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Motorcycle Fatalities Revisited: A Classical and Bayesian Analysis

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Abstract

This paper examines the determinants of motorcycle fatality rates using panel data and classical and Bayesian statistical methods. It focuses on five variables in particular: universal helmet laws, partial helmet laws, cell phone use, suicidal propensities, and beer consumption. Universal helmet laws are found to be favored over partial helmet laws to reduce motorcycle fatality rates while cell phone use is found to be a significant contributor to motorcycle fatalities as is alcohol consumption. Suicidal propensities are also shown to contribute to these accidents.

Keywords: motorcycle fatalities, cell phones, helmet laws, alcohol consumption, suicide, Bayesian econometrics.
JEL Classification: I18, C11

Motorcycle Fatalities Revisited: A Classical and Bayesian Analysis

I. 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) which is 34 times higher than experienced in other motor vehicles.[1] In 2006, motorcycles (2-3 wheel vehicles) accounted for three percent of the all motor vehicles registered in the U.S. However, motorcycle accidents accounted for eleven percent of motor vehicle accidents 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.[3] In 2009, fatalities decreased to 4,469 but then started increasing again. By 2011, the number of cyclists killed was 4,612.[4]

The causes of motorcycle fatalities have been attributed to the avoidance of the use of 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.[5]

This paper examines the determinants of motorcycle fatalities using econometric models and two Bayesian techniques. The analysis employs a rich panel data set by state

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[1] See Lin and Kraus (2009).
[2] See NHTSA (2008).
[3] In Appendix 3 we provide a time series plot of motorcycle fatality rates for the fifty US states and Washington DC.
[4] See National Highway Traffic Safety Administration (2011).
[5] An early review of the causes of motorcycle accidents along with other transportation related accidents can be found in Loeb et al. (1994).

for the period 1980 through 2010. The models examined not only consider the traditional factors found in many econometric studies but this paper is the first paper to extend those models to include the effects of cell phone usage and suicidal propensities. Both of these latter two factors are recent additions to variables thought to influence motor vehicle accidents and have been found significant in explaining motor vehicle accidents overall as seen, for example in Blattenberger et al. (2012, 2013).[6]

II. Background

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 percent 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

[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) and French et al. (2009) and Lin and Kraus (2009).

Transportation Act of 1991 which provided grants to states that imposed helmet and seatbelt laws. However, this law was repealed in 1995.[7]

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 which 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 percent 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 29-33 percent decrease in motorcycle fatalities per capita. Weiss (1992) examining head injuries found that helmet laws decrease such injuries by 42 percent. 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 one percent. This is clearly a very different result than what would have been expected, a priori, from other studies.

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

Alcohol consumption has almost uniformly been found to have a significant deleterious effect on motor vehicle safety in general. This has 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.[8]

Blood Alcohol Thresholds (BAC) have also been examined in the literature regarding the influence of alcohol on motor vehicle accidents in general. For example, Loeb et al. (2009) has 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 percent 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."[9] 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. French et al. (2009) did find that beer consumption per capita was positively correlated to motorcycle fatalities in a statistically significant manner.

In addition, studies to address the effects of alcohol on safety, have examined the effect of the minimum legal drinking age on motor vehicle accidents. 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

[8] See Loeb et al. (1994) for additional reviews, some showing opposite or insignificant results.
[9] See Lin and Kraus (2009, pp. 712-713) for a review of this literature.

Minimum Legal Drinking Age on motor vehicle fatalities.[10] 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." However, the general effects noted above are based on data inclusive of all motor vehicle fatalities.

Motor vehicle speed and speed variance were considered as potentially important determinants of motor vehicle accidents 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.[11]

The effect of speed limits on fatality rates pertaining to the general motor vehicle fleet has been examined in the past. 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

[10] See Loeb et al. (1994) for additional reviews.
[11] See Lin and Kraus (2009), and Shankar (2001).

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 similarly 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 accidents. 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 accidents. 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 automobiles for lower powered (less expensive) motorcycles and thus increase the number of motorcycle accidents.

