Sturdy Inference: A Bayesian Analysis of U.S. Motorcycle Helmet Laws

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Motorcycle related fatalities continue to be a major concern for public health officials, economists, and policy makers interested in such matters. In 2006, 3% of all motor vehicles registered in the United States were 2-3 wheelers (motorcycle type vehicles), while riders of these vehicles accounted for 11% of vehicle related deaths. Such a disproportionate number of fatalities associated with motorcycles is certainly grounds for concern.

Most studies of motorcycle fatalities attribute deaths to the avoidance of wearing helmets and the lack of helmet laws, speed, and alcohol usage. This study makes use of a rich panel data set for the period 1980 to 2010 by state and the District of Columbia to examine these factors and others. It is the first study to differentiate between the effects of universal and partial helmet laws on motorcycle fatalities. It also accounts for the effects of cell phone use, alcohol consumption, and suicidal propensities on these crashes after adjusting for a whole host of socioeconomic and driving related factors. The analysis is conducted using a new Bayesian technique, which examines the sturdiness of regression coefficients. This new method uses statistics referred to as S-values that addresses both estimation and model ambiguity. Results indicate that the variables we focus on, i.e., cell phones, alcohol consumption, and helmet laws affect motorcycle fatalities. Further, universal helmet laws appear to have a larger effect on such fatalities than partial helmet laws.

INTRODUCTION

Motorcycle fatalities continue to be of concern to public health officials, economists, and policy makers. It is estimated that motorcyclists have a risk of death in a crash (measured as fatalities per vehicle mile) 34 times higher than experienced in other motor vehicles.[1] In 2006, motorcycles (2-3 wheel vehicles) accounted for 3% of the all motor vehicles registered in the United States. However, motorcycle crashes accounted for 13.7% of motor vehicle crashes that same year.[2] Looking at national trends, one can see that motorcycle fatalities trended downward from 5,144 in 1980 to 2,116 in 1997. The trend then reversed, increasing to 5,312 in 2008. In 2009, fatalities decreased to 4,469 but then started increasing again. By 2011, the number of cyclists killed was 4,612.[3]

The causes of motorcycle fatalities have been attributed to not using helmets and the lack of universal or partial helmet laws, speeding, alcohol, and poor body protection, among others. A great deal of research has gone into estimating the marginal contributions of these factors. However, the results of these studies have not always been convincing or have resulted in significant different estimates of the marginal effects of these factors.[4]

This paper examines the determinants of motorcycle fatalities using traditional econometric models and a new Bayesian technique developed by Leamer (2014, 2016). This new technique extends the analysis presented by Fowles et al. (2015) to examine the sturdiness of regression coefficients with what Leamer refers to as S-values. The analysis employs a rich panel data set by state and the District of Columbia for the period 1980 through 2010.

The models examined not only consider the traditional factors found in many econometric studies, but this paper is one of the first to extend those models to include the effects of cell phone usage and suicidal propensities to motorcycle crashes.[5] Both these latter two factors are recent additions to variables thought to influence motor vehicle crashes and have been found significant in explaining motor vehicle crashes overall as seen, for example, in Blattenberger et al. (2012, 2013).[6] In addition, unlike other studies, this research addresses the relative importance of universal helmet laws versus partial helmet laws in reducing motorcycle fatalities relative to a no helmet law requirement.[7] As such, the paper focuses attention on five factors, i.e., cell phone, two helmet law, and alcohol effects as well as suicidal propensities after adjusting the models for various combinations of normalizing factors.

BACKGROUND

The Focus Variables

The 1966 Highway Safety Act attempted to address safety conditions on U.S. roadways. The act required states to implement a universal helmet law by imposing the risk of reducing up to 10% of their federal highway construction funds for noncompliance. The imposition of a helmet law was expected to increase helmet usage in that head injuries are the most common cause of motorcyclist deaths. The act resulted in 48 states adopting some measure of the law by 1976. However, there was strong opposition to this law by such groups as the American Motorcycle Association. They argued that the act violated a citizen's right of choice. Alternative arguments against requiring the use of helmets were that they were heavy for the riders, impaired vision, and limited hearing. The outcome of these disagreements was the passage of the 1976 Federal Highway Safety Act, which revised the requirement that all riders wear helmets to requiring only those under the age of 18 to wear helmets. Approximately 25% of the states then either abolished or reduced the requirements of the universal helmet law by 1980. Another attempt to increase helmet usage was through the Intermodal Surface Transportation Act of 1991, which provided grants to states that imposed helmet and seatbelt laws. However, this law was repealed in 1995.[8]

Research efforts to establish the efficacy of helmet laws were generally of two types. One method was to compare motorcycle fatalities (and injuries) before and after a state imposed some form of helmet law or, alternatively, the use of regression models to estimate the effect of helmet laws on fatalities.

Hartunian et al. (1983) examined the effect of the repeal of the federal helmet law on motorcycle fatalities. They found an increase in fatalities among the 28 states that repealed or weakened their helmet laws as well as a cost imposed on society of at least $180 million. Graham and Lee (1986) found a 12% to 22% decrease in motorcycle fatalities when a helmet law was in effect. However, they also found some risk-compensation behavior so that the increase in fatalities after deregulation of the helmet law was dissipated over time. Sass and Zimmerman (2000), on the other hand, found helmet laws were associated with a 29% to 33% decrease in motorcycle fatalities per capita. Weiss, (1992) in examining head injuries, found that helmet laws decrease such injuries by 42%. French et al., (2009) using panel data for 48 states and the period 1990-2005, found a significant effect of universal helmet laws on motorcycle fatalities. Sass and Leigh, (1991) using a selectivity model, found that states with helmet laws would experience on average a lower fatality rate than states without such a law by less than 1%. This is clearly a very different result than what would have been expected, a priori, from other studies.

The above studies did not attempt to distinguish between the potential life-saving effects of universal helmet laws as compared with partial helmet laws. Rather, the emphasis was placed on the general viability of helmet laws on motorcycle fatality measures. The present study is the first, other than that of Fowles et al. (2015), using different Bayesian techniques, that separates these effects.

Alcohol consumption has almost uniformly been found to have a significant deleterious effect on motor vehicle safety in general. Although this is not a new factor for consideration, it is of such import that it deserves to be focused on. Alcohol effects on overall motor vehicle fatalities have been found using both classical and Bayesian methods as seen in Loeb et al. (2009), Fowles et al. (2010), and Blattenberger et al. (2012), among others.[9] French et al. (2009) did find that beer consumption per capita was positively correlated to motorcycle fatalities in a statistically significant manner.

