OFFSETTING OR ENHANCING BEHAVIOR: AN EMPIRICAL ANALYSIS OF MOTORCYCLE HELMET SAFETY LEGISLATION

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ABSTRACT

This study uses state level panel data from a 33-year period along with repeated cross-sectional individual level crash data to test the hypotheses of offsetting and enhancing behavior with regards to motorcycle helmet legislation. Results presented in this paper find no evidence of offsetting behavior and are consistent with the presence of enhancing behavior. State motorcycle helmet laws are estimated to reduce motorcycle crashes by 18.2% to 33.1%. These results do not appear to be driven by omitted variable bias or non-classical measurement error in motorcycle crashes. Furthermore, individual motorcyclists who are incentivized to wear helmets in order to comply with mandatory helmet laws are estimated to have a 4.2 to 4.8 percentage point reduced probability of receiving a traffic citation for reckless driving behavior. Overall, the results strongly suggest that mandatory helmet laws result in significant reductions in risky driving behavior among motorcyclists.

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

1. INTRODUCTION

Traditional economic theory suggests that the overall efficacy of mandatory motorcycle helmet legislation will be reduced as a result of offsetting behavior.[2] Peltzman[(1)] provides an overview of the theory of offsetting behavior, and Blomquist[(2)] presents the theory within a utility maximizing framework. The basic premise is that individuals will increase risk taking activities in response to mandated safety legislation thereby offsetting some of the effectiveness of the legislation for improving safety. In the context of helmet legislation, offsetting behavior may take the form of increased traveling speeds and reckless driving.

Numerous empirical studies to date have examined offsetting behavior in regards to various automobile safety legislation and equipment, and the results have been mixed. Peltzman[(1)] and Calkins and Zlatoper[(3)] find evidence of offsetting behavior following mandatory seatbelt laws. Peterson et al.[(4)] find evidence of offsetting behavior among drivers of airbag equipped vehicles, and estimate the drivers of these vehicles to be at fault in 85% of the crashes they are involved in. However, Harless and Hoffer[(5)] replicate the methodology of Peterson et al.[(4)] with an alternative dataset and find no significant offsetting behavior among drivers with airbags.

Recently, Thaler and Sunstein[(6)] have noted that safety legislation may be improved by nudging: "When social influences have caused people to have false or biased beliefs, then some nudging may help." If safety legislation such as helmet laws change cultural attitudes toward safety among motorcycle groups nudging could result in the opposite of offsetting behavior; an adaptive response termed enhancing behavior for lack of a better expression. In the presence of enhancing behavior, motorcycle helmet law efficacy is improved because motorcyclists reduce risky driving behavior in response to the legislation.

[2] Offsetting behavior is also commonly referred to as risk compensation or the Peltzman effect in the literature.

The following analysis makes two key contributions to the literature on motorcycle helmet effectiveness. First, a structural model for state-level data is developed whereby it is possible to quantify the extent to which changes in motorcyclists' driving behavior alters the efficacy of motorcycle helmet legislation. State fixed effects regressions suggest enhancing behavior is present and helmet laws are estimated to <u>reduce</u> motorcycle crashes by 18.2% to 33.1%. The enhancing behavior associated with helmet law adoption is estimated to increase the efficacy of helmet laws in preventing motorcycle fatalities by 5.2 to 11.3 percentage points. The results do not appear to be driven by non-classical measurement error in motorcycle crashes or simultaneity bias.

Second, the analysis uses individual crash data to more directly test for the presence of enhancing behavior by examining the impact of helmet use on the likelihood of receiving a traffic citation for reckless driving. The findings using the individual level crash data are also consistent with enhancing behavior as opposed to offsetting behavior in the context of helmet legislation. Results suggest that motorcyclists who are incentivized to wear helmets in order to comply with mandatory helmet laws have a 4.2 to 4.8 percentage point lower probability of receiving a traffic citation for risky driving behavior.

The remainder of the analysis proceeds as follows. Section 2 presents the state-level and individual-level crash data that is used for this analysis. Section 3 provides the state-level structural model and results supporting the hypothesis of enhancing behavior. Section 4 tests for the presence of omitted variable bias and non-classical measurement error in motorcycle crashes as possible explanations of the non-traditional results supporting the enhancing behavior theory. Section 4 then directly tests for the presence of enhancing behavior using individual level crash data to estimate the effects of helmet use on traffic citations. Finally, section 5 concludes the paper.

2. DATA

The analysis that follows uses two alternative data sources to test for the presence of offsetting or enhancing behavior with regards to motorcycle helmet legislation. The first data set consists of aggregate state-level data, and is used for estimating changes in state motorcycle fatality rates and crash rates in response to adoption of motorcycle safety legislation. The state-level data consists of an unbalanced panel of the 50 U.S. states during the time period 1975-2007 for which data on state-level motorcycle crashes and fatalities are available. A total of 1,239 state observations (75% of the total observations for the period) are available for analysis. Data was gathered from a wide variety of sources, and details of the variables used are summarized in Table I.

There are an average of 2,582 annual state motorcycle crashes during the 1975-2007 time period, and approximately 79 (3%) of those crashes result in a motorcycle fatality. When isolating the effects of mandatory helmet laws it is important to control for all relevant safety legislation affecting motorcyclists that may be correlated with the passage of a helmet law. In addition to helmet laws, the empirical analysis that follows includes controls for the following motorcycle safety legislation: laws requiring motorcyclist to use headlights during the daytime, laws establishing state sponsored rider training programs, laws that require rider training programs prior to licensing, and laws requiring a motorcycle skills (driving) test prior to licensing. Skills test laws are the most prevalent form of safety legislation (92%) followed by rider education laws (59%) and universal helmet laws (45%). Helmet laws are expected to reduce the average severity of crashes, but the remaining laws with the exception of skills tests are expected to influence motorcycle fatalities through reductions in motorcycle crash rates.[3]

Temperature and precipitation are variables that help approximate the amount of motorcycle utilization that takes place in a state, because motorcyclist are presumed to ride more in warmer drier states. The scatterplot given in Figure 1 illustrates this trend as the number of motorcycle registrations per 1,000 residents generally increases as average annual temperature rises from a low of 29° F. Eventually, however, as temperatures continue to rise motorcycle registrations start to fall as higher temperatures are associated with higher rainfall in the humid subtropical climate of the southeastern U.S.

Traffic congestion will also likely have a significant impact on motorcycle crashes. There are many factors that can lead to congestion: road work, road condition, number of road lanes, time of day, speed limit, and number of motorist. The following analysis attempts to proxy the effects of road congestion by including variables on speed limit laws and annual vehicle miles traveled.[4]

State attitudes toward alcohol consumption are reflected in the measure of alcohol consumption per capita. Per capita alcohol consumption is likely to be overstated in Nevada and Vermont due to the disproportionate sale of alcohol in these states to nonresidents so the empirical specifications also include interaction terms for these states and alcohol consumption.(7, 8) Finally, total number of registered motorcycles per state and number of state motorcycle crashes are included as alternative measures of risk exposure.

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[3] States requiring skills tests also require U.S. Department of Transportation (DOT) approved helmets to take the test, and may encourage helmet utilization even when state laws do not require helmet use fulltime.

[4] Total state roadway miles was also considered as an additional measure of congestion. This measure was not available for all years (1975-1980 was unavailable) and was not included in the main results. Nonetheless the results are robust the inclusion of roadway miles over the subset of data from 1980-2007.

The second dataset contains individual level crash data, and is used for estimating the effects of motorcycle helmet use on motorcyclists' likelihood of receiving traffic citations. The individual crash data comes from the National Automotive Sampling System (NASS) General Estimates System (GES) for the years 2002-2008 and is a probability based sample of police accident reports (PARs) (see, for example, U.S. DOT[9] and Shelton[10] for details of the NASS GES data sampling design). Because the NASS GES data oversamples more severe crashes all of the estimators are weighted by the inverse probability weights to correct for sample selection bias (see Manski & Lerman[11] for an overview of the weighted exogenous sample maximum likelihood estimator).

Details of the variables used from the individual level NASS GES data set are summarized in Table II. The key outcome variable of interest is a binary indicator variable equal to 1 if an individual receives a traffic citation for risky driving and equal to zero otherwise. Approximately 11% of the observations in the dataset receive traffic citations.

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. Approximately 41% of all U.S. states have universal motorcycle helmet legislation in place over the same time period from 2002 to 2008, so the NASS GES sample appears to be fairly representative in terms crashes in helmet law states.

Several individual factors that may affect the likelihood of receiving a citation for reckless driving 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. The vast majority of individuals are male motorcycle drivers (91% are drivers, and 86% are male) with an average age of 37 years.

Variables measuring crash characteristics are also included in the analysis to control for varying citation likelihood among different crash classes. 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, collision with a fixed object such as a tree or boulder, and posted speed limit. 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. Collisions with moving vehicles (39%) and rear end collisions (12%) account for the majority of crash observations in the dataset, and the average posted speed limit is 42 miles per hour. The empirical section that follows uses the state-level data described in Table I to measure the magnitude of any behavioral adaptation as a result of mandatory helmet laws.