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 accidents given the number of older individuals purchasing motorcycles in the last two decades.[12]

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, forty start using motorcycles infrequently and, as such, fail to gain significant experience driving motorcycles.

Recently there have been two additional factors which have been examined for their influence on motor vehicle related fatalities. They are the effects of cell phones and suicidal propensities. 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 thousand subscribers to over 310 million

[12] Between 1985 and 2003, the percentage of motorcycle owners who are fifty or older steadily grew from 8.1 to 25.1 percent. See Morris (2009).

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 ten percent of all drivers are on their cell phone while driving during daylight hours. Given the apparent danger of using cell phones while driving, fourteen states plus 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 ban of cell phone use by drivers has generally been in support of such bans, but not consistently. Redelmeier and Tibshirani (1997) find cell phones are linked to a four-fold increase in property damage while Violanti (1998) finds that cell phones are responsible for a nine-fold increase in fatalities. McEvoy et al. (2005) also finds evidence linking cell phone use with motor vehicle accidents 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 accidents 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

[13] See CTIA (2011).
[14] See Governors Highway Safety Association (2015) for the list of states banning cell phone use.

by victims themselves) increases the likelihood of a timely medical response. Sulliman 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 among the population was first associated with increasing fatalities when there was a low volume of cell phones in use among the public followed by a life-saving effect on net with the growth of cell phone subscribers in the U.S. 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 U.S., 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. Importantly, cell phone using drivers in other types of motor vehicles may put motorcyclists at risk as well.

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

However, there are no studies, that we are aware of, that evaluate the cell phone effect just on motorcycle fatalities. This present study will address that omission.

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 propensity and motor vehicle collisions. One can make a case for this association based on economic grounds in that suicide via motor vehicle may reduce 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 vehicle 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 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.

III. Data

We utilize a rich set of 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 literature reviewed in Section II that highlights the importance of policy, safety, demographic, 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 motorcycle 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.[16]

Another major change observed in the data relates to changes in Federal law that allowed individual states to modify the 55 mile per hour speed limit on their interstate highways. Our data records 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.[17] Alcohol consumption, BAC thresholds for addressing issues of driving under the influence of alcohol and helmet laws have

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

[17] 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.

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 Section II.

We investigate the effect of suicides on motorcycle accidents 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.[18]

The data are organized by the geographical coding of states into eleven regions.[19] The variables are defined and described in Table 1 along with their expected effects (priors) on fatality rates.[20] Descriptive statistics are provided in Table 2.

[18] 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.
[19] The use of regions mirrors the US standard federal regions, but we isolate Alaska and Hawaii since they are non-contiguous. In all analyses the regional variables are included but results are not presented.
[20] 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 serving as a proxy for infrastructure such as improved highways and faster emergency response. Income inequality and crime are anticipated to have positive signs that may reflect social malaise or risky behaviors (see Blattenberger et al. (2013)). Mixed results in previous literature are associated with young riders, so we are uncertain as to the anticipated sign of this variable.

Table 1
Explanatory Variables [a]
Cross Sectional - Time Series Analysis of Motorcycle Fatality Rates
For 50 States and DC 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) of 0.1 or lower. PERSELAW=1 indicates the existence of such a law and PERSELAW=0 indicates the absence of such a law.	-
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 inequality (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 DC 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

IV. Classical Econometric Results

Various specifications of the standard form:

(1) $Y=X\beta + \mu$ are estimated using Ordinary Least Squares. The Full Ideal Conditions[21] are assumed to be upheld where:

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

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

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.

[21] See Ramsey (1974) and Ramsey and Zarembka (1971).

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.[22] 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.[23]

Note that model uncertainty 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.

[22] 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).

[23] Some additional insight on the relative importance of the focus variables (as well as other explanatory variables) from a classical perspective can be obtained using standardized data and our OLS regression results. Appendix 2 provides these standardized OLS Regression Coefficients for the classical full model specification. The focus variables ranked in order of importance using this technique are: cell phones, universal helmet laws, partial helmet laws, alcohol, and suicides.