Blood alcohol concentration (BAC) thresholds measured in terms of grams of alcohol per deciliter of blood (g/dL), have also been examined in the literature regarding the influence of alcohol on motor vehicle crashes in general. For example, Loeb et al. (2009) found some evidence that diminishing the acceptable limits on BAC to designate driving while impaired reduced vehicle fatalities. Motorcycle fatalities seem to correlate similarly with alcohol usage and BAC measures found in general transportation studies. French et al. (2009, p. 831) note that, "An estimated 34% of all motorcyclists who were fatally injured in 2006 had BAC levels above 0.01 g/dL (NHTSA 2008). In addition, it has been demonstrated that motorcycle riders have a lower helmet usage rate if they were drinking as compared to non-drinkers."[10] However, French et al. (2009) did not find a significant effect on motorcycle fatalities when evaluating a BAC limit equal to or less than 0.08.

In addition, studies to address the effects of alcohol on safety have examined the effect of the minimum legal drinking age on motor vehicle crashes. The results from these studies have not been consistent. For example, Sommers (1985) found a negative relationship between legal drinking age and fatality rates while recently, Blattenberger et al. (2012) and Fowles et al. (2010) found fragile results regarding the effect of the minimum legal drinking age on motor vehicle fatalities.[11] Lin and Kraus (2009, p.716) indicate, "The effects of other possible interventions such as a minimal legal drinking age, …, for motorcycle riders have not been examined."

Recently, two additional factors have been examined for their influence on motor vehicle related fatalities. They are the effects of cell phones and suicidal propensities.[12]

It is argued that cell phone usage contributes to motor vehicle fatalities due to its distracting effect on the driver, the reduction of attention spans, and its propensity to increase reaction time. Cell phone subscriptions have increased exponentially since 1985 when there were 340,000 subscribers to more than 310 million in 2010.[13] Not only has the number of cell phones available to the public increased, but so has the propensity to use them for both phone use and texting. Glassbrenner (2005) has estimated that approximately 10% of all drivers are on their cell phones while driving during daylight hours. Given the apparent danger of using cell phones while driving, 14 states and the District of Columbia have banned their use by drivers (California, Connecticut, Delaware, Hawaii, Illinois, Maryland, Nevada, New Hampshire, New Jersey, New York, Oregon, Vermont, Washington, and West Virginia.)[14]

The statistical evidence regarding the crash effect of a ban on cell phone use by drivers has generally been in support of such bans but not consistently. Redelmeier and Tibshirani (1997) found cell phones are linked to a four-fold increase in property damage while Violanti (1998) found that cell phones are responsible for a nine-fold increase in fatalities. McEvoy et al. (2005) also found evidence linking cell phone use with motor vehicle crashes as did Neyens and Boyle (2007). Consiglio et al. (2003), using a laboratory environment, found that both hand-held and hands-free devices increase brake reaction time while Beede and Kaas (2006) found hand-held devices adversely affected driver performance. However, other researchers found results inconsistent with those above.

Laberge-Nadeau et al. (2003) found a relation between phone use by drivers and crashes, but this relation diminished as their models were expanded. Chapman and Schoefield (1998) argued that cell phones were life-saving due to the "golden hour rule" allowing victims of crashes or onlookers to call for help and get quick medical responses. The probability of surviving an accident increases with the speed aid can be obtained for the victim, and sufficient cell phones in the hands of the public (and possibly by victims themselves) increases the likelihood of a timely medical response. Sullman and Baas (2004) added to these findings with their investigation, which did not find a significant correlation between cell phone use and crash involvement. Similarly, Poysti et al. (2005) found that, "phone-related accidents have not increased in line with the growth of the mobile phone industry."[15]

These inconsistent results led to a study by Loeb et al. (2009) using classical econometrics and specification error tests where cell phones were found to have a non-linear effect on motor vehicle fatalities. Cell phone usage was first associated with increasing fatalities when there was few cell phones in use, which was followed by a life-saving effect on net with the growth of U.S. cell phone subscribers until slightly fewer than 100 million were in use, after which they were associated with increases in fatalities on net. Since, there are over 300 million cell phone subscriptions in the United States, one anticipates a life-taking effect of cell phones. Blattenberger et al. (2012) and Fowles et al. (2010) have also demonstrated a relationship between cell phones and motor vehicle fatalities using Bayesian methods.

Motorcycle drivers have access to cell phones as do all other motor vehicle drivers. They can accommodate their cell phone activities directly through their helmets (if worn) as well as using devices to attach their cell phones to their bikes. One would anticipate a similar distracting effect and reaction time effect due to cell phone use on motorcyclists as found in the general motor vehicle driving population. In addition, drivers using cell phones in other types of motor vehicles may put motorcyclists at risk as well. However, there are no published studies we are aware of that evaluate the cell phone effect just on motorcycle fatalities. This present study will address that omission.[16]

Suicides and suicide rates have rarely been used as determinants in motor vehicle fatality models. However, there is some statistical evidence that suicides and motor vehicle fatality rates are related. For example, Phillips (1979) examined the importance of imitation and found a 31% increase in automobile fatalities three days following a publicized suicide. Pokorny et al. (1972) and Porterfield (1960) also found a relation between suicides and motor vehicle fatalities. Murray and De Leo (2007), using Australian data, also found a relation between suicidal propensities and motor vehicle collisions. One can make a case for this association based on economic grounds in that suicide via automobile may dismiss the stigma to the victim's family and there may be an insurance component to the decision in that death due to an accident may leave the victim's estate with an asset, i.e., a life insurance policy.

However, the association between suicides and automobile crashes is not consistent among studies. For example, Connolly et al. (1995), Huffine (1971), and Souetre (1988) found strong support for this relationship, while others, e.g., Etzerdorfer (1995), question the ability to determine if the victim of the crash was indeed a suicide.

Most recently, Blattenberger et al. (2012), using a large panel data set and Bayesian and classical econometric methods, found a strong statistically significant and non-fragile positive effect of suicides on motor vehicle fatalities. This leads one to consider whether suicidal propensities may have an effect on motorcycle fatalities. As far as we know, this has never been examined in prior research other than by Fowles et al. (2015) using different methods than those employed in this paper. Fowles et al. (2015) found some indication of suicidal influences on motorcycle fatality rates using classical econometric models. However, their results were fragile when using Extreme Bounds Analysis. Their research also used Bayesian Model Averaging procedures, which selected the suicidal influences on motorcycle fatality rates in only 47.1% of the models. This must be normalized by the fact that millions of models were considered. S-values may add some information to the ambiguity these results provide.

Other Normalizing Variables

Motor vehicle speed and speed variance were considered as potentially important determinants of motor vehicle crashes and fatalities in general. Speed adds utility by diminishing travel time and by providing, at least for some, thrills and excitement. Yet speed is associated with an increase in the probability of crashes and deaths. Peltzman (1975), Forrester et al. (1984), Zlatoper (1984), Sommers (1985), and Loeb (1987, 1988) early on found evidence of the life-taking property of speed. However, Lave (1985) argued that speed variance was the speed related factor that led to motor vehicle fatalities. Additional evidence for this was found by Levy and Asch (1989) and Snyder (1989) while Fowles and Loeb (1989) found evidence relating both speed and speed variance to motor vehicle related fatalities. As with the case of motor vehicles in general, speed has been found to have an impact on motorcycle fatalities.[17]

The effect of speed limits on fatality rates pertaining to the general motor vehicle fleet has been previously examined. These statistical results have provided varying conclusions depending on model specification and data used. Forester et al. (1984) and Loeb (1991) found speed limits contributed to fatalities while Garbacz and Kelly (1987) and Loeb (1990) concluded that they seemed to reduce measures of crash fatalities. To confound matters more, Keeler (1994), Blattenberger et al. (2012), and Fowles et al. (2010) found varying results. French et al. (2009) investigated the effect of speed limits on rural interstates and found no significant effect on various measures of motorcycle fatalities, although they did find a negative and significant effect on measures of non-fatal injuries. As such, it appears as if speed limits affect motorcycle fatalities similar to that in the general motor vehicle population based on this limited comparison.