3. EMPIRICAL MODEL AND RESULTS

State-level motorcycle fatalities are expected to follow a basic count model design of the following form:

$$fatalities_i = a_i * exposure_i, \tag{1}$$

where the fatalities in state i are a function of the number of exposed motorcyclists, $exposure_i$ and the fraction those exposed who are killed, a_i. In the analysis that follows two separate exposure variables, motorcycle crashes and motorcycle registrations, are considered in order to partially isolate the impacts of changes in motorcyclists' riding behavior on the effectiveness of mandatory motorcycle helmet laws in preventing motorcycle fatalities. For ease of exposition, the exposure variables and mandatory helmet laws are the focus of the initial structural design, and a more detailed set of estimation equations including all the control variables are given subsequently.

Motorcycle fatalities are assumed to depend on the number of motorcycle crashes as follows:

$$fatalities_i = e^{\beta * Helmetlaw_i + u_i} * crashes_i, \tag{2}$$

where u_i is an iid error term, and β is the estimated impact of mandatory helmet law on the natural log of motorcycle fatalities. Similarly, motorcycle crashes are assumed to depend on the number of registered motorcycles based on the following:

$$crashes_i = e^{\lambda * Helmetlaw_i + v_i} * regmoto_i. \tag{3}$$

Combining equations (2) and (3) it is possible to express fatalities as a function of the number of registered motorcycles:

$$fatalities_i = e^{(\beta + \lambda) * Helmetlaw_i + \varepsilon_i} * regmoto_i. \tag{4}$$

In other words according to equation (4), the overall effect of mandatory helmet laws on the natural log of motorcycle fatalities is given by the sum of the effect on crashes, λ, and the direct impact on fatalities holding crashes constant, β. If the theory of offsetting behavior is correct, it is expected that the estimated coefficient λ will have a positive sign, and provide a measure of the degree to which helmet law effectiveness is mitigated through increased motorcycle crashes. Alternatively, in the presence of enhancing behavior λ will have a negative sign and measure the degree to which helmet law effectiveness is increased due to reduced risk taking among motorcycle riders.

Note however, the estimated coefficient λ does not measure the entire impact of offsetting or enhancing behavior on the effectiveness of mandatory helmet legislation. If present, such behavior in the form of increased or reduced driving intensity may also increase or reduce the average severity of crashes in helmet law states in comparison to an unobserved counterfactual with no offsetting or enhancing behavior (i.e. the estimated β coefficient is also reduced in absolute terms in the presence of offsetting behavior, and increased in absolute terms in the presence of enhancing behavior).

In order to formally test for the existence and measure the magnitude of offsetting or enhancing behavior through the impact on motorcycle crashes the following fixed effects models are estimated:

$$\ln fatalities_{i,t} = a_1 + SC_{i,t}\theta_1 + ML_{i,t}\phi_1 + \beta * Helmetlaw_{i,t} + \eta_1 * \ln crashes_{i,t} + S_i + \varepsilon_{i,t}, \qquad (5)$$

$$\ln crashes_{i,t} = a_2 + SC_{i,t}\theta_2 + ML_{i,t}\phi_2 + \lambda * Helmetlaw_{i,t} + \eta_2 * \ln regmoto_{i,t} + S_i + \varepsilon_{i,t}, \qquad (6)$$

$$\ln fatalities_{i,t} = a_3 + SC_{i,t}\theta_3 + ML_{i,t}\phi_3 + \varphi * Helmetlaw_{i,t} + \eta_3 * \ln regmoto_{i,t} + S_i + \varepsilon_{i,t}, \qquad (7)$$

where the natural log of motorcycle fatality and crash counts in state i at time t are a function of a vector of time varying state characteristics, $SC_{i,t}$, including *Temp*, *Precip*, *lnVmt*, *lnRuralvmt*, *lnCapita*, *lnAlcohol*, and *Speedlimit*; and interaction terms for *lnAlcohol* by Vermont and Nevada state indicator variables (see Table I for definitions). Each model also contains a vector of indicator variables for motorcycle safety legislation, $ML_{i,t}$, that include the following: *Skilltest*, *Rideredlic*, *Ridered*, and *Headlight*. In equation (5), motorcycle crashes serve as the risk exposure variable, and in equations (6) and (7) the number of registered motorcycles is used as a measure of risk exposure.

Following the structural design in equations (1) through (4), it is expected that the estimated coefficient on exposure, η, will be statistically indistinguishable from one. Finally, the estimated coefficients on $Helmetlaw_{i,t}$ are the main coefficients of interest for estimating the impact of changes in rider behavior on the effectiveness of mandatory helmet laws in reducing motorcycle fatalities. In equation (5), β measures the impact of helmet laws net of any offsetting or enhancing effects on motorcycle crashes. The estimated coefficient λ in equation (6) measures the behavioral effect of motorcycle helmet laws on motorcycle crashes, and is expected to have a significant positive effect if the theory of offsetting behavior is correct and a negative effect in the presence of enhancing behavior. The estimated coefficient φ in equation (7) measures the overall impact of motorcycle helmet laws on fatalities ($\beta+\lambda$ assuming the estimated coefficients η are equal to one). Finally, each model includes a set of state fixed effects, S_i, and a random error term $\varepsilon_{i,t}$ clustered at the state-level to allow for correlation over time within clusters.

Results from the estimation of equations (5) through (7) are presented in Table III for two separate specifications that vary based on whether state fixed effects or state and year fixed effects are included in the model. The first two columns correspond to equation (5) where the number of motorcycle fatalities is the dependent variable and risk exposure is measured by the number of motorcycle crashes. Focusing on the results for the specification with state and year fixed effects, the estimated coefficient on mandatory helmet laws, β, is negative as expected indicating that the technological efficacy of motorcycle helmets in preventing fatalities is not fully offset by any increases in motorcyclists' driving intensity. Mandatory helmet laws are predicted to reduce motorcycle fatalities by 20.9%, and the estimated effect is significant at the 1% level. Interestingly, a 1% increase in motorcycle crashes is associated with a 0.44% (95% confidence interval of 0.28% to 0.60%) increase in motorcycle fatalities. Recall, that the estimated coefficient on risk exposure, η, was expected to be 1 based on the structural setup given in equations (2) through (4). However, Wald tests reject the null hypothesis that η_1 is equal to one at a significance level less than 1%.

Results from the estimation of equation (6) are given in columns 3 and 4 of Table III. Consistent with the theory of enhancing behavior, mandatory helmet laws are predicted to reduce motorcycle crashes by 19.0%. Similar to the results from equation (5), the estimated coefficient on risk exposure is significantly less than 1. A 1% increase in the number of registered motorcycles is estimated to increase motorcycle crashes by 0.15% (95% confidence interval of 0.01% to 0.28%).

Columns 5 and 6 of Table III give the results from the estimation of equation (7) measuring the overall impact of helmet laws on motorcycle fatalities. In the presence of enhancing behavior, it was predicted that the estimated coefficient on helmet laws, φ, would larger in absolute terms than the coefficient on helmet laws estimated in equation (5). The reduction in motorcycle crashes estimated in equation (6) is further reflected in the coefficient on helmet laws in equation (7), where the implementation of a universal helmet law is associated with a 26.0% reduction in motorcycle fatalities overall. The overall reduction is 5.2 percentage points larger than the impact of helmet laws when the number of crashes is controlled for. The full 19.0% estimated reduction in motorcycle crashes from equation (6) is not completely passed through to fatalities, but this is likely due to the fact that the estimated coefficients on the exposure variables are all significantly less than one in the results presented in Table III.

The analysis that follows focuses on the results from equations (6) and (7), which are contradictory to the expectations formulated based on a theory of offsetting behavior and in accordance with those of a theory of enhancing behavior. Specifically, the possibility of omitted variable bias, non-classical measurement error in motorcycle crashes, and enhancing behavior in the form of reduced risk-taking among motorcyclists are investigated as possible explanations for the 19.0% reduction in motorcycle crashes estimated in equation (6).

4. ROBUSTNESS TESTS

The five following scenarios are considered as possible explanations for the negative correlation between mandatory helmet laws and state motorcycle crashes estimated in section 3:

1. Increased conspicuity of helmeted motorcyclists.
2. Non-classical measurement error in motorcycle utilization.
3. Simultaneity and Omitted variable bias.
4. Non-classical measurement error in motorcycle crashes.
5. Enhancing behavior of motorcyclists.

To date, there is limited evidence that motorcycle helmets may increase the conspicuity of motorcyclists to other motorists. Wells et al.[12], for example, match crash data with roadside survey data in New Zealand, and find that motorcyclists wearing a white helmet as opposed to a black helmet have a 24% lower risk of crashing. Unfortunately, the aggregate state-level data, and the individual-level crash data used in this analysis do not allow the researcher to isolate the conspicuity effects on fatality and crash rates. The individual-level crash data for example, only contains information on whether or not motorcyclists were wearing helmets at the time of a crash, and contains no information on the color/conspicuity of the aforementioned helmets. The remainder of this section therefore focuses on items 2-5 in the list of possible scenarios, because these explanations can be explicitly tested with the data available.