Table 3
OLS Motorcycle Fatality Rate Models for US States from 1980 to 2010
Estimates and (t values)

	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[a]	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[a]	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
	(2.838)	(2.926)	(2.606)	(2.638)	(4.391)
GINI	4.899	4.346			
	(5.321)	(4.902)			

Table 3
OLS Motorcycle Fatality Rate Models for US States from 1980 to 2010
Estimates and (t values) (Continued) [24]

	Full Model	Model 2	Model 3	Model 4	Model 5
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 [b]	96.210	99.480	109.500	125.900	133.800

[a] Coefficients on income and crime < .00001 but coded as .0001
[b] n = 1581

V. Bayesian Model Averaging (BMA)

Although it is common to report regression results for a variety of model specifications, reported statistics are valid on the presumption of a given model's truth. Often alternative tests are made on a multitude of competing models, each sequentially assumed to be a true model. Inferences based on sequential search procedures are fraught with problems of doubt regarding the statistical validity of reported summary statistics. Bayesian theory, however, can directly address model uncertainty and 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, 1985, and 1997) who, in a book and series of articles, dealt

[24] 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. 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 as a factor. Again, the results are similar to those presented in Table 3.

with specification searches. Bayesian Model Averaging (BMA) was a product of this work and is discussed in depth by Raftery et al. (1997).

By averaging across many model specifications, BMA is able to explicitly account for model uncertainty as it relates to parameter estimation. As presented in Hoeting et al. (1999), BMA provides a straightforward method to summarize the effects of explanatory variables as measured by their regression coefficients as they are manifested in assorted models.

Table 4 summarizes BMA analysis for the full model presented above (in Table 3), regressing fatality rates on the core set of explanatory variables.[25] Thousands of models are considered and the top models ranked in terms of highest posterior probabilities (linked to measures of fit) are retained.[26] From among these, the top five are shown in Table 4. The column headed "p!=0" gives the posterior probability that the particular variable is included in the model. The "EV" column shows the average posterior mean for that variable's coefficient in the BMA runs and "SD" is the average posterior standard deviation for that variable's coefficient. Over all models, BMA never chooses to include PERSELAW, SPEED, YOUNG, and INCOME, and rarely chooses to include UNPLOY (2.1 percent). The procedure always includes YEAR, BEER, MLDA21, CELLPOP, ED_COL, GINI, UNIVERSAL, and PARTIAL. In addition, CRIME is included in 90.4 percent of the top models, SUICIDE in 47.1 percent, and ED_HS in 24.8 percent. POVERTY is included in just under ten percent of the models. One might note that OLS and BMA results are in complete agreement in the sense that all variables that are always included in BMA have extraordinarily high t values (absolute

[25] BMA results were obtained using the bicreg procedure. See Raftery et al. (2009).
[26] Here, we chose to retain models with a posterior odds ratio greater than 20 to 1.

values > 4.5) in Table 3 (Full Model). Once again, as with the OLS results, both the universal and partial helmet laws appear to be important in diminishing motorcycle fatality rates.

Table 4
Bayesian Model Averaging for
Motorcycle Fatality Rate Models for US States from 1980 to 2010 [27]

	p!=0	EV	SD	model 1	model 2	model 3	model 4	model 5
(Intercept)	100	235.400	14.440	237.200	242.100	220.400	239.600	236.600
YEAR	100	-0.118	0.007	-0.119	-0.122	-0.110	-0.120	-0.119
PERSELAW	0	0.000	0.000	.	.	.	.	.
SPEED	0	0.000	0.000	.	.	.	.	.
BEER	100	0.443	0.086	0.465	0.396	0.400	0.440	0.498
MLDA21	100	-0.263	0.057	-0.260	-0.271	-0.271	-0.253	-0.269
YOUNG	0	0.000	0.000	.	.	.	.	.
CELLPOP	100	0.029	0.001	0.029	0.029	0.028	0.029	0.029
POVERTY	9.8	-0.001	0.003	.	.	.	.	.
UNPLOY	2.1	0.000	0.002	.	.	.	.	.
INCOME [a]	0	0.000	0.000	.	.	.	.	.
ED_HS	24.8	-0.003	0.006	.	.	-0.013	.	.
ED_COL	100	-0.041	0.006	-0.044	-0.041	-0.033	-0.044	-0.043
CRIME [a]	90.4	0.000	0.000	0.000	0.000	0.000	0.000	0.000
SUICIDE	47.1	0.011	0.013	.	0.023	0.028	.	.
GINI	100	4.549	0.891	4.265	5.006	4.024	4.653	4.412
UNIVERSAL	100	-0.813	0.059	-0.803	-0.833	-0.834	-0.786	-0.803
PARTIAL	100	-0.279	0.054	-0.280	-0.291	-0.284	-0.282	-0.265
Number of Variables				14	16	17	15	15
R^2				0.618	0.621	0.623	0.619	0.619
Posterior Probability				0.179	0.173	0.14	0.072	0.054