Measures of income are of particular interest to economists when studying motor vehicle crashes. Assuming that driving intensity and safety are normal goods, then the demand for each should increase with income. Peltzman (1975) argued that income would have an ambiguous effect on crashes given its offsetting effects. The net effect of income would depend on the relative strengths of these offsetting effects. In addition, Peltzman argues that transitory income would have a smaller life-saving effect than permanent income. Furthermore, one might notice a different effect using time series data in an analysis, possibly portraying short-run effects, as opposed to models using cross-sectional data which would possibly portray long-run effects. One would anticipate that income might also affect motorcycle purchases and then crashes. Higher incomes might induce affluent and older members of society to purchase large motorcycles, which might be used infrequently, and thus exacerbate motorcycle fatality rates. Similarly, low levels of income and high measures of unemployment rates might result in substituting lower powered (less expensive) motorcycles for automobiles and thus increase the number of motorcycle crashes.

Additional socio-economic factors used to normalize model specifications have been incorporated in the past. These include measures of poverty, measures of education, and the distribution of the population among different age categories. One might expect young drivers to have less experience than older ones and thus take more risks while driving. Asch and Levy (1987), Garbacz (1990), Loeb (1990), and Saffer and Grossman (1987a, 1987b) find such a relationship. However, McCarthy (1992) and Loeb (1985) find a significant negative association between youthful drivers and fatality and injury measures. One might expect either of these to occur with motorcycle crashes given the number of older individuals purchasing motorcycles in the last two decades.[18]

Education levels, crime rates, and poverty have also been used as normalizing factors in models explaining motor vehicle fatality rates. Higher levels of education might be associated with greater stocks of human capital, which would be then expected to be inversely related with risky behavior. At the overall motor vehicle level, Blattenberger et al. (2012) did indeed find some evidence of this. One might expect the same relationship when one only examines motorcycle fatalities. However, higher levels of education are also associated with higher levels of income and there may be some confounding effects if higher income individuals over the age of, for example, 50, start using motorcycles infrequently and, as such, fail to gain significant experience driving motorcycles.

DATA

We utilize data collected on 50 states and Washington, D.C., over the period from 1980 to 2010. The number of motorcycle fatalities per billion vehicle miles traveled is our dependent variable. Our choice of explanatory variables is based on a rich literature (reviewed in the previous section) highlighting the importance of policy, safety, demographics, and economic determinants of fatality rates. Issues related to the choice of these variables, as well as the general form of the models, are well described in Blattenberger et al. (2012, 2013), Fowles et al. (2010), and Loeb et al. (2009). Our data cover years during which there were significant changes in several important variables that are a priori plausible predictors of fatalities. Notably, the data record the complex and changing pattern of helmet laws across states and over time. The data also capture the explosive growth in cell phone subscriptions from effectively zero to over 300 million. Annual subscription data at the state level were only available beginning in year 2000. For the earlier years we used national level data and imputed state level subscriptions to be proportional to state population proportions for the prior years.[19]

Another major change observed in the data relates to changes in federal law that allowed individual states to modify the 55-mph speed limit on their interstate highways. Our data record the highest posted urban interstate speed limit that was in effect during the year for each state. Within the data, per se blood alcohol concentration (BAC) laws vary widely, even though by 2005 all states and the District of Columbia had mandated a .08 BAC illegal per se law.[20] Alcohol consumption, BAC thresholds for addressing issues of driving under the influence of alcohol, and helmet laws have generally been found to be significant, or of interest, as determinants of motorcycle fatalities. These are of particular interest given the review of the literature in the second section.

We investigate the effect of suicides on motorcycle crashes as well, in that individuals may use motorcycles as the instrument in such actions so as to minimize stigma and for a possible insurance/economic benefit to the estate. In addition, suicide in the model may measure to some extent changes in societal risk taking or life preferences. Also, measures of the percent of young males in the population, the minimum legal drinking age, a measure of poverty, the unemployment rate, education levels, the crime rate, and real income are included in the model as normalizing factors as well as a time trend to adjust for changes over time not specifically picked up by the other regressors in the model. However, we focus in particular on five variables: cell phones, suicidal propensities, alcohol consumption, and two helmet factors.[21] The data are organized by the geographical coding of states into 11 regions.[22] The variables are defined and described in Table 1 along with their expected effects (priors) on fatality rates.[23] Descriptive statistics are provided in Table 2.

Table 1: Explanatory Variables Cross Sectional – Time Series Analysis of Motorcycle Fatality Rates for 50 States and D.C. from 1980 to 2010

	Description	Expected Sign
YEAR	A time trend.	-
PERSELAW	Dummy variable indicating the existence of a law defining intoxication of a driver in terms of Blood Alcohol Concentration (BAC). PERSELAW=1 indicates the existence of such a law and PERSELAW=0 indicates the absence of such a law. (More precisely, PERSELAW = 1 when the BAC indicating driving under the influence is 0.1 or lower.)	-
SPEED	Maximum posted speed limit, urban interstate highways, in miles per hour.	?
REGION	Dummy for Regional Fixed Effects (geographical coding from north to south and east to west).	?
BEER	Per capita beer consumption (in gal) per year.	+
MLDA21	Dummy variable indicating the minimum legal drinking age is 21.	-
YOUNG	Proportion of males (16-24) relative to population of age 16 and over.	?
CELLPOP	Number of cell phone subscriptions per 10,000 population.	+
POVERTY	Poverty rate (percentage).	+
UNPLOY	Unemployment rate (percentage).	+
INCOME	Real per household income in 2000 dollars.	?
ED_HS	Percent of persons with a high school diploma.	-
ED_COL	Percent of persons with a college degree.	-
CRIME	Violent crime rate (crimes per million persons).	+
SUICIDE	Suicide rate (suicides per 100,000 population).	?
GINI	The Gini coefficient. An index measuring income einequality (0 as complete equality and 1 as complete inequality).	+
PARTIAL	Dummy variable indicating the presence of a partial helmet law in a given state for a given year.	-
UNIVERSAL	Dummy variable indicating the presence of a universal helmet law in a given state for a given year.	-

[a] For data sources, see Appendix 1.