4.1 Non-classical measurement error in motorcycle utilization

The issue of mismeasured motorcycle utilization is primarily data driven. Currently, the US Department of Transportation (USDOT) does not collect "true" data on motorcycle vehicle miles traveled (vmt) in the United States.[13] The USDOT simply proxies for motorcycle vmt by making an adjustment to total vmt based on the number of registered motorcycles in the state. Furthermore, according to the National Transportation Safety Board[13] there is also reason to believe that the USDOT's measurement of state motorcycle registrations may be flawed. If helmet laws are negatively correlated with utilization the estimated impact on crash rates and fatality rates in equations (6) and (7) will be biased downward. In order to investigate this possibility further the Motorcycle Industry Council's (MIC's) estimated number of motorcycles used on highway is employed as an alternative exposure variable in estimation of the crash and fatality equations (6) and (7) given above. The MIC's alternative exposure variable is only available for a subset of the years used in the main analysis, so equations (6) and (7) are also re-estimated over the same subsample using the natural log of registered motorcycles as the exposure variable for comparison purposes. The results from the analysis of alternative exposure variables are presented in Table IV for the specifications that include state and year fixed effects.[5] The estimated coefficient on $HelmetLaw_{i,t}$ remains negative and significant regardless of the exposure used. Finally, the last row of Table IV reports Akaike information criterion (AIC) and Bayesian information criterion (BIC) measures of model fit. The results do not yield a dominant choice of exposure variable, because both criteria favor using the DOT's natural log of registered motorcycles as the exposure variable in equation (6) and the MIC's natural log of motorcycles used on highway in equation (7). Nevertheless, the estimated coefficients on the exposure variables are all significantly less than one, and therefore suggest that alternative measures of motorcycle vmt are necessary.

4.2 Simultaneity and Omitted Variable Bias

Simultaneity in the sense that states with high motorcycle crash rates are more likely to adopt mandatory helmet laws, and/or unobserved variables that simultaneously affect the likelihood of helmet law adoption and state crash rates could bias estimates and explain the unexpected negative coefficient on helmet laws in the crash equation (6). Instrumental variables (IV) estimation techniques can be used to correct for such bias, but it is important to note that the

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[5] In terms of analyzing goodness of fit, the specifications including only state fixed effects give the same interpretation.

IV estimation results discussed herein are not robust to the mismeasurement of motorcycle utilization discussed in sub-section 4.1 (see, for example, Cameron and Trivedi[14] and Pearl[15] for an illustration of identifiable parameters using IV). In order to investigate this possibility further, the following system of equations is estimated:

$$\ln Helmetlaw_{i,t} = \gamma_1 + SC_{i,t}\gamma_2 + ML_{i,t}\gamma_3 + Z_{i,t}\gamma_4 + \gamma_5 * \ln exposure_{i,t} + S_i + \varepsilon_{i,t}, \tag{8}$$

$$\ln outcome_{i,t} = a_1 + SC_{i,t}\theta_1 + ML_{i,t}\phi_1 + \beta * Helm\hat{e}tlaw_{i,t} + \eta_1 * \ln exposure_{i,t} + S_i + \varepsilon_{i,t}, \tag{9}$$

where all variables are as defined in equations (5) through (7), and an IV analogue is estimated for each of the models presented in Table III. As such, $outcome_{i,t}$ is the dependent variable of interest consisting of either motorcycle fatalities or crashes depending on model choice. Similarly, $exposure_{i,t}$ consists of motorcycle crashes or registered motorcycles. The instrument set, $Z_{i,t}$, includes a measure of state government ideology reflecting the overall ideology of state governments on a liberal to conservative continuum (for an overview of the NOMINATE ideology measure see Poole[16] and Berry et al.[17], where government ideology is estimated based on U.S. representatives' roll call votes). Government ideology is expected to capture the likelihood of different political groups adopting mandatory helmet laws, but the validity of this instrument relies on the control of confounding safety legislation.

The specifications in equations (8) and (9) include a vector of relevant motorcycle safety legislation, $ML_{i,t}$, and the results are robust to the inclusion of indirect safety legislation such as primary and secondary seatbelt enforcement laws. Other legislation such as cellphone and texting bans are likely to be positively correlated with helmet laws and negatively correlated with crashes, however, according to Cheng[18] no states adopted texting bans prior to 2008, and only New York and Connecticut adopted cellphone bans during the 1975-2007 timeframe analyzed herein. The results are robust to exclusion of data post 2001 when New York and Connecticut adopted their cellphone bans.

In addition to government ideology, the instrument set for the specifications without year fixed effects include an indicator variable equal to one for years under which the 1966 U.S. Highway Safety Act is operational, and equal to zero otherwise. The 1966 U.S. Highway Safety Act remained in place from 1966 until May of 1976 when Congress passed the replacement Federal-Aid Highway Act. Before its repeal, the U.S. Highway Safety Act required states to adopt mandatory helmet laws in order to avoid up to 10% reductions in their federal highway construction funds.[(8)]

Results from the estimation of equations (8) and (9) are presented in Table V. Overall, the estimated coefficients on $Helmetlaw_{it}$ are similar in sign albeit larger in absoluter terms when compared to the OLS results presented in Table III. Davidson-Mackinnon exogeneity tests generally fail to reject the null hypothesis that OLS estimates are consistent at a significance level of 10% or more. The null hypothesis of exogeneity is rejected in column 4 where the natural log of motorcycle crashes is the dependent variable and the specification includes state and year fixed effects. However, in column 4 helmet laws are estimated to reduce motorcycle crashes by 33.1%, so omitted variable/simultaneity bias doesn't appear to change the enhancing behavior interpretation of the OLS results from section 3.

Focusing on the specifications that include year and state fixed effects, helmet laws are estimated to reduce state motorcycle fatalities by 26.0% when motorcycle crashes are used as the exposure variable. The last column in Table V presents the overall impact of helmet laws on motorcycle fatalities, and helmet laws are estimated to reduce state motorcycle fatalities by 35.2%. Once again, the results are consistent with the theory of enhancing behavior because the overall reduction in motorcycle fatailities is 9.2 percentage points larger than the estimated reduction in column 2 when motorcycle crashes is used as the exposure variable.

Finally, Table V presents Kleibergen-Paap F-statistics testing the null hypothesis that the estimated coefficients on the instrument set, $Z_{i,t}$ in equation (8) are jointly equal to zero. As a rule of thumb, Bound et al.[(19)] and Staiger and Stock[(20)] suggest an F-statistic from the first stage regression of 10 or more in order for an instrument to meet the requirements of a relevant strong instrument. In all specifications, the instrument set appears to satisfy the strong instrument requirements. In addition to tests for strong instruments, Table V presents Hansen J statistic overidentification tests of instrument exogeneity for the specifications that do not include year fixed effects.[6] The overidentification tests' null hypothesis of instrument validity is not rejected at any conventional level of significance.

4.3 Non-classical Measurement Error in Motorcycle Crashes

Data on total state motorcycle crashes is not available for analysis. Rather the data available only include crashes that are reported on official police accident reports (PARs). Total reported crashes are given by the following equation:

$$reported\ crashes_{i,t} = r_{i,t} * crashes_{i,t} \tag{10}$$

where $crashes_{i,t}$ are the total motorcycle crashes in state i and time t, and $r_{i,t}$ is the fraction of total crashes that are actually recorded on PARs.

In a classical measurement error context, E($r_{i,t}$) is equal to one and the natural logarithm of reported crashes is measured with an additive error term with mean zero that is uncorrelated with the other explanatory variables. In such a setting, the estimated coefficient on $Helmetlaw_{i,t}$ in the crash equation (6) is unbiased, but the coefficients from equation (5) are biased. The

[6] Overidentification tests are not possible in the specifications with year fixed effects, because two or more relevant instruments are required to perform the tests.

direction of the bias on *Helmetlaw*$_{i,t}$ in equation (5) can be inferred from the OLS estimate presented in equation (A4) in the appendix. In the event of offsetting behavior the bias term is positively signed, and in the event of enhancing behavior the bias is negative. Traditional IV estimators that instrument for motorcycle crashes yield unbiased estimates of the coefficients of interest in equation (5).

However, if the measurement error in reported crashes is non-classical in the sense that the reporting rate, $r_{i,t}$, is correlated with motorcycle helmet laws both equations (5) and (6) will yield biased estimates of the coefficient on *Helmetlaw*$_{i,t}$. Research suggests that crash reporting rates are generally smaller for less severe crashes (see, for example, Loo & Tsui[(21)], Amoros et al.[(22)], and Alsop & Langley[(23)], for a discussion of under-reporting of crashes by severity and vehicle type). Because helmets are expected to reduce the severity of injuries for motorcyclists involved in crashes, it is possible that helmet laws are negatively correlated with state crash reporting rates. Non-classical measurement error of this sort could fully explain the negative estimated coefficient on helmet laws in the crash equation (6), and traditional IV corrections for measurement error in motorcycle crashes will still yield inconsistent estimates in equation (5) even if the instruments are valid in the sense that they are uncorrelated with crash reporting rates (see equations A5 and A6 in the appendix for the bias from an IV estimator).

