	**Moderate Damage**	**Severe Damage**	**Moderate Damage**	**Severe Damage**	**Moderate Damage**	**Severe Damage**
Helmet	-0.071	-0.044	-1.381***	-2.179***	-1.003***	-1.499***
	(0.077)	(0.072)	(0.187)	(0.177)	(0.133)	(0.090)
Sex	-0.023	0.175	-0.036	0.167	-0.046	0.142
	(0.140)	(0.131)	(0.144)	(0.131)	(0.138)	(0.131)
Age	-0.032**	-0.041***	-0.041***	-0.054***	-0.034***	-0.044***
	(0.013)	(0.012)	(0.013)	(0.012)	(0.013)	(0.012)
Age Squared	0.0003*	0.0004***	0.0004**	0.0005***	0.0003**	0.0004***
	(0.0002)	(0.0001)	(0.000)	(0.000)	(0.0002)	(0.0001)
Driver	0.151	0.032	0.388**	0.407**	0.328**	0.300**
	(0.165)	(0.154)	(0.169)	(0.163)	(0.162)	(0.149)
Fire	-1.473*	1.049	-1.646	0.835	-1.737***	0.706
	(0.807)	(0.790)	(4.713)	(5.051)	(0.630)	(0.514)
Alcohol Involved	-0.0008	0.205	-0.326**	-0.332**	-0.255**	-0.196*
	(0.132)	(0.126)	(0.138)	(0.132)	(0.126)	(0.116)
Major Moving Collision	0.024	-0.193	0.040	-0.161	0.051	-0.140
	(0.151)	(0.133)	(0.152)	(0.138)	(0.136)	(0.122)
Minor Moving Collision	0.104	-0.579***	0.185	-0.461**	0.215	-0.409**
	(0.211)	(0.195)	(0.199)	(0.188)	(0.205)	(0.173)
Collision With Fixed Object	0.107	0.235**	0.127	0.267**	0.101	0.222**
	(0.123)	(0.113)	(0.129)	(0.115)	(0.120)	(0.106)
Rear End	-0.006	0.065	-0.024	0.026	-0.018	0.027
	(0.180)	(0.152)	(0.178)	(0.153)	(0.161)	(0.137)
Head On	-0.094	0.823***	-0.183	0.670**	-0.236	0.589**
	(0.263)	(0.260)	(0.284)	(0.280)	(0.249)	(0.252)
Angle	0.102	0.610***	0.042	0.494***	-0.008	0.425***
	(0.160)	(0.147)	(0.161)	(0.152)	(0.147)	(0.136)
Side Swipe Same Direction	0.077	-0.497***	0.101	-0.469***	0.146	-0.400**
	(0.194)	(0.171)	(0.198)	(0.172)	(0.186)	(0.160)
Side Swipe Opp. Direction	-0.869***	-0.219	-0.893***	-0.237	-0.842***	-0.180
	(0.334)	(0.315)	(0.345)	(0.322)	(0.309)	(0.280)
Speed limit	0.007**	0.015***	0.013***	0.026***	0.010***	0.020***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Generalized Probit Residual	----	----	0.963***	1.554***	----	----
	----	----	(0.118)	(0.112)	----	----
Constant	0.316	0.387	0.921***	1.313***	0.571*	0.912***
	(0.307)	(0.296)	(0.316)	(0.309)	(0.295)	(0.286)
Number of obs.	11,159		11,159		11,159	
χ^2-Statistic	----		572.98		597.62	
(p-value)	----		(0.000)		(0.000)	
ΔPredicted Damage Probability for Helmeted Motorcyclists:	-0.011	-0.003	-0.002***	-0.345***	-0.024***	-0.296***

[a] Statistical Significance at the 1 percent, 5 percent, and 10 percent level are represented by ***,**,and *, respectively.

[b]Standard errors for the two-step control function estimator were calculated using bootstrapping with 2,000 reps.

Table A4. Multinomial Probit Models Using the No Injury Group as the Comparison Group.[a]