Table 2: Selected Statistics for Cross Sectional – Time Series Analysis of Motorcycle Fatality Rates for 50 States and D.C. from 1980 to 2010

	Median	Mean	Range	Standard Deviation
Fatality Rate	1.468	1.654	6.753	8.947
YEAR	1995	1995	30	0.308
PERSELAW	1	0.8937	1	0.311
SPEED	65	64.32	25	6.474
BEER	1.3	1.308	1.52	0.227
MLDA21	1	0.8684	1	0.338
YOUNG	0.19	0.1849	0.19	0.027
CELLPOP	12.856	28.221	207.571	32.238
POVERTY	12.5	13.05	24.3	3.949
UNPLOY	5.6	6.012	15.8	2.137
INCOME	22321	23749	64037	10013.310
ED_HS	81.9	80.54	39.7	7.950
ED_COL	22.3	22.82	39.7	6.003
CRIME	4455	4586	10383	1464.556
SUICIDE	12.4	12.8	24.16	3.376
GINI	0.4053	0.4102	0.261	0.036
NO LAW	0	0.09614	1	0.295
UNIVERSAL	0	0.4314	1	0.495
PARTIAL	0	0.4605	1	0.499

CLASSICAL ECONOMETRIC RESULTS

Various specifications of the standard form:

(1) $Y=X\beta + \mu$ are estimated using Ordinary Least Squares. The Full Ideal Conditions[24] are assumed to be upheld where:

(2) $b = (X^TX)^{-1}X^TY$ and

(3) $\mu \sim N(0,\sigma^2 I)$

with Y as the vector of fatality rates, X a matrix of explanatory variables whose composition conceivably varies across specified models, β a vector of unknown slope parameters, μ a vector of disturbance terms, σ^2 a scalar variance parameter, and b the OLS estimator.

Table 3 presents a sample of regression results starting from a fully inclusive model using all of the variables from Table 1 to a simpler model using our focus variables along with a trend, a minimum legal drinking age dummy, an intercept, and regional dummies.[25] The results are generally in compliance with our a priori expectations. Most notably, with regard to our focus variables, all five (cell phones, suicides, helmet laws, and alcohol) are stable in terms of the sign of their respective coefficients and all are statistically significant at a 1% significance level. Of particular interest is the consistent effects of both the universal and partial helmet laws.

Note that model ambiguity is implicit in Table 3 and thus the standard notion of significance level testing assuming any given model is true (the sampling distribution is known) must be relaxed. This issue is addressed in the following section.

BAYESIAN S-VALUES AND THE DETERMINANTS OF MOTORCYCLE FATALITY RATES

Although it is common to indicate regression results for a variety of model specifications, reported statistics are valid on the presumption of a given model's truth. In practice, alternative tests are made on competing models, each sequentially assumed to be true. Inferences based on sequential search procedures are fraught with problems regarding the statistical validity of models' reported summary statistics. Bayesian theory, however, can directly address both estimation uncertainty and model ambiguity. In this paper we utilize advances in Bayesian research regarding model choice as discussed, for example, in Key et al. (1999), and Clyde (1999). An early investigator in model uncertainty was Leamer (1978, 1982, 1983) who, in a book and series of articles, dealt with specification searches.

One Bayesian approach that addresses model uncertainty is Extreme Bounds Analysis (EBA), developed by Leamer (1978). It is a methodology of global sensitivity analysis that computes the possible maximum and minimum values for Bayesian posterior means in the context of linear regression models.[26] One might think of this as an examination of the stability or lack of fragility of coefficients in the models. This is done by examining a multitude of models, which vary in terms of linear combinations of different regressors. The number of models can easily exceed several million.[27] The global bounds are illustrated in Figure 1 for a two-variable regression model. A typical likelihood ellipse is centered at the OLS estimate. The other ellipse is the same shape and passes through the origin (the prior mean) and the OLS estimate. It contains the set of possible posterior means that could be obtained for all prior variance matrices that are positive definite. This larger ellipse is called the feasible ellipse and highlights a main drawback of EBA: that bounds are very wide. In this example, only the second quadrant (negative Beta1, positive Beta 2) is excluded as a possible joint region that could contain the posterior mean. Marginally, both Beta 1 and Beta 2 are fragile in the sense that there are prior variance matrices that could result in negative or positive posterior estimates for either variable.

That the coefficients for all variables in a regression are necessarily fragile from a global EBA perspective highlights the importance of the prior variance. We incorporate a new perspective on the prior variance developed by Leamer (2014, 2016). S-values (sturdiness statistics) reveal aspects of parameter fragility for minimally specified prior variance matrices that "tame" the global bounds from EBA. Figure 2 illustrates how S-values are obtained for a two-variable regression problem. As in Figure 1, we plot typical likelihood ellipses that are centered at the OLS estimate. There are also two circles centered at the origin that represent two iso-prior probability contours that would result from a prior that is centered at zero with spherically symmetric prior variances. The points of tangencies trace the posterior mean from zero to the OLS point. From a non-Bayesian perspective, this is exactly the ridge regression trace (Hoerl and Kennard (1970)). If the prior variance increases, the posterior mean will fall closer to the OLS point, and if the prior variance decreases, the mean falls closer to the origin. Two middle points are associated with two values of the prior variance. These values translate to prior R-square (variance).[28] The larger prior R-square gives more weight to the explanatory variables in the model, and thus the trace is closer to the OLS point. In Figure 2 there is also a shaded ellipse that contains the possible posterior means associated with all linear combinations of the two explanatory variables. Here, notice that the limits for Beta 2 are fragile, but that the limits for Beta 1 are unambiguously positive. The extreme values for means within such an ellipse form the basis for S-values, which are computed as the midpoint of the extremes divided by half their length.

Table 3: OLS Motorcycle Fatality Rate Models for U.S. States from 1980 to 2010 Estimates and (t values)[a]

	Full Model	Model 2	Model 3	Model 4	Model 5
(Intercept)	212.000	218.300	193.100	195.600	263.100
	(13.622)**	(14.259)**	(13.789)**	(15.560)**	(25.824)**
YEAR	-0.106	-0.109	-0.095	-0.096	-0.132
	(-13.225)**	(-13.873)**	(-13.342)**	(-15.011)**	(-25.638)**
PERSELAW	0.027	0.010	0.060		
	(0.489)	(0.179)	(1.111)		
SPEED	-0.004	-0.004	-0.005		
	(-1.051)	(-1.017)	(-1.245)		
BEER	0.409	0.410	0.421	0.422	0.501
	(5.156)**	(5.166)**	(5.314)**	(5.349)**	(6.480)**
MLDA21	-0.262	-0.258	-0.274	-0.272	-0.253
	(-4.574)**	(-4.510)**	(-4.808)**	(-4.802)**	(-4.363)**
YOUNG	-0.035	0.118	0.209		
	(-0.048)	(0.161)	(0.293)		
CELLPOP	0.029	0.029	0.028	0.028	0.030
	(15.944)**	(16.010)**	(18.969)**	(21.060)**	(23.628)**
POVERTY	-0.013				
	(-2.191)*				
UNPLOY	-0.008	-0.013			
	(-0.932)	(-1.646)			
INCOME [b]	0.0001	0.0001			
	(-1.282)	(-0.838)			
ED_HS	-0.016	-0.014	-0.025	-0.025	
	(-2.985)**	(-2.582)**	(-5.444)**	(-5.441)**	
ED_COL	-0.033	-0.032	-0.023	-0.023	
	(-5.198)**	(-4.984)**	(-4.370)**	(-4.354)**	
CRIME [b]	0.0001	0.0001	0.0001	0.0001	
	(2.809)**	(3.095)**	(4.854)**	(5.129)**	
SUICIDE	0.023	0.024	0.021	0.021	0.031
UNIVERSAL	-0.812	-0.815	-0.762	-0.773	-0.668
	(-14.171)**	(-14.205)**	(-13.441)**	(-13.761)**	(-11.789)**
PARTIAL	-0.275	-0.286	-0.252	-0.256	-0.168
	(-5.108)**	(-5.313)**	(-4.695)**	(-4.792)**	(-3.113)**
Adjusted R^2	0.619	0.618	0.612	0.6125	0.588
F-stat [c]	96.210	99.480	109.500	125.900	133.800