Fortunately, the IV estimators' overidentification test also provides a test of non-classical measurement error. In the presence of non-classical measurement error the overidentification test statistic is expected to be statistically significant suggesting that the exogenous variables are correlated with the structural error term.[7] In order to test for non-classical measurement error, the following IV system of equations is estimated:

[7] Proof is given in appendix section A1.

$$\ln crashes_{i,t} = \gamma_1 + SC_{i,t}\gamma_2 + \gamma_3 * skilltest_{i,t} + Z_{i,t}\gamma_4 + \gamma_5 * Helmetlaw_{i,t} + S_i + \varepsilon_{i,t}, \quad (11)$$

$$\ln fatalities_{i,t} = a_1 + SC_{i,t}\theta_1 + \phi_1 * skilltest_{i,t} + \beta * Helmetlaw_{i,t} + \eta_1 * \ln cra\hat{s}hes_{i,t} + S_i + \varepsilon_{i,t}, \quad (12)$$

where all variables are as defined in equation (5), except annual state temperature and laws requiring motorcycle rider education prior to licensing are used as instruments, $Z_{i,t}$ for state motorcycle crashes. Both rider education licensing laws and temperature are expected to affect fatalities only through their impact on crashes. Furthermore, these instruments are expected to be correlated with motorcycle crashes and uncorrelated with crash severity.

For comparison purposes the OLS estimates of equation (5) are presented in the first two columns of Table VI. Results from the IV estimates of equation (12) are presented in the last two columns of Table VI. F-statistics from the first stage regression of equation (11) are all greater than 10 suggesting the instruments are relevant. Hansen J overidentification test statistics are reported in the last row of Table VI, and the overidentification tests fail to reject the null hypothesis of instrument exogeneity at the 20% level and 70% level in the specifications with state fixed effects and state and year fixed effects, respectively. The results are inconsistent with non-classical measurement error in motorcycle crashes, and the estimated coefficient on motorcycle crashes, η_1, is larger in magnitude than the OLS estimates and statistically indistinguishable from 1 at the 18% level (1 was the postulated coefficient on η_1 in the structural model given in equation 2). Consistent with the theory of classical measurement error and enhancing behavior, the estimated coefficient on $Helmetlaw_{i,t}$ is smaller in absolute terms than the OLS estimates given in columns 1 and 2 of Table VI. In the IV models, mandatory helmet laws are estimated to reduce motorcycle fatalities by 17.1% and 16.6% in the specification with state fixed effects and state and year fixed effects, respectively.

In Figure 2, an Anderson-Rubin (A-R) version of the overidentification test that is robust to weak instruments is used to more thoroughly investigate the exogeneity of the instrument set (see Finlay et al.[24] for an overview of the weakiv command used to calculate the A-R overidentification test statistics). Finlay & Magnusson[25] demonstrate that the traditional A-R test statistic can be decomposed into a test that η_1=0 given that E[$Z\varepsilon$]=0 (in this notation Z is the full set of all exogeneous variables in equations 11 and 12) and an overidentification test that E[$Z\varepsilon$]=0 given that $\eta_1=\eta$. The A-R results presented in Figure 2 are for the model with state and year fixed effects, and are calculated over a grid search that is twice as large as the confidence interval for the estimated coefficient η_1 in equation (12) above. As revealed in Figure 2, the A-R overidentification test fails to reject the null hypothesis of instrument exogeneity at a significance level of 30% or more for all possible values of η_1 over the grid. Overall, the overidentification tests strongly suggest that helmet laws are uncorrelated with the reporting rates of crashes, r_{it}. Given this result, the analysis that follows uses individual crash data from PARs to test for additional evidence of enhancing behavior.

4.4 Enhancing Behavior of Motorcyclists

In order to more directly test for the presence of enhancing behavior associated with motorcycle helmet laws this section uses individual PAR crash data to analyze whether helmeted motorcyclists are less likely to receive citations for the following risky driving behavior: 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:

$$Citation_{n,t} = a + x_{n,t} * \beta + c_{n,t} * \gamma + \theta * Helmet_{n,t} + T_t + \varepsilon_{n,t}, \qquad (13)$$

where $Citation_{n,t}$ is an indicator variable equal to one if the individual received a ticket for risky driving behavior and equal to zero otherwise. Equation (13) includes year fixed effects, T_t, a vector of individual characteristics, $x_{n,t}$, that include the following variables: *Sex*, *Age*, *Age*^{2}, and *Driver*.[8] Equation (13) 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*. Finally, the equation includes an indicator variable for helmet use, $Helmet_{n,t}$, that is equal to 1 if the individual was wearing a helmet at the time of the crash, 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.

The first column in Table VII presents the OLS estimates of equation (13). 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 VII presents the results of the probit analogue to equation (13) where helmet use is estimated to reduce the probability of ticket citation by 2.6 percentage points.

One cause for concern with the OLS estimates given in equation (13) 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 OLS and probit estimates of citation probability given in columns 1 and 2 of Table VII are biased downward.

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

In order to correct for potential selection bias IV is used to estimate the following system of equations:

$$Helmet_{n,t} = \partial + x_{n,t}\varphi + c_{n,t}\eta + \phi * Helmetlaw_{n,t} + T_t + \mu_{n,t}, \tag{14}$$

$$Citation_{n,t} = a + x_{n,t} * \beta + c_{n,t} * \gamma + \theta * Hel\hat{m}et_{n,t} + T_t + \varepsilon_{n,t}, \tag{15}$$

where mandatory motorcycle helmet laws, $Helmetlaw_{n,t}$, serve as an instrument for helmet use in equation (14), and the predicted helmet use from equation (14) is used as an explanatory variable, $Hel\hat{m}et_{n,t}$, in equation (15). The first stage regressions of helmet use are given in Table AI in the appendix. The estimated coefficient on $Helmetlaw_{n,t}$ is positive as expected, and statistically significant at the 1% level. Predicted helmet use is roughly 88% in mandatory helmet law states and 47% in states without mandatory helmet laws.

Estimates of the IV structural equation (15) are given in column 3 of Table VII. 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 enhancing behavior following mandatory helmet laws as it is void of any advantageous or adverse selection effects from using individuals' selected helmet use. The IV results from column 3 of Table VII 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 given at the bottom of Table VII and is equal to 1,029.97. As a result, mandatory helmet laws appear to be a strong instrument for predicting motorcycle helmet use.

The last two columns of Table VII present two alternative probit estimators that are capable of correcting for selection bias similar to the IV estimator given in equations (14) and (15). Details of the control function probit estimator (CF Probit) and bivariate probit estimator (BV Probit) are given in Appendix section A2. The underlying premise of both estimators is the same; estimation of equation (13) is biased because the error components (μ_n and ε_n) in equations (14) and (15) have a non-zero covariance. CF Probit corrects for this bias in a two-step procedure that uses the predicted generalized probit residuals from the probit analogue of equation (14) as an additional explanatory variable in the estimation of the probit analogue to equation (15). BV Probit on the otherhand, estimates the probit analogues of equations (14) and (15) simultaneously by maximizing their joint likelihood function, and is implemented in Stata using the cmp command (see Roodman[26], for an overview of the nonofficial Stata cmp command capable of estimating systems of equations for mixed processes with normally distributed error terms). Selection bias is corrected in the BV Probit model because the covariance of the error terms (μ_n and ε_n) is a free parameter to be estimated when maximizing the likelihood function.

Overall, 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. These findings are consistent with the theory of enhancing behavior resulting from motorcycle helmet laws.[9]

CONCLUSION

State motorcycle helmet laws are estimated to reduce motorcycle crashes by 18.2% to 33.1%. This finding does not appear to be driven by omitted variable bias or non-classical measurement error in motorcycle crashes, and is consistent with a theory of enhancing behavior as opposed to the traditional economic theory of offsetting behavior. Given that motorcycle helmet laws appear to be uncorrelated with state motorcycle crash reporting rates, data from individual motorcycle crash PARs is used to more directly test for the existence of enhancing behavior. Results using the individual crash data suggest that helmeted motorcyclists incentivized by mandatory helmet laws have a 4.2 to 4.8 percentage point lower probability of receiving a traffic citation for risky driving behavior defined as alcohol or drugs, speeding, reckless driving, failure to yield a right of way, and running a traffic signal or stop sign. These findings are also consistent with the existence of enhancing behavior as opposed to offsetting behavior in the context of motorcycle helmet legislation.

Given these findings, it is important to analyze the avenues through which mandatory helmet laws may influence the driving behavior of motorcyclists. Teresi[(27)] provides a discussion of the arguments against motorcycle helmet laws made by rights groups such as ABATE; among the more popular arguments are that helmets are ineffective and actually increase risk of neck injury.[10] In this context, Thaler & Sunstein[(6)] provide examples of behavioral responses that

[9] Evidence of enhancing behavior was also apparent in terms of significant reductions in estimated travel speed for helmeted motorcyclists, but the results were not included because travel speed was not collected for more than half of the total observations.

[10] As of 2013 there are local ABATE organizations currently or previously operating in all U.S. States. Due to the grass-roots nature of the organizations there is no uniform definition of what the acronym ABATE stands for; some of the more popular interpretations include the following: American Bikers Aiming Toward Education, A

would be consistent with enhancing behavior following helmet law adoption. Cultural bias and anchoring may lead motorcyclists to believe that helmets are ineffective in reducing fatality risks and actually increase the likelihood of severe neck injuries. Such bias regarding the initial beliefs of helmet law inefficacy would likely lead motorcyclists to reduce risky driving behavior if forced to wear helmets. Alternatively, helmet laws may nudge motorcyclists to be more safety conscious. Finally, motorcyclists may believe that helmets reduce their field of vision and increase their risk of being involved in a crash in which case they can reduce driving intensity to reduce crash probability. Understanding the relative importance of the behavioral mechanisms leading to enhancing behavior in motorcycle helmet legislation is beyond the scope of this paper, but it is an important area for safety policy analysis and may have implications beyond the immediate context of mandatory helmet laws.