[a] Coefficient on CRIME and INCOME < .00001 but EV and SD coded as 0.000

VI. Extreme Bounds Analysis

As a final test of inferential stability, we examine the motorcycle fatality model using Bayesian Extreme Bounds Analysis (EBA) developed by Leamer (1978). It is a methodology of global sensitivity analysis that computes the maximum and minimum values for Bayesian posterior means in the context of linear regression models. Here we use a simple normal-gamma model in standard notation:

$$Y_{it} = X_{it}\beta + \mu_{it}$$
$$i = 1, 2, \ldots, 51 \qquad (4)$$
$$t = 1, 2, \ldots, 31$$

[27] Regional variables were included, but results are not reported.

The standard conjugate prior distributions for this model are specified

$$\beta \sim N(\beta_0, \Sigma_0)$$

$$\text{(5)} \qquad \mu \sim N(0, \pi^{-1})$$

$$\pi \sim \Gamma(v, \lambda).$$

We can visualize how EBA works using a two-dimensional simplification. The basic model is illustrated in Figure 1. The likelihood contours implied by the data are shown along with the maximum likelihood (MLE) or OLS estimate, b. In addition, the prior contours implied by the prior location, β_0, and the prior precision, Σ_0^{-1}, are shown.[28] The posterior mean for this sample and prior is a matrix weighted average of the sample and prior values:

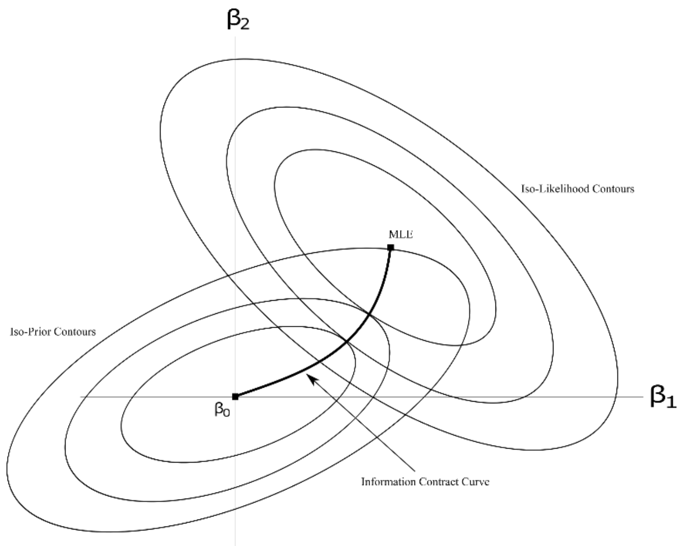
$$\text{(6)} \quad \beta = (\Sigma_0^{-1} + X'X)^{-1}(\Sigma_0^{-1}\beta_0 + X'Xb)$$

The potential set of posterior means for this prior and likelihood are indicated by the relation labeled the information contract curve which is comprised of the locus of tangencies between the iso-likelihood contours and the iso-prior contours. The exact position of the posterior mean along this curve is a function of the relative sample and prior precisions. With strong priors, the posterior mean is pulled closer to the prior mean and with strong data, the posterior mean is closer to the MLE estimate. EBA is illustrated in the context of this model.[29]

[28] As is common in Bayesian statistics, we use Σ_0^{-1} as prior precision, the inverse of the prior variance/covariance matrix for the vector β. The precision parameters associated with the gamma distribution for the prior distribution are accounted for in EBA where prior precision is allowed to vary from zero to infinity.