a Regional dummy variables were included in the regressions; all are estimated as negative and mostly significant given that the region including Hawaii was the reference region. Hawaii has the highest motorcycle fatality rate. The reference group for helmet laws is NO LAW. OLS estimates using state factor variables were also obtained and results are similar to those above (results available upon request). As noted above, we believe a time trend is an appropriate specification for the gradual improvements in technology and of permanent income, but we also estimated the OLS model using time fixed effects. Again, the results are similar to those presented in Table 3. Significance at the 5% level is indicated by * and at the 1% level by **.
b Coefficients on income and crime < .00001 but coded as .0001
c n = 1581

Figure 1: Feasible Bounds

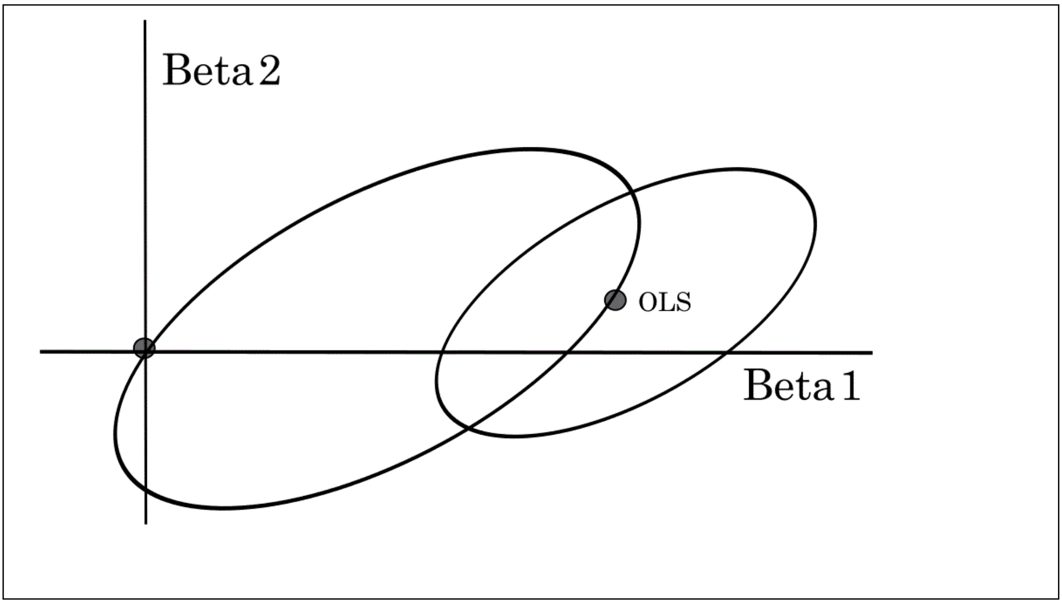
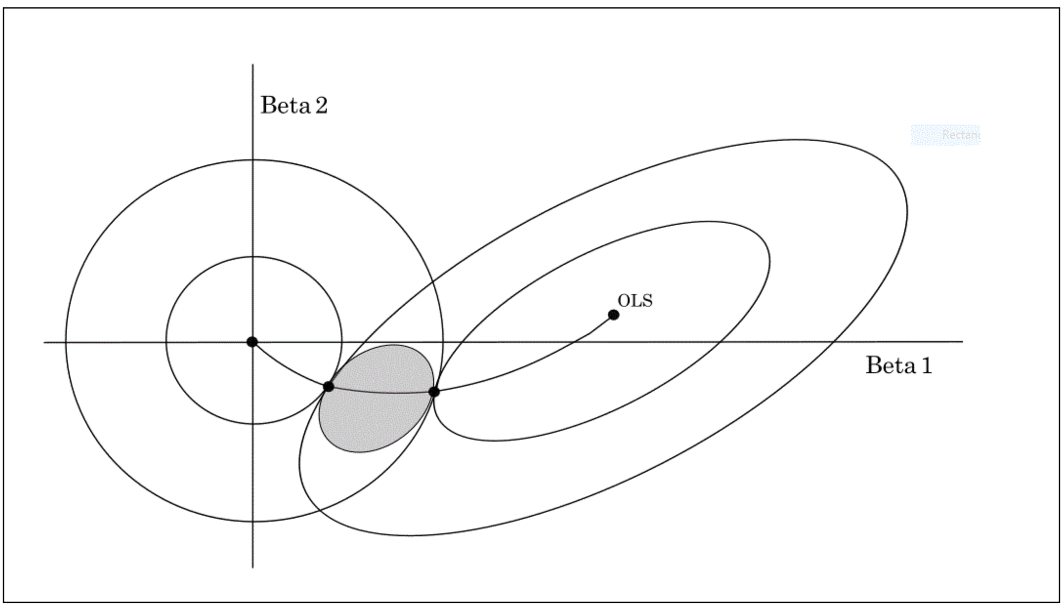


Figure 2: Prior R-square Bounds



As suggested by Leamer (2014, 2016), useful prior R-squares are associated with values of .1 to 1 (wide), .1 to .5 (pessimistic), and .5 to 1 (optimistic). A pessimistic belief is that the explanatory variables would not account for much of the variation in the dependent variable, whereas an optimistic belief is that they do and thus the prior defers to the data.[29]

Table 4 summarizes the findings for our variables of interest based on standardized data.[30] The column "Simple OLS Beta Coefficients" regresses the fatality rate on only the one specified explanatory variable and measures the pairwise correlation between the two variables. Leamer argues that these simple correlations "are a feature of the data, while the 'partial' regression coefficients are cooked up by the analyst when he or she selects the control variables."[31] A different sign in the simple correlation and the partial correlation then "requires scrutiny."[32] It is here that S-values are particularly useful. The next six columns provide lower and upper extreme values for the three specified prior variances, the first two for the wide prior (prior R-squared from 0.1 to 1), the second two for the pessimist prior (prior R-squared from 0.1 to 0.5), and the third two for the optimistic prior (prior R-square from 0.5 to 1). The ninth column, "Multiple OLS Beta Coefficients," provides the standard estimates for the complete model (the t-statistics are shown in the last column). S-values for the wide and optimistic prior are in columns 10 and 11. The shaded cells in Table 4 highlight aspects of model and parameter uncertainty. There are four variables, YEAR, BEER, MLDA, and UNIVERSAL for which all cells are shaded. For these variables, the signs of parameters are always the same, the absolute value of the S-values are greater than one, and the absolute values of the t-statistics are greater than two. These four variables exhibit the highest level of sturdiness. CELLPOP shows sturdiness on the basis of S-values and the S-values conform with t-statistics, in addition, all bounds are non-fragile. However, there is sign switching when viewing the SIMPLE correlation and the coefficient in the full model. This result is due to an aspect of falling fatality rates when cellphones became popular. Again, when other control variables are introduced, CELLPOP is regarded as a sturdy variable.