Finally, this paper highlights important shortcomings with current data and empirical approaches including measurement error in motorcycle utilization and lack of data on rider conspicuity. Due to these imperfections in the data it is not possible to quantify with certainty the degree to which enhancing behavior accounts for the estimated 18.2% to 33.1% reduction in state motorcycle crashes. The overall importance of enhancing behavior in reducing motorcycle crashes and fatalities therefore remains an empirical question for future research with improved data.

Table I. Aggregate State Level Data.

Variable Name	Sample Mean (Std. Dev.)	Variable Definition	Variable Location
Fatalities	78.52 (100.8)	Number of motorcycle occupant fatalities in a state.	Data compiled from annual Fatal Accident Reporting System, and provided by the National Highway Traffic Safety Administration. Available: ftp://ftp.nhtsa.dot.gov/FARS (last accessed February, 2013)
Crashes	2,582 (3,485)	Number of motorcycle crashes in a state.	Data compiled from state highway transportation organizations, and the Motorcycle Industry Council's yearly periodical the Motorcycle Statistical Annual.
Helmetlaw	0.447 (0.493)	Variable equal to the proportion of the year that a state had a helmet law requiring helmet usage for all motorcyclists.	Data from National Highway Traffic Safety Administration. Available: http://www-fars.nhtsa.dot.gov/States /StatesLaws.aspx (last accessed February, 2013)
Skilltest	0.918 (0.274)	Dummy variable =1 if a state has a motorcycle skill test requirement for obtaining a license, and equal to 0 otherwise.	Data from the Motorcycle Industry Council's Motorcycle Statistical Annual
Rideredlic	0.270 (0.444)	Dummy variable=1 if a state has a motorcycle rider education requirement for obtaining a license, and equal to zero otherwise.	Data from the Motorcycle Industry Council's Motorcycle Statistical Annual
Ridered	0.591 (0.486)	Dummy variable=1 if a state has a state funded motorcycle rider education program irrespective of licensing requirements, and equal to 0 otherwise.	Data from the Motorcycle Safety Foundation. Available: http://www.msf-usa.org/Downloads/2012-Rider-Ed-Programs-CSI.pdf (last accessed February, 2013)
Headlight	0.440 (0.496)	Dummy variable =1 if a state requires motorcyclist to burn headlights at all times, and equal to 0 otherwise.	Data from the Motorcycle Industry Council's Motorcycle Statistical Annual
Motouse	92,640 (99,040)	Number of motorcycles used on highway in the state during the year	Data from the Motorcycle Industry Council's Motorcycle Statistical Annual

Continued, next page

Table I (continued)

Variable Name	Sample Mean (Std. Dev.)	Variable Definition	Variable Location
Temp	52.42 (8.396)	Average annual state temperature.	Data from National Climatic Data Center. Available: http://www.ncdc.noaa.gov/oa/climate/research/cag3/cag3.html (last accessed February, 2013)
Precip	35.21 (15.27)	Average annual state precipitation levels.	Same as Temp Location.
Vmt	45,772 (45,688)	Annual state vehicle miles traveled.	Data from the Federal Highway Administration. Available: http://www.fhwa.dot.gov/policyinformation/quickfinddata/qftravel.cfm (last accessed February, 2013)
Ruralvmt	18,594 (13,429)	Number of rural vehicle miles traveled.	Same as Vmt Location.
Regmoto	105,849 (111,716)	Number of registered motorcycles in a state.	Data from the Federal Highway Administration. Available: http://www.fhwa.dot.gov/policyinformation/quickfinddata/qfvehicles.cfm (last accessed February, 2013)
Capita	$5.319e^6$ ($5.422e^6$)	Total state population age 16 years and over.	Data from the U.S. Census Bureau. Available: http://www.census.gov/popest/data/historical/ (last accessed February, 2013)
Alcohol	0.002 (0.0005)	State annual alcohol consumption per capita.	Data from National Institute on Alcohol Abuse and Alcoholism. Available: http://pubs.niaaa.nih.gov/publications/Surveillance95/pcyr19702010.txt (last accessed February, 2013)
Speedlimit	62.31 (6.903)	Maximum state speed limits on rural highways.	Data from Reasonable Drivers Unanimous. Available: http://www.ibiblio.org/rdu/sl-attud/chart.html (last accessed February, 2013)
Hwysfty	0.055 (0.206)	Dummy variable=1 if the 1966 federal Highway Safety Act is in operation, and equal to 0 otherwise.	N/A
Instid	52.69 (20.56)	NOMINATE measure of state government ideology based on average roll call votes of U.S. legislators.	Data from Richard C. Fording. Available: http://rcfording.wordpress.com/state-ideology-data/ (last accessed October, 2013)

Table II. Individual Motorcycle Crash Data[a]

Variable Name	Sample Mean (Std. Dev.)	Variable Definition
Citation	0.107 (0.309)	Dummy Variable = 1 if a traffic citation is given, and equal to zero otherwise.
Helmetlaw[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.
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 III. Fixed-Effects Models of Motorcycle Helmet Law Offsetting Behavior, 1975-2007.[a]

	Dependent Variable [Exposure Variable]:					
	Lnfatalities [Lncrashes]:		**Lncrashes [Lnregmoto]:**		**Lnfatalities [Lnregmoto]:**	
Variable Name	**Estimated Coefficient (Std. Error)**		**Estimated Coefficient (Std. Error)**		**Estimated Coefficient (Std. Error)**	
Helmetlaw	-0.213***	-0.234***	-0.201***	-0.211***	-0.286***	-0.301***
	(0.041)	(0.038)	(0.050)	(0.053)	(0.048)	(0.046)
Skilltest	-0.128*	-0.048	-0.076	-0.027	-0.130*	-0.053
	(0.072)	(0.079)	(0.066)	(0.057)	(0.071)	(0.081)
Rideredlic	0.004	-0.034	-0.168***	-0.123***	-0.114**	-0.093**
	(0.037)	(0.035)	(0.050)	(0.039)	(0.043)	(0.041)
Ridered	-0.032	0.042	-0.044	0.016	-0.046	0.045
	(0.033)	(0.029)	(0.037)	(0.035)	(0.038)	(0.034)
Headlight	0.044	-0.054	-0.063	-0.121**	0.005	-0.096*
	(0.059)	(0.042)	(0.075)	(0.058)	(0.078)	(0.054)
Temp	0.009	0.001	0.014***	0.018**	0.014***	0.009
	(0.006)	(0.008)	(0.005)	(0.007)	(0.005)	(0.007)
Precip	-0.004***	-0.006***	-0.003***	-0.002**	-0.006***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lnvmt	0.396*	-0.044	-0.499**	0.178	-0.007	0.009
	(0.205)	(0.245)	(0.231)	(0.334)	(0.193)	(0.288)
Lnruralvmt	-0.323***	-0.056	-0.035	0.112	-0.207	0.020
	(0.118)	(0.137)	(0.095)	(0.090)	(0.134)	(0.138)
Lncapita	0.758**	0.634**	0.930**	0.218	1.044***	0.669**
	(0.315)	(0.240)	(0.372)	(0.366)	(0.321)	(0.291)
Lnalcohol	0.918***	0.355	1.157***	0.191	1.443***	0.464*
	(0.245)	(0.218)	(0.195)	(0.179)	(0.225)	(0.263)
Lnspeedlimit	-0.143	-0.287	-0.916***	0.143	-0.537**	-0.154
	(0.273)	(0.401)	(0.182)	(0.321)	(0.249)	(0.434)
Lnalcoholbynev	1.024***	0.524*	-0.659	-0.566	0.510	0.284
	(0.331)	(0.296)	(0.525)	(0.438)	(0.453)	(0.363)
Lnalcoholbyvt	-1.941***	-1.241***	1.260***	1.738***	-0.704**	-0.372
	(0.252)	(0.299)	(0.242)	(0.248)	(0.317)	(0.295)
Lnregmoto	----	----	0.332***	0.149**	0.455***	0.173**
	----	----	(0.079)	(0.067)	(0.085)	(0.066)
Lncrashes	0.650***	0.440***	----	----	----	----
	(0.082)	(0.080)	----	----	----	----
R-squared	0.577	0.646	(0.136)	0.764	----	0.610
Number of obs.	1,239	1,239	1,239	1,239	1,239	1,239
Fixed Effects Included	State	State; Year	State	State; Year	State	State; Year
% Fatality/Crash Differential –Helmet Law	-19.1%	-20.9%	-18.2%	-19.0%	-24.9%	-26.0%
Offsetting (+)/Enhancing (-) Behavioral Effect	----	----	----	----	-5.7pp	-5.2pp

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

Table IV. Examination of Alternative Exposure Variables, 1975-1998.[a]