[29] Mathematical developments are found in Leamer (1982).

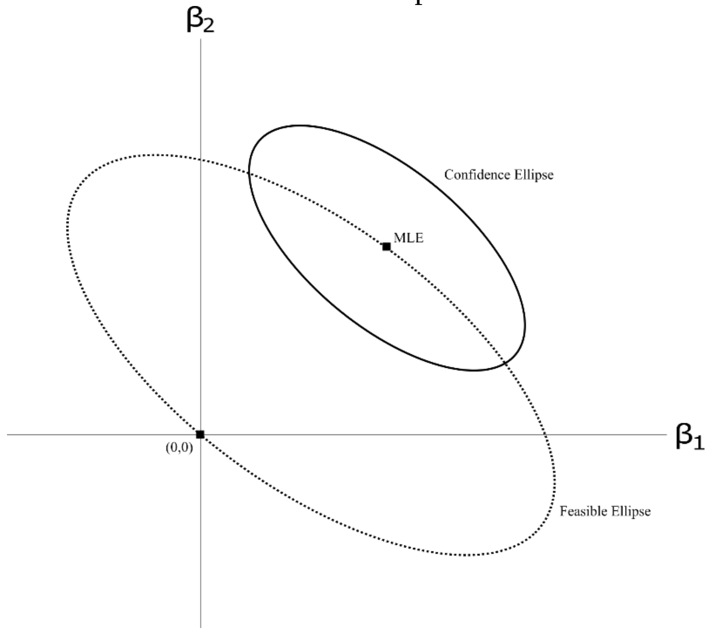
Figure 1
Likelihood/Prior Contours & Information Contract Curve



The analysis depicted in Figure 1 requires specifying both a prior mean vector, β_0, and a prior precision matrix, Σ_0^{-1}. Variables that have a well specified prior mean at zero are called doubtful variables since a researcher would be comfortable including or excluding such variables. Sets of variables that would not be excluded are called free variables and there are no priors associated them.[30] In a remarkable result of Chamberlain and Leamer (1976), posterior means fall within a feasible ellipse for both doubtful and free variables under minimal assumptions regarding the nature of the precision matrix, Σ_0^{-1}. The feasible ellipse is illustrated in Figure 2 along with an example of a confidence ellipse, from which the feasible ellipse takes its shape. As indicated by this figure, the range of potential posterior values associated with the feasible ellipse, called global bounds, necessarily encompasses zero. In terms of priors, these bounds are associated with prior precisions swept from zero to infinity. Without further restrictions all variables are necessarily fragile with global bounds covering zero.

[30] Priors that are completely uninformative (or diffuse) are associated with free variables. Because proper prior information is required for some parameters for meaningful EBA, we select variables that one might be comfortable dropping from a model specification. From a Bayesian perspective, dropping a variable is exactly the same as imposing a proper prior on that variable with a prior mean of zero and perfect precision (the prior variance also zero). In this sense, EBA results reflect the free/doubtful mix of variables.

Figure 2
Feasible Ellipse



Because the global bounds are wide, we can focus attention to values of bounds that are highly likely, for example those falling within the 95% confidence ellipsoid. Bounds within the 95% ellipsoid are referred to as being data favored. Figure 3 illustrates the implication of this restriction for the extreme bounds on the parameter values. In this illustration the extreme bounds on β_2 are positive and X_2 is not a fragile variable while bounds on β_1 cover zero and thus X_1 is fragile. It is also reasonable to specify the doubtful/free mix. In Figure 4, we illustrate EBA bounds when X_2 is set as a doubtful variable and X_1 is considered as a free variable. As shown here, bounds on β_1 do not cover zero, and thus X_1 is not considered fragile.