For non-Bayesians, Table 4 also demonstrates that there is agreement between calculated S-values and t-statistics.[33] Notice that the variable YOUNG has a large optimistic S value (column 11) and a small t statistic (column 12). This is because the bounds for the optimistic prior are not fragile. If one is dubious that YOUNG is an important explanatory variable, then its bounds are fragile (the wide prior) and the corresponding S-value as shown is less than 1. An important feature of this reporting style is that each reader can come to the table with his or her own attitude toward the importance of the variable shown.

These relationships from Table 4 are illustrated in Figure 3 with horizontal lines at the origin and +/- 1 and vertical lines at the origin and +/- 2. Variables in the northeast and southwest quadrants are associated with more certain and sturdy estimates.

CONCLUDING COMMENTS

One of the most important statistical problems is the task of inference in the context of parameter uncertainty and model ambiguity. This challenging task is due to the magnitude of the number of models that need to be considered, often numbering in the millions. In this paper we have looked at the determinants of motorcycle crashes focusing on five specific variables, i.e., alcohol consumption, universal helmet laws, partial helmet laws, cell phone use, and suicidal propensities, after normalizing for other vehicle, economic, and other factors commonly found in the transportation safety literature.

While the effectiveness of helmet laws has been investigated previously, this is the first study which distinguishes universal helmet laws from partial helmet laws and ranks them in importance based on strong Bayesian statistical criteria, i.e., S-values. Cell phone use, while considered in models of overall transportation safety, has not previously been examined with respect to motorcycle fatality rates. Finally, we consider the impact of suicidal propensities on these crashes along with the well-established alcohol effect.

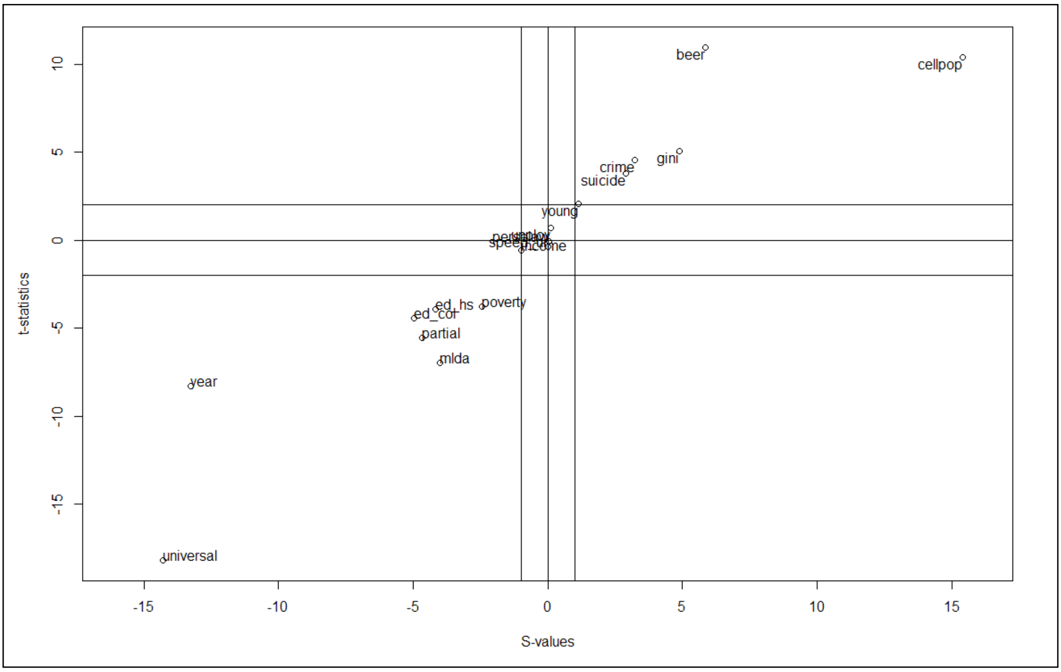
Models are proposed to examine the above factors using a new Bayesian procedure developed by Leamer (2014, 2016), i.e., S-values, along with ordinary least squares. S-values, otherwise known as sturdiness statistics, examine parameter stability among hundreds of thousands or millions of potential models. The estimates are provided in three domains: a pessimistic view of the impact of the explanatory variables on the dependent variable, an optimistic view, and an indifferent or unknowing view. The reviewer of the models can then select the prior view they hold to and compare it to other views, or simply come to some conclusion based on their own prior belief. In addition, we

Table 4: Coefficients, Bounds, and S-values for U.S. Motorcycle Fatality Rates[a]