	Dependent Variable [Exposure Variable]:			
	Lncrashes [Lnregmoto]	**Lncrashes [Lnmotouse]**	**Lnfatalities [Lnregmoto]**	**Lnfatalities [Lnmotouse]**
Variable Name	**Estimated Coefficient**	**(Std. Error)**	**Estimated Coefficient**	**(Std. Error)**
Helmetlaw	-0.240***	-0.267***	-0.372***	-0.392***
	(0.053)	(0.050)	(0.051)	(0.040)
Skilltest	0.001	-0.006	-0.106	-0.114*
	(0.052)	(0.057)	(0.073)	(0.065)
Rideredlic	-0.062*	-0.062*	-0.039	-0.048
	(0.034)	(0.034)	(0.037)	(0.036)
Ridered	-0.004	-0.001	-0.001	-0.003
	(0.031)	(0.032)	(0.030)	(0.028)
Headlight	-0.109**	-0.095*	-0.112*	-0.079
	(0.053)	(0.055)	(0.057)	(0.057)
Temp	0.021***	0.022***	0.009	0.010
	(0.005)	(0.005)	(0.008)	(0.008)
Precip	-0.001	-0.001	-0.004**	-0.005***
	(0.001)	(0.001)	(0.002)	(0.002)
Lnvmt	0.324	0.188	-0.312	-0.569
	(0.358)	(0.356)	(0.343)	(0.342)
Lnruralvmt	0.064	0.096	0.011	0.099
	(0.132)	(0.130)	(0.189)	(0.176)
Lncapita	0.083	0.105	1.055***	1.012***
	(0.423)	(0.446)	(0.345)	(0.315)
Lnalcohol	0.403**	0.345*	0.834***	0.752***
	(0.188)	(0.194)	(0.257)	(0.256)
Lnspeedlimit	0.141	0.238	-0.340	-0.091
	(0.283)	(0.282)	(0.490)	(0.498)
Lnalcoholbynev	-0.649	-0.637	0.802**	0.832***
	(0.450)	(0.417)	(0.334)	(0.304)
Lnalcoholbyvt	1.529***	1.251***	-0.541*	-0.910***
	(0.212)	(0.264)	(0.271)	(0.265)
Lnregmoto	0.181**	----	0.191**	----
	(0.076)	----	(0.086)	----
Lnmotouse	----	0.177***	----	0.307***
	----	(0.059)	----	(0.076)
R-squared	0.815	0.814	0.636	0.644
Number of obs.	887	887	887	887
Fixed Effects Included:	State; Year	State; Year	State; Year	State; Year
AIC:	-717.303	-716.553	-72.167	-93.801
BIC	-544.94	-544.191	100.196	78.561

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

Table V. IV Models of Motorcycle Helmet Law Offsetting Behavior, 1975-2007.[a]

	Dependent Variable [Exposure Variable]:					
	Lnfatalities [Lncrashes]:		Lncrashes [Lnregmoto]:		Lnfatalities [Lnregmoto]:	
Variable Name	Estimated Coefficient (Std. Error)		Estimated Coefficient (Std. Error)		Estimated Coefficient (Std. Error)	
Helmetlaw	-0.271***	-0.301*	-0.280***	-0.402**	-0.431***	-0.434***
	(0.087)	(0.161)	(0.097)	(0.192)	(0.090)	(0.162)
Skilltest	-0.135*	-0.053	-0.086	-0.043	-0.149**	-0.064
	(0.072)	(0.076)	(0.068)	(0.062)	(0.070)	(0.082)
Rideredlic	0.003	-0.033	-0.163***	-0.106**	-0.105**	-0.082*
	(0.037)	(0.034)	(0.049)	(0.046)	(0.044)	(0.044)
Ridered	-0.035	0.041	-0.048	0.014	-0.054	0.043
	(0.033)	(0.029)	(0.038)	(0.035)	(0.040)	(0.034)
Headlight	0.029	-0.069	-0.082	-0.159**	-0.030	-0.123*
	(0.064)	(0.057)	(0.078)	(0.077)	(0.087)	(0.065)
Temp	0.009	0.002	0.014***	0.018***	0.015***	0.009
	(0.006)	(0.008)	(0.005)	(0.007)	(0.005)	(0.007)
Precip	-0.004***	-0.006***	-0.003***	-0.003***	-0.006***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lnvmt	0.361*	-0.056	-0.529**	0.143	-0.062	-0.015
	(0.200)	(0.241)	(0.227)	(0.339)	(0.203)	(0.296)
Lnruralvmt	-0.340***	-0.070	-0.067	0.046	-0.265*	-0.026
	(0.123)	(0.135)	(0.101)	(0.113)	(0.141)	(0.142)
Lncapita	0.798***	0.656***	0.975***	0.301	1.127***	0.726**
	(0.304)	(0.239)	(0.363)	(0.363)	(0.319)	(0.295)
Lnalcohol	0.907***	0.335	1.118***	0.102	1.372***	0.403
	(0.248)	(0.222)	(0.207)	(0.227)	(0.255)	(0.286)
Lnspeedlimit	-0.118	-0.244	-0.864***	0.212	-0.442*	-0.106
	(0.267)	(0.375)	(0.179)	(0.289)	(0.248)	(0.407)
Lnalcoholbynev	1.018***	0.508*	-0.640	-0.571	0.543	0.281
	(0.323)	(0.291)	(0.525)	(0.456)	(0.460)	(0.363)
Lnalcoholbyvt	-1.943***	-1.240***	1.192***	1.532***	-0.825***	-0.516
	(0.249)	(0.293)	(0.229)	(0.288)	(0.294)	(0.315)
Lnregmoto	----	----	0.307***	0.072	0.410***	0.119
	----	----	(0.082)	(0.091)	(0.076)	(0.078)
Lncrashes	0.628***	0.411***	----	----	----	----
	(0.081)	(0.111)	----	----	----	----
R-squared	0.576	0.644	0.677	0.749	0.502	0.603
Number of obs.	1,239	1,239	1,239	1,239	1,239	1,239
Fixed Effects Included:	State	State; Year	State	State; Year	State	State; Year
Instruments Included:	*Hwysfty; Instid*	*Instid*	*Hwysfty; Instid*	*Instid*	*Hwysfty; Instid*	*Instid*
K-P F-statistic	19.092	11.079	21.790	11.930	21.790	11.930
Overidentification [p-value]	0.169	----	0.213	----	0.528	----
	[0.681]	----	[0.645]	----	[0.468]	----
% Fatality/Crash Differential –Helmet Law	-23.7%	-26.0%	-24.4%	-33.1%	-35.0%	-35.2%
Offsetting (+)/Enhancing (-) Behavioral Effect	----	----	----	----	-11.3pp	-9.2pp

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

Table VI. IV as a Test for Non-classical Measurement Error

	Dependent Variable is Lnfatalities			
	OLS		**IV**	
Variable Name	**Estimated Coefficient (Std. Error)**		**Estimated Coefficient (Std. Error)**	
Helmetlaw	-0.213***	-0.234***	-0.187***	-0.182***
	(0.041)	(0.038)	(0.058)	(0.069)
Skilltest	-0.128*	-0.048	-0.112	-0.042
	(0.072)	(0.079)	(0.074)	(0.075)
Rideredlic	0.004	-0.034	----	----
	(0.037)	(0.035)	----	----
Ridered	-0.032	0.042	----	----
	(0.033)	(0.029)	----	----
Headlight	0.044	-0.054	----	----
	(0.059)	(0.042)	----	----
Temp	0.009	0.001	----	----
	(0.006)	(0.008)	----	----
Precip	-0.004***	-0.006***	-0.004***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Lnvmt	0.396*	-0.044	0.420*	-0.053
	(0.205)	(0.245)	(0.227)	(0.249)
Lnruralvmt	-0.323***	-0.056	-0.302**	-0.077
	(0.118)	(0.137)	(0.121)	(0.137)
Lncapita	0.758**	0.634**	0.639	0.551**
	(0.315)	(0.240)	(0.397)	(0.255)
Lnalcohol	0.918***	0.355	0.773**	0.336
	(0.245)	(0.218)	(0.381)	(0.208)
Lnspeedlimit	-0.143	-0.287	0.002	-0.296
	(0.273)	(0.401)	(0.304)	(0.378)
Lnalcoholbynev	1.024***	0.524*	1.130***	0.618*
	(0.331)	(0.296)	(0.367)	(0.323)
Lnalcoholbyvt	-1.941***	-1.241***	-1.940***	-1.626***
	(0.252)	(0.299)	(0.222)	(0.402)
Lncrashes	0.650***	0.440***	0.753***	0.652**
	(0.082)	(0.080)	(0.187)	(0.260)
R-squared	0.577	0.646	0.573	0.635
Number of obs.	1,239	1,239	1,239	1,239
Fixed Effects Included:	State	State; Year	State	State; Year
Instruments Included:	*Rideredlic; Temp*	*Rideredlic; Temp*	*Rideredlic; Temp*	*Rideredlic; Temp*
K-P F-statistic	----	----	15.745	11.227
Overidentification [p-value]	----	----	1.509	0.138
	----	----	[0.219]	[0.711]

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

Table VII. 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^2	-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. Scatter Plot of Motorcycle Registrations, Temperature, and Precipitation