Figure 3
Extreme Global and Data Favored Bounds Within 95% Likelihood Contour
With X_1 and X_2 Doubtful

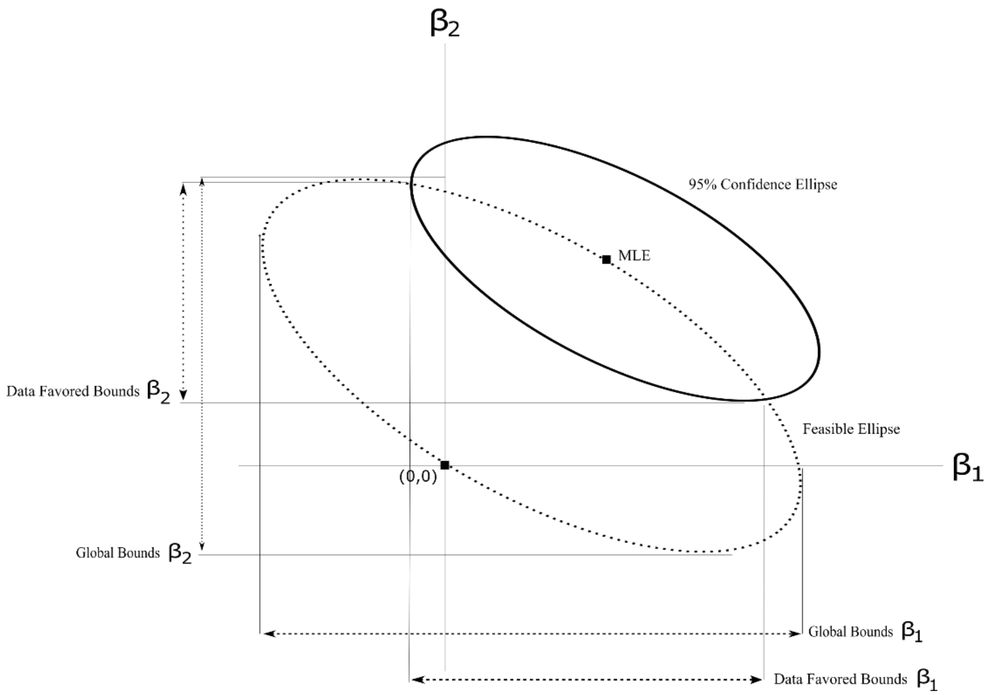
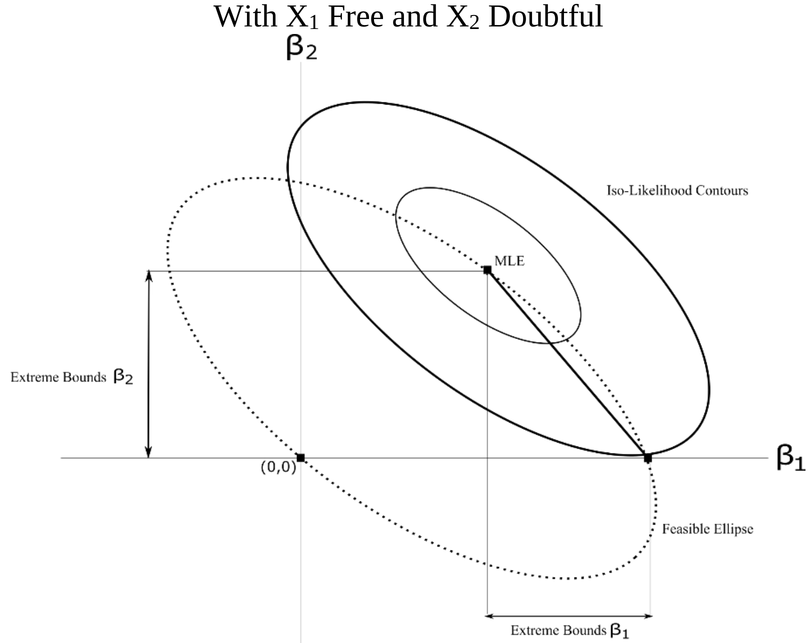