	Simple OLS Beta Coefficients	R .1 to 1 (wide)		R .1 to .5 (pessimistic)		R .5 to 1 (optimistic)		Multiple OLS Beta Coefficients	R .1 to 1	R .5 to 1	t stat
		Lower	Upper	Lower	Upper	Lower	Upper		S-value	S-value	
YEAR	-4.24E-01	-1.14322	-0.1932	-0.96616	-0.2291	-0.97721	-0.76714	-1.15E+00	-1.40673	-8.30348	-13.2755
PERSELAW	-2.55E-01	-0.06387	0.046331	-0.0562	0.035789	-0.00961	0.008327	3.93E-03	-0.15918	-0.07137	0.041689
SPEED_UR	-1.13E-01	-0.09318	0.055941	-0.08478	0.037264	-0.01835	0.008678	1.58E-02	-0.24971	-0.35782	0.014241
BEER	3.39E-01	0.068837	0.200662	0.083893	0.193137	0.111426	0.133819	1.08E-01	2.044368	10.95176	5.862222
MLDA	-4.40E-01	-0.18508	-0.04362	-0.17988	-0.06459	-0.10451	-0.07835	-6.02E-02	-1.6166	-6.99032	-4.02307
YOUNG	2.95E-01	-0.02218	0.153478	0.005519	0.146652	0.01814	0.052644	-5.98E-03	0.747514	2.051458	1.150619
CELLPOP	-1.97E-01	0.288631	1.050289	0.311952	0.907686	0.773657	0.938028	1.09E+00	1.757903	10.41357	15.42076
POVERTY	6.04E-02	-0.16926	0.037176	-0.15311	0.017714	-0.08398	-0.04862	-5.86E-02	-0.63983	-3.74999	-2.45375
UNPLOY	2.74E-01	-0.03544	0.092132	-0.01797	0.086952	-0.00329	0.019272	-1.56E-02	0.444435	0.708197	0.094037
INCOME	-3.45E-01	-0.48659	0.424038	-0.37493	0.336205	-0.15429	0.043188	-1.07E-01	-0.06869	-0.56261	-0.97521
ED_HS	-3.46E-01	-0.49376	0.029645	-0.45774	-0.04059	-0.26185	-0.15582	-1.33E-01	-0.88672	-3.93928	-4.18701
ED_COL	-2.90E-01	-0.39925	0.056817	-0.34662	0.019582	-0.24393	-0.15412	-2.29E-01	-0.75084	-4.43204	-4.97298
CRIME	1.76E-01	-0.01788	0.197853	0.005535	0.18282	0.067745	0.106064	6.74E-02	0.834274	4.535849	3.2187
SUICIDE	2.04E-01	-0.04983	0.217488	-0.02612	0.194798	0.065006	0.111119	8.42E-02	0.627159	3.819459	2.908027
GINI	-2.48E-01	-0.03791	0.320832	-0.0139	0.27867	0.134479	0.200593	2.05E-01	0.788665	5.068143	4.89885
UNIVERSAL	-3.29E-01	-0.54115	-0.26033	-0.51031	-0.27818	-0.46371	-0.41533	-4.60E-01	-2.85404	-18.1727	-14.2902
PARTIAL	2.18E-01	-0.23208	0.038613	-0.20059	0.022223	-0.15572	-0.10803	-1.58E-01	-0.71471	-5.53049	-4.67269

[a] S-values are obtained by simply taking the ratio of sum of the upper and lower bounds to the difference between them, so the S-values for the pessimistic prior can be obtained from columns 5 and 6.

Figure 3: t-statistics & S-values



compare these Bayesian estimates with that of ordinary least squares. Surprisingly, we find strong agreement between the Bayesian and frequentist approach, given that S-values greater than "1" quite often correspond to t-values of 2 or greater, both in absolute value.

Reviewing the statistical results associated with our focus variables, we find that BEER, our alcohol variable, has a potent effect on the motorcycle fatality rate as seen from all statistics presented. The "Simple" regression result has the same sign as the OLS result. All bounds reported are non-fragile and the S-values all have values (in absolute value) greater than "1" while the t-statistics are greater than "2." This result conforms with the result found by French et al. (2009).

The Partial Law results show a sign change between the "Simple" correlation and the partial correlation found in the OLS regression. The wide bounds and the pessimistic bounds are fragile, while the optimistic bounds are stable. Finally, the S-value for the wide bounds does not show relevance, given that its value is less than "1" in absolute value, while both the optimistic bounds and the t-statistics are favorably portrayed as having an effect on the dependent variable. These inconsistent results can be compared with those associated with the Universal Law effect. Here consistent results are found throughout. That is, the "Simple" result is of the same sign as found in the OLS model. In addition, all bounds, i.e., wide, optimistic, and pessimistic, are non-fragile and finally, the S-values reported for both the wide and optimistic bounds are greater than "1" in absolute value while the t-statistic is greater than "2" in absolute value. Clearly, there is wide support for the importance of the universal law on motorcycle fatality rates.

The statistical results associated with the suicide effect are not uniform. The "Simple" correlation conforms to the OLS results, but both the wide and pessimistic bounds are fragile. However, the optimistic bounds are stable. Only the optimistic S-value and the t-statistic conform with reason to believe SUICIDE is influential. This mixed set of results leaves one in the position of deciding the importance of this factor based on one's prior with respect to optimism or pessimism.

Finally, the results regarding cell phone usage, i.e., CELLPOP, are almost always supportive regarding the importance of this variable. All bounds are stable and the S-values for both the wide and the optimistic bounds are greater than "1." In addition, the t-statistic is greater than "2."

However, the "Simple" result differs from the OLS result in terms of sign. Leamer would argue that this requires scrutiny. However, these results are expected. The negative coefficient in the SIMPLE result is due to the association between cell phones and the time trend. Over time, the number of cell phones increased exponentially. The time trend shows a strong negative association with the fatality rate as seen in the OLS result. Hence, we argue that the "SIMPLE" result in this case is not at odds with all of the other results. This suggests that cell phone usage is indeed a contributor to motorcycle fatality rates.

The statistical results, both Bayesian and classical, support potential public policies on alcohol, universal helmet laws, and cell phone usage as they impact motorcycle fatality rates. For example, they suggest stricter policing and strong fine structures be imposed on motorcyclists driving while under the influence of alcohol and perhaps funding for substance abuse treatment centers be considered by governments.[34]

In addition, we have found strong evidence that universal helmet laws are superior to partial helmet laws. This suggests that Congress or the states might consider imposing once again legislation promoting such universal helmet laws.

Cell phone usage has been found to contribute to motorcycle fatality rates. It is not unusual for motorcyclists to have the ability to use cell phones while driving along with other drivers and pedestrians. Evidence has been provided at length about the effect of cell phone use on other modes of transportation, and perhaps this is the time to investigate the appropriateness of imposing bans on cell phone use on all drivers beyond the 14 states and DC where such bans exist for hand-held devices and expanding the ban further to include hands-free devices. This could be accomplished by stricter policing of such laws and a viable fine structure.

The suicide effect was not found as significant on motorcycle fatality rates as on motor vehicle fatality rates in general.[35] However, to review, support for this variable is found with regard to the consistency of signs in the "SIMPLE" and OLS results along with stable optimistic bounds and a large S-value associated with optimistic bounds and a large t-statistic. It may prove beneficial to consider this factor further since high suicide states are also high motor vehicle fatality states.[36] In addition, suicides are a leading cause of death among young people in the United States, making it an important factor from a public health perspective.[37] Interestingly, suicides have also been found to be an area of concern with other modes of transportation, in particular with railroads.[38] It may be that suicidal propensities are measuring changes in risk taking propensities by individuals or society in general. A potential avenue of future research may be to investigate the effectiveness of posting phone numbers/help lines for those suffering from emotional or psychiatric issues who might benefit from this and/or the investment of public monies to reduce reckless or violent behaviors while driving.[39] However, it seems that suicidal propensities are not as pronounced for motorcycle fatalities as they are for automobile fatalities.

Endnotes

1. See Lin and Kraus (2009).

2. See NHTSA (2006).

3. See National Highway Traffic Safety Administration (2011).

4. An early review of the causes of motorcycle crashes along with other transportation related crashes can be found in Loeb et al. (1994).