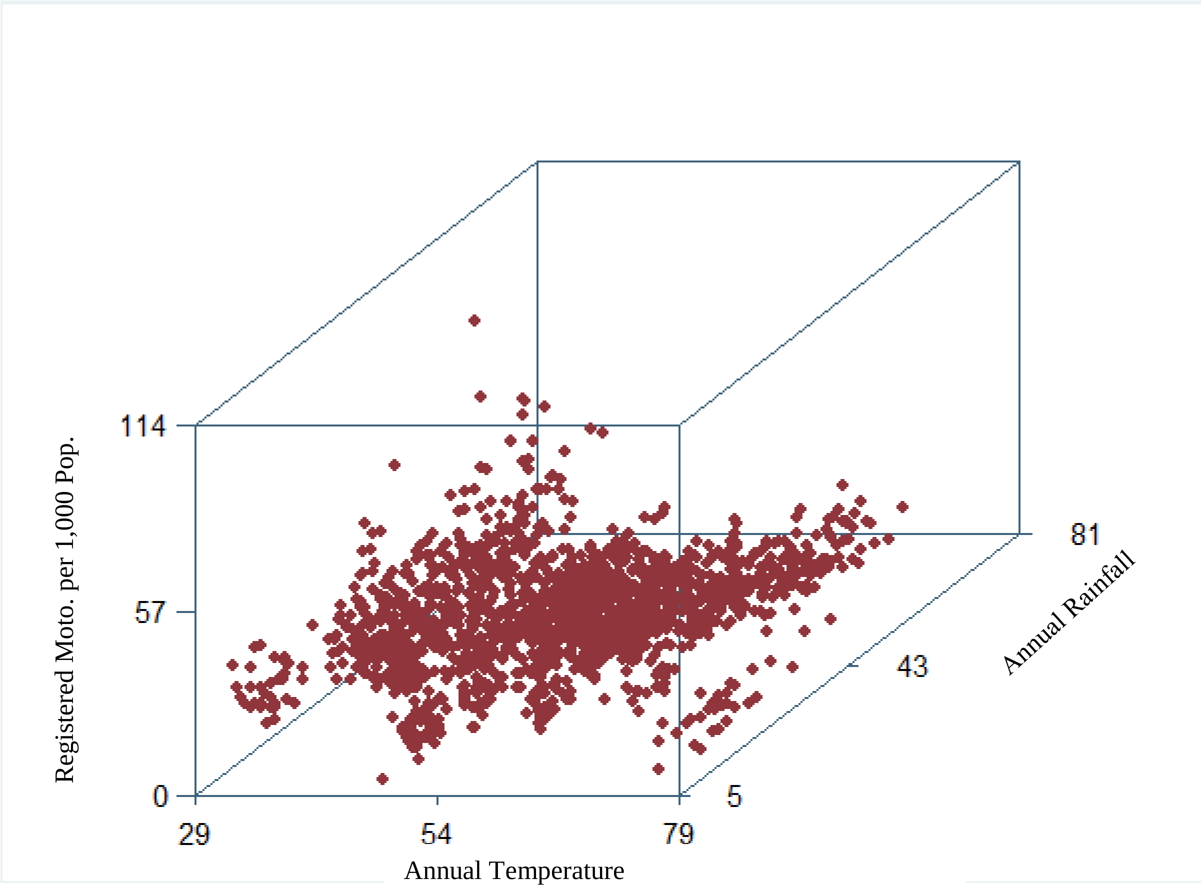
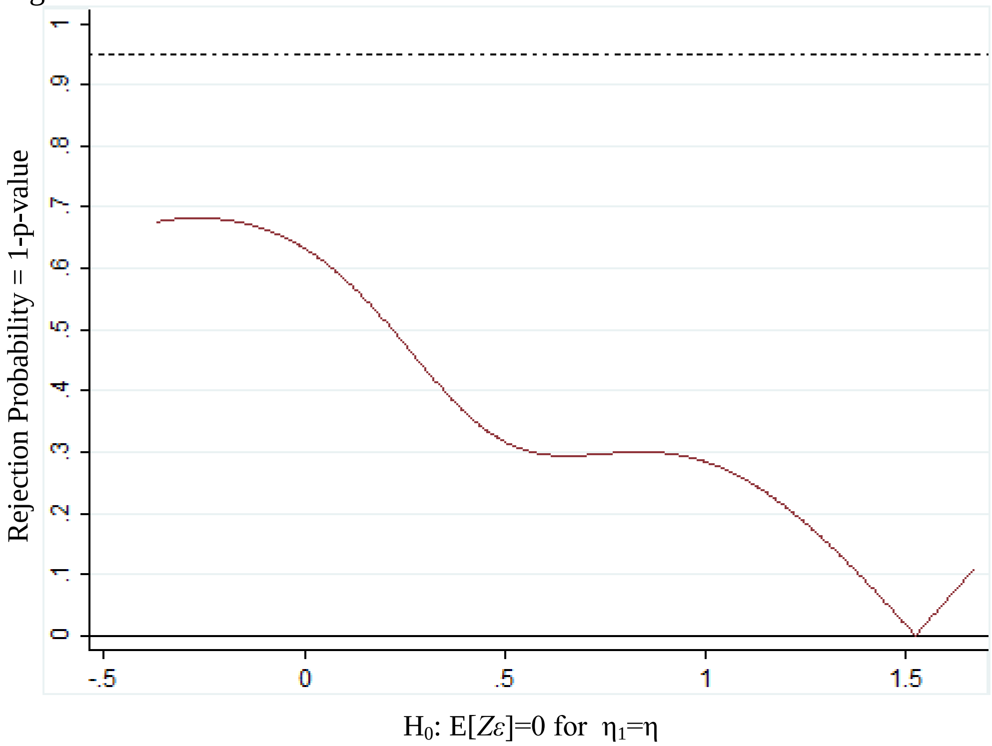


Figure 2. A-R Overidentification J-test.



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APPENDIX

A.1 Non-classical Measurement Error Bias

For Simplicity, assume a two variable model of the following form:

$$\ln\ fatalities_{\ i} = \mathrm{A} + \beta * Helmetlaw_i + \Gamma * \ln crashes_i + \varepsilon_i, \qquad \text{(A1)}$$

where the natural log of motorcycle fatalities is a function of the natural log of motorcycle crashes, ln*crashes*$_i$, and an indicator variable $Helmetlaw_i$ that is equal to 1 if the state has a universal helmet law and equal to zero otherwise. Finally, ε_i is an iid error term with mean zero, and $a, \beta,$ and γ are the parameters to be estimated. In the case of traffic accidents total crash counts ($crashes_i$) are likely unobserved. Instead only reported crashes are observed, and it is assumed that reported crashes equal the following:

$$Reportedcrashes_i = r_i * crashes_i, \qquad \text{(A2)}$$

where $crashes_i$ is a count of the total number of motorcycle crashes, and r_i is the measurement error defined as the fraction of total crashes that are reported to police in state i. Because total crashes are unobserved estimating equation (A1) with reported crashes results in the following:

$$\ln\ fatalities_{\ i} = a + b * Helmetlaw_i + \gamma * (\ln crashes_i + \ln r_i) + \varepsilon_i. \qquad \text{(A3)}$$

Letting $\hat{b}^{OLS}$ denote the OLS estimate of b from equation (A3), it can be shown that:

$$\mathrm{p}\lim(\hat{b}^{OLS}) = \beta + \frac{(\sigma_{cr}\sigma_{hc} + \sigma_{rr}\sigma_{hc} - \sigma_{hr}\sigma_{cc} - \sigma_{hr}\sigma_{cr}) * \Gamma}{\sigma_{hh}\sigma_{cc} + 2\sigma_{hh}\sigma_{cr} + \sigma_{hh}\sigma_{rr} - \sigma_{hc}\sigma_{hc} - 2\sigma_{hr}\sigma_{hc} - \sigma_{hr}\sigma_{hr}}, \qquad \text{(A4)}$$

where σ_{cr} is the covariance of motorcycle crashes, *lncrashes*$_i$, and the measurement error, r_i. Similarly, σ_{hc} is the covariance of helmet laws and crashes, and σ_{hr} is the covariance of helmet laws and crash measurement error. Finally, σ_{hh}, σ_{cc}, and σ_{rr} are the variance of helmet laws, motorcycle crashes, and crash measurement error, respectively. Equation 3 reveals that the OLS estimate of b is a biased estimate of the true parameter value of interest measuring the effect of helmet laws on motorcyclists' fatalities, β. Furthermore, without making assumptions regarding the covariance and variance of helmet laws, crashes, and the measurement error term it is not possible to place a sign on the direction of the bias.