Variable Name	Model 1 (Probit/Probit) Estimated Coefficient (Std. Error)		Model 2 (Probit/Logit) Estimated Coefficient (Std. Error)		Model 3 (Probit/LPM) Estimated Coefficient (Std. Error)	
Group:	**Injury**	**Fatality**	**Injury**	**Fatality**	**Injury**	**Fatality**
Helmet	-0.487**	-0.923***	-0.566***	-0.982***	-0.592***	-1.043***
	(0.214)	(0.253)	(0.218)	(0.259)	(0.221)	(0.260)
Sex	-0.346*	-0.283	-0.347*	-0.283	-0.347*	-0.283
	(0.199)	(0.221)	(0.199)	(0.222)	(0.200)	(0.222)
Age	-0.012	-0.017	-0.012	-0.0176	-0.0123	-0.018
	(0.015)	(0.019)	(0.015)	(0.019)	(0.015)	(0.019)
Age Squared	0.00006	0.0002	0.00007	0.0002	0.00007	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Driver	0.026	0.128	0.040	0.139	0.047	0.148
	(0.229)	(0.264)	(0.230)	(0.265)	(0.231)	(0.265)
Fire	-0.179	0.760	-0.189	0.753	-0.192	0.757
	(0.874)	(0.881)	(0.876)	(0.883)	(0.880)	(0.890)
Alcohol Involved	0.070	0.452**	0.0492	0.436**	0.039	0.419*
	(0.194)	(0.221)	(0.194)	(0.221)	(0.195)	(0.223)
Major Moving Collision	-0.652***	-0.301	-0.652***	-0.302	-0.652***	-0.301
	(0.180)	(0.233)	(0.180)	(0.233)	(0.180)	(0.233)
Minor Moving Collision	-0.788***	-1.478***	-0.783***	-1.471***	-0.781***	-1.462***
	(0.235)	(0.396)	(0.235)	(0.395)	(0.235)	(0.395)
Collision With Fixed Object	-0.021	0.660***	-0.019	0.661***	-0.017	0.664***
	(0.181)	(0.200)	(0.181)	(0.200)	(0.181)	(0.200)
Rear End	-0.468**	-0.681***	-0.467**	-0.681***	-0.469**	-0.682***
	(0.197)	(0.254)	(0.197)	(0.254)	(0.197)	(0.254)
Head On	0.402	1.012***	0.400	1.011***	0.397	1.005***
	(0.338)	(0.364)	(0.338)	(0.364)	(0.338)	(0.364)
Angle	0.218	0.396	0.216	0.395	0.214	0.392
	(0.198)	(0.252)	(0.197)	(0.252)	(0.198)	(0.252)
Side Swipe Same Direction	-0.532**	-1.502***	-0.532**	-1.501***	-0.533**	-1.496***
	(0.222)	(0.362)	(0.222)	(0.362)	(0.222)	(0.362)
Side Swipe Opp. Direction	-0.773**	0.163	-0.772**	0.164	-0.775**	0.155
	(0.324)	(0.443)	(0.324)	(0.444)	(0.326)	(0.445)
Speed limit	0.005	0.043***	0.006	0.044***	0.006	0.044***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)
Gen. Probit Residual	0.360***	0.542***	----	----	----	----
	(0.136)	(0.167)				
Gen. Logit Residual	----	----	0.704***	0.982***	----	----
			(0.237)	(0.292)		
Gen. LPM Residual	----	----	----	----	0.731***	1.051***
					(0.241)	(0.292)
Constant	2.704***	-1.690***	2.742***	-1.659***	2.752***	-1.634***
	(0.381)	(0.459)	(0.380)	(0.460)	(0.380)	(0.459)
Number of obs.	13,610	13,610	13,610	13,610	13,610	13,610
ΔPredicted Risk Prob. for Helmeted Motorcyclists:	-0.053**	-0.026***	-0.065***	-0.026***	-0.067***	-0.028***

[a]Statistical Significance at the 1 percent, 5 percent, and 10 percent level are represented by ***,**,and *, respectively.

Table A5. Multinomial Logit Models Using the No Injury Group as the Comparison Group.[a]

Variable Name	Multinomial Logit Estimated Coefficient (Std. Error)		CF Multinomial Logit[b] Estimated Coefficient (Std. Error)	
Group:	**Injury**	**Fatality**	**Injury**	**Fatality**
Helmet	-0.008	-0.318*	-0.740***	-1.619***
	(0.117)	(0.187)	(0.285)	(0.444)
Sex	-0.463*	-0.519	-0.470*	-0.536
	(0.278)	(0.375)	(0.284)	(0.388)
Age	-0.015	-0.032	-0.017	-0.036
	(0.020)	(0.032)	(0.021)	(0.034)
Age Squared	0.00008	0.0004	0.0001	0.0004
	(0.0002)	(0.0004)	(0.0002)	(0.0004)
Driver	-0.063	0.149	0.056	0.365
	(0.321)	(0.444)	(0.330)	(0.460)
Fire	-0.103	1.274	-0.154	1.212
	(1.203)	(1.344)	(9.086)	(9.300)
Alcohol Involved	0.338	1.112***	0.150	0.764**
	(0.263)	(0.344)	(0.279)	(0.375)
Major Moving	-0.841***	-0.444	-0.833***	-0.430
Collision	(0.237)	(0.395)	(0.240)	(0.410)
Minor Moving	-1.070***	-2.763***	-1.030***	-2.707
Collision	(0.287)	(0.828)	(0.304)	(5.536)
Collision With Fixed	-0.002	1.098***	0.027	1.136***
Object	(0.259)	(0.327)	(0.264)	(0.333)
Rear End	-0.572**	-0.966**	-0.585**	-0.990**
	(0.256)	(0.438)	(0.257)	(0.441)
Head On	0.652	1.921***	0.607	1.826***
	(0.467)	(0.597)	(0.502)	(0.647)
Angle	0.302	0.779*	0.282	0.723*
	(0.262)	(0.424)	(0.266)	(0.431)
Side Swipe Same	-0.668**	-2.681***	-0.666**	-2.654**
Direction	(0.281)	(0.782)	(0.284)	(1.147)
Side Swipe Opp.	-0.935**	0.561	-0.932**	0.564
Direction	(0.392)	(0.697)	(0.419)	(2.810)
Speed limit	0.006	0.072***	0.009*	0.077***
	(0.005)	(0.008)	(0.005)	(0.008)
Err. Correlation	----	----	0.903***	1.586***
Coeff.			(0.302)	(0.489)
Constant	3.073***	-3.684***	3.392***	-3.124***
	(0.502)	(0.758)	(0.515)	(0.796)
Number of obs.	13,610	13,610	13,610	13,610
ΔPredicted Risk Prob. for Helmeted Motorcyclists:	0.006	-0.008*	-.061***	-.029***

[b]Standard errors for the two-step control function estimator were calculated using bootstrapping with 2,000 rep