5. The only other paper investigating these, and the other focus variables mentioned as applied to motorcycle fatalities, is that of Fowles et al. (2015). But that paper makes use of different

Bayesian techniques, i.e., Extreme Bounds Analysis (EBA) and Bayesian Model Averaging (BMA). The approach applied here extends that analysis and is heuristically more accessible.

6. The general form of the models estimated and the independent variables included in the models are based on the general work dealing with regulations suggested by Peltzman (1975), French et al. (2009) and Lin and Kraus (2009). The models take into account that motorcycle fatality rates are related to driver characteristics, road characteristics, and a host of other socio-economic factors commonly found in studies dealing with crashes.

7. Universal helmet laws require all motorcyclists to wear a helmet while partial helmet laws require only some motorcyclists to wear a helmet.

8. See National Highway Traffic Safety Administration (NHTSA), (2003) for a review of legislative history.

9. See Loeb et al. (1994) for additional reviews, some showing opposite or insignificant results.

10. See Lin and Kraus (2009, pp. 712-713) for a review of this literature.

11. See Loeb et al. (1994) for additional reviews.

12. Some preliminary work on these factors using alternative Bayesian techniques have been investigated by Fowles et al. (2015).

13. See CTIA (2011).

14. See Governors Highway Safety Association (2015) for the list of states banning cell phone use.

15. See Poysti et al. (2005, p. 50).

16. See Fowles et al. (2015) for further discussion.

17. See Lin and Kraus (2009), and Shankar (2001).

18. Between 1985 and 2003, the percentage of motorcycle owners who were 50 or older steadily grew from 8.1 to 25.1%. See Morris (2009).

19. Our method of imputing cell phone subscriptions correlates with the actual data with a correlation coefficient of .9943.

20. The per se law refers to legislation that makes it illegal to drive a vehicle at a blood alcohol level at or above the specified BAC level. BAC is measured in grams per deciliter.

21. We are interested not only in the effects of universal helmet laws and partial helmet laws, but which has a stronger and less uncertain effect on motorcycle fatality rates.

22. The use of regions mirrors the U.S. standard federal regions, but we isolate Alaska and Hawaii since they are non-contiguous. In all analyses in the paper, the regional variables are included, but results are not presented.

23. The anticipated sign for YEAR as a time trend is negative because it proxies advances in technology and possibly permanent income. Poverty is anticipated to have a positive effect as it serves as a proxy for state infrastructure, such as improved highways, traffic enforcement, and faster emergency response times. Income inequality and crime are anticipated to have positive

signs that may reflect social malaise or risk seeking behaviors. These variables are discussed in Blattenberger et al. (2013). As noted above, mixed results in previous literature are associated with young riders, so we are uncertain as to the anticipated sign of this variable.

24. See Ramsey (1974) and Ramsey and Zarembka (1971).

25. Similar models for total motor vehicle fatality rates have been investigated in prior research for specification errors of omission of variables, misspecification of the structural form of the regressors, simultaneous equation bias, serial correlation, and non-normality of the error term and found to be in compliance with the Full Ideal Conditions. See, for example, Loeb, et al. (2009). In addition, see Fowles et al. (2013) and Loeb and Clarke (2009).

26. Mathematical developments are found in Leamer (1982).

27. See, for example, Leamer (1978, 1982, 1983), Blattenberger et al. (2012, 2013), and Fowles et al. (2015).

28. The Bayesian natural conjugate model that corresponds with the classical model presented above (equations 1-3), sets the prior variance for the β's = var(β) = $v^2 I_{\mathbf{kxk}}$ where I_{kxk} is the k by k identity matrix. Bounds are obtained via the scalar v^2, which is set to the minimum or maximum expected R-square divided by k. See Leamer (2014, 2016) for details. Calculations are performed in the software R (R Development Core, 2016).

29. A super pessimist prior is to exclude a variable from a regression, so the prior mean is at zero and the variance is zero as well (prior R-square zero). In this paper, we do not consider this kind of strict prior.

30. Regional dummies were included as explanatory variables but results are not shown in Table 4.

31. See Leamer (2014).

32. See Leamer (2014).

33. For the prior R-square at 1, the correlation is .9329.

34. See Chaloupka et al. (1993) and Freeborn and McManus (2007).

35. See, for example, Blattenberger et al. (2013).

36. See Blattenberger et al. (2013).

37. See Centers for Disease Control and Prevention (2012).

38. See, for example, Savage (2007).

39. See Savage (2007) and Connner et al (2001).

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Appendix 1: Data Sources

Name	Data Source
MCFATAL	Highway Statistics (various years), Federal Highway Administration, Traffic Safety Facts (various years), National Highway Traffic Safety Administration
PERSELAW	Digest of State Alcohol-Highway Safety Related Legislation (various years), Traffic Laws Annotated 1979, Alcohol and Highway Safety Laws: A National Overview 1980, National Highway Traffic Safety Administration
SPEED	Highway Statistics (various years), Federal Highway Administration
BEER	U.S. Census Bureau, National Institute on Alcohol Abuse and Alcoholism
MLDA21	A Digest of State Alcohol-Highway Safety Related Legislation (various years), Traffic Laws Annotated 1979, Alcohol and Highway Safety Laws: A National Overview of 1980, National Highway Traffic Safety Administration, U.S. Census Bureau
YOUNG	State Population Estimates (various years), U.S. Census Bureau http://www.census.gov/population/www/estimates/statepop.html
CELLPOP	Cellular Telecommunication and Internet Association Wireless Industry Survey, International Association for the Wireless Telecommunications Industry.
POVERTY	Statistical Abstract of the United States (various years), U.S. Census Bureau website http://www.census.gov/hhes/poverty/histpov19.html
UNPLOY	Statistical Abstract of the United States (various years), U.S. Census Bureau
INCOME	State Personal Income (various years), Bureau of Economic Analysis website http://www.bea.doc.gov/bea/regional/spi/dpcpi.htm
ED_HS	Digest of Education Statistics (various years), National Center for Education Statistics, Educational Attainment in the United States (various years), U.S. Census Bureau
ED_COL	Digest of Education Statistics (various years), National Center for Education Statistics, Educational Attainment in the United States (various years), U.S. Census Bureau
CRIME	FBI Uniform Crime Reporting Statistics website http://www.ucrdatatool.gov
SUICIDE	Statistical Abstract of the United States (various years), U.S. Census Bureau
GINI	University of Texas Inequality Project website http://utip.gov.utexas.edu
UNIVERSAL PARTIAL	Governors Highway Safety Association http://www.ghsa.org/html/stateinfo/laws/helmet_laws.html (accessed 6/6/2015)
REGION	US States 1: ME, NH, VT; 2: MA, RI, CT; 3: NY, NJ, PA; 4: OH, IN, IL, MI, WI, MN, IA, MO; 5: ND, SD, NE, KS; 6: DE, MD, DC, VA, WV; 7: NC, SC, GA, FL; 8: KY, TN, AL, MS, AR, LA, OK, TX; 9: MT, ID, WY, CO, NM, AZ, UT, NV; 10: WA, OR, CA; 11: AK, HI