Suppose now, there exists an instrumental variable, z_i, for motorcycle crashes that satisfies requirements for a strong instrument, and is statistically independent of the measurement error term r_i (i.e. $\sigma_{zr} = 0$). Letting $\hat{\beta}^{IV}$ and $\hat{\Gamma}^{IV}$ denote the IV estimates of β and Γ, respectively, results in the following characterizations:

$$\text{plim}(\hat{\beta}^{IV}) = \beta + \frac{-\sigma_{hr}\sigma_{zc}\Gamma}{\sigma_{hh}\sigma_{zc} - \sigma_{hc}\sigma_{zh} - \sigma_{hr}\sigma_{zh}}, \tag{A5}$$

$$\text{plim}(\hat{\Gamma}^{IV}) = \Gamma + \frac{\sigma_{hr}\sigma_{zh}\Gamma}{\sigma_{hh}\sigma_{zc} - \sigma_{hc}\sigma_{zh} - \sigma_{hr}\sigma_{zh}}. \tag{A6}$$

Comparison of equations (A5) and (A6) reveals that IV estimates of Γ and β are both biased if measurement error is non-classical in the sense that σ_{hr} is not equal to zero. Furthermore, letting E_i^{IV} denote the error term for the IV estimator, δ_β the additive bias term on β $\left(\frac{-\sigma_{hr}\sigma_{zc}\Gamma}{\sigma_{hh}\sigma_{zc}-\sigma_{hc}\sigma_{zh}-\sigma_{hr}\sigma_{zh}}\right)$ in equation (A5), and δ_Γ the additive bias term on Γ $\left(\frac{\sigma_{hr}\sigma_{zh}\Gamma}{\sigma_{hh}\sigma_{zc}-\sigma_{hc}\sigma_{zh}-\sigma_{hr}\sigma_{zh}}\right)$ in equation (A6) results in the following characterization of the IV estimator error term in the limit:

$$\text{E}_i^{IV} = \varepsilon_i - \delta_\beta * Helmetlaw_i - \delta_\Gamma * \ln crashes_i, \tag{A7}$$

where ε_i is the error term from the model without measurement error given in equation (A1). The variables for universal helmet laws and motorcycle crashes show up in the IV error term in an additive fashion in the presence of non-classical measurement error when helmet laws are correlated with the measurement error term. Assuming there is a second valid and relevant instrument available that is also uncorrelated with the measurement error r_i and strongly correlated with ln*crashes*$_i$, over-identification tests of the instrument set, z_i ,that regress the predicted error term $\hat{E}_i^{IV}$ on all exogenous variables including helmet law classification will be rejected in the presence of this type of non-classical measurement error. On the other hand, if helmet laws are uncorrelated with the measurement error in crashes, σ_{hr} is equal to zero and bias terms in equation (A7) drop out. In this case, the IV estimates of β and Γ are unbiased estimates of the true population parameters in equation (A1), and over-identification tests will not be rejected at any conventional significance level.

A.2 BV Probit and CF Probit Endogeneity Correction

Suppose there is a binary indicator variable C_n that is equal to one if individual n is observed in a particular state and equal to zero otherwise. Underlying the observed classification C_n, is a latent continuous variable, $C_n{}^*$, that can be expressed using the following:

$$C_n^* = V_n + \varepsilon_n = a + x_n\beta + \theta h_n + \varepsilon_n \,, \tag{A8}$$

where x_n is a vector of exogenous explanatory variables, h_n is a binary explanatory variable, and ε_n ~ N[0,1] is a normally distributed random error term. The observed classification, C_n is determined as follows:

$$C_n = \begin{pmatrix} 1 \; if \; V_n > -\varepsilon_n, \\ 0 \quad otherwise \end{pmatrix}. \tag{A9}$$

Letting E denote the set of all possible error terms, ε, that satisfy the inequality V_n>-ε_n, the probability of observing C_n=1 can be stated alternatively as the following:

$$P_n = \int_{\varepsilon_n \in E} \phi(\varepsilon_n) d\varepsilon_n \,, \tag{A10}$$

where $\phi(\cdot)$ is the probability density function for the normal distribution. The standard probit model is estimated by finding the values of a, β, and Θ that maximize the log-likelihood function given by the following:

$$LL(a,\beta,\theta) = \sum_n \left[C_n \ln(P_n) + (1-C_n)\ln(1-P_n) \right]. \tag{A11}$$

The standard probit estimates of *a*, β, and Θ that maximize the log-likelihood function (A11) will be biased, however, if the binary variable h_n is endogenous due to omitted variable bias, measurement error, or some other source of endogeneity.

Under the CF Probit and BV Probit approach, there is a latent variable framework for the endogenous binary covariate, h_n, of the following form:

$$h_n^* = G_n + \mu_n = d + z_n\gamma + \mu_n, \tag{A12}$$

where μ_n is an unobserved error term that is presumed to be uncorrelated with the instrument set, z_n . Following the notation of equation (A8) and (A12), the error term in the structural equation can be decomposed as follows:

$$\varepsilon_n = CF(\mu_n) + \hat{\varepsilon}_n, \tag{A13}$$

where the error component $\hat{\varepsilon}_n$ ~ N[0,1] and uncorrelated with the explanatory variables x_n and h_n. $CF(\cdot)$ is the control function designed to capture the covariance between the error terms ε_n and μ_n.

The difference between CF Probit and BV Probit, is a difference in methodology for estimating the unknown covariance between the error terms. BV Probit estimates equations (A8) and (A12) simultaneously by finding the values of *a*, β, Θ, *d*, γ, and ρ to maximize the joint log-likelihood function given by the following:

$$\begin{aligned} LL(a,\beta,\theta,d,\gamma,\rho) = \textstyle\sum_n [&C_n h_n \ln P(V_n > -\varepsilon_n, G_n > -\mu_n) + (1-C_n)h_n \ln P(V_n < -\varepsilon_n, G_n > -\mu_n) \\ &+ C_n(1-h_n)\ln P(V_n > -\varepsilon_n, G_n < -\mu_n) + (1-C_n)(1-h_n)\ln P(V_n < -\varepsilon_n, G_n < -\mu_n)], \end{aligned} \tag{A-14}$$

where the error terms are distributed bivariate normal as follows:

$$\begin{pmatrix} \varepsilon_n \\ \mu_n \end{pmatrix} \sim N\begin{pmatrix} 0 & 1 & \rho \\ 0 ,& \rho & 1 \end{pmatrix}. \tag{A15}$$

The covariance between the error terms, ρ, is one of the free parameters estimated in order to maximize the log-likelihood function, and allowing the error terms to be correlated removes the endogeneity bias from the estimated coefficient β in the structural equation (A-8). The BV Probit methodology is preferred because it makes no functional form assumptions regarding the shape of the control function, $CF(\cdot)$, when estimating the error covariance, ρ.

The CF Probit approach assumes an explicit functional form for the control function. In the simplest form the error terms are assumed to follow a linear relationship as follows:

$$\varepsilon_n = \rho\mu_n + \hat{\varepsilon}_n, \tag{A16}$$

where all variables are as defined in equation (A13), except ρ is the estimated covariance between the error terms ε_n and μ_n. Because the error terms are unobserved, the CF approach first estimates the generalized residual from the helmet use equation (A12) and then includes these residuals in the structural equation (A8) as an additional covariate. Following Gourieroux et al.[28], the probit generalized residuals from (A12) are calculated from the inverse mills ratio as follows:

$$\hat{\mu}_n = h_n\left(\frac{\theta(\hat{G}_n)}{\phi(\hat{G}_n)}\right) - (1-h_n)\left(\frac{\theta(\hat{G}_n)}{1-\phi(\hat{G}_n)}\right), \tag{A17}$$

where $\theta(\hat{G}_n)$ and $\phi(\hat{G}_n)$ are the pdf and cdf for the normal distribution evaluated at the predicted values of G_n from equation (A12).

The CF Probit estimator is a two-step estimator. In the first stage the generalized residuals are estimated in equation (A17). Then in the second stage those residuals are used as additional explanatory variable in the structural equation as follows:

$$C_n^* = V_n + \varepsilon_n = a + x_n\beta + \theta h_n + \rho\hat{\mu}_n + \hat{\varepsilon}_n. \tag{A18}$$

Equation (A18) can then be estimated using probit with a correction to the standard errors to account for the fact that the generalized residuals are estimated. Murphy & Topel[29] provide a general standard error correction for two-stage maximum likelihood models, or the standard errors can be estimated using bootstrapping methods.[30]

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

	First Stage Model Choice:	
	OLS	**Probit**
Variable Name	**Estimated Coefficient (Std. Error)**	**Estimated Coefficient (Std. Error)**
Helmetlaw	0.405***	1.260***
	(0.013)	(0.047)
Sex	-0.050*	-0.135
	(0.027)	(0.087)
Age	-0.008***	-0.021***
	(0.002)	(0.008)
Age^2	0.0001***	0.0003***
	(0.00003)	(0.0001)
Driver	0.137***	0.397***
	(0.032)	(0.098)
Fire	0.052	0.155
	(0.109)	(0.315)
Major Moving Collision	-0.014	-0.063
	(0.024)	(0.075)
Minor Moving Collision	0.017	0.052
	(0.046)	(0.164)
Collision With Fixed Object	-0.022	-0.071
	(0.021)	(0.067)
Rear End	-0.036	-0.087
	(0.027)	(0.088)
Head On	-0.083*	-0.251*
	(0.046)	(0.140)
Angle	-0.031	-0.081
	(0.026)	(0.081)
Side Swipe Same Direction	-0.031	-0.061
	(0.033)	(0.113)
Side Swipe Opposite Direction	0.066	0.226
	(0.063)	(0.200)
Speed limit	0.004***	0.013***
	(0.001)	(0.002)
Constant	0.398***	-0.367**
	(0.056)	(0.174)
R-squared	0.191	----
Pseudo R-squared	----	0.161
Number of obs.	13,610	13,610
F-Statistic (p-value)	1,029.97	----
	(0.000)	----
χ^2-Statistic (p-value)	----	724.18
	----	(0.000)
Predicted Helmet Use:		
Helmet Law States	88.3%	88.0%
States w/o Helmet Law	47.3%	47.3%

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