Figure 4
Extreme Global Bounds
With X_1 Free and X_2 Doubtful



Empirical results for data favored bounds when all seventeen explanatory variables are set to be doubtful are presented in Table 5.[31] With this very agnostic specification, the three variables YEAR, CELLPOP, and UNIVERSAL are shown to be non-fragile. In Table 6, data favored and global bounds are shown when our five focus variables, BEER, CELLPOP, SUICIDE, UNIVERSAL, and PARTIAL are set as free variables (and the other twelve set as doubtful).[32] In this specification YEAR, BEER, CELLPOP, UNIVERSAL, and PARTIAL are seen to be non-fragile within 95% data favored bounds. Further, Table 6 shows that UNIVERSAL is non-fragile globally and is the only variable with this characteristic. For these data, no matter what other variables are included or excluded (or even all possible linear combination of the other variables), the posterior mean for UNIVERSAL is always negative.

[31] Regional variables and a constant were designated as free variables, results are not shown.
[32] Regional variables and a constant were included but results are not shown.

Table 5
Maximum Likelihood and EBA Upper and Lower Bounds within 95% Confidence Ellipsoids
All Variables Considered Doubtful
Non-Fragile Bounds Shaded

Variable	MLE	Upper 95%	Lower 95%
YEAR	-0.1055	-0.0541	-0.1524
PERSELAW	0.0270	0.3783	-0.3253
SPEED	-0.0039	0.0197	-0.0272
BEER	0.4086	0.9036	-0.1014
MLDA21	-0.2616	0.1064	-0.6201
YOUNG	-0.0352	4.6824	-4.7515
CELLPOP	0.0287	0.0390	0.0171
POVERTY	-0.0131	0.0252	-0.0508
UNPLOY	-0.0077	0.0449	-0.0599
INCOME	0.0000	0.0000	-0.0001
ED_HS	-0.0161	0.0185	-0.0501
ED_COL	-0.0331	0.0079	-0.0728
CRIME	0.0000	0.0001	-0.0001
SUICIDE	0.0228	0.0736	-0.0288
GINI	4.8996	10.6471	-1.0271
UNIVERSAL	-0.8118	-0.4430	-1.1459
PARTIAL	-0.2752	0.0716	-0.6120

Table 6
Maximum Likelihood, EBA Upper and Lower Bounds within 95% Confidence Ellipsoids, and EBA Global Bounds with BEER, CELLPOP, SUICIDE, UNIVERSAL, and PARTIAL as Free Variables
Non-Fragile Bounds Shaded

Variable	MLE	Upper 95%	Lower 95%	Global Upper	Global Lower
YEAR	-0.1055	-0.0541	-0.1510	0.1132	-0.2187
PERSELAW	0.0270	0.3771	-0.3244	1.1612	-1.1342
SPEED	-0.0039	0.0196	-0.0272	0.0746	-0.0784
BEER	0.4086	0.6612	0.1816	1.4577	-0.1631
MLDA21	-0.2616	0.1063	-0.6171	1.0598	-1.3214
YOUNG	-0.0352	4.6690	-4.7378	15.3707	-15.4059
CELLPOP	0.0287	0.0377	0.0174	0.0481	-0.0237
POVERTY	-0.0131	0.0251	-0.0506	0.1176	-0.1306
UNPLOY	-0.0077	0.0448	-0.0597	0.1671	-0.1748
INCOME	0.0000	0.0000	-0.0001	0.0001	-0.0001
ED_HS	-0.0161	0.0185	-0.0499	0.1041	-0.1202
ED_COL	-0.0331	0.0079	-0.0724	0.1159	-0.1490
CRIME	0.0000	0.0001	-0.0001	0.0004	-0.0003
SUICIDE	0.0228	0.0648	-0.0194	0.1569	-0.1171
GINI	4.8996	10.5912	-1.0266	21.6122	-16.7127
UNIVERSAL	-0.8118	-0.6115	-1.001	-0.0448	-1.350
PARTIAL	-0.2752	-0.1159	-0.4277	0.3056	-0.7168

VII. Concluding Comments

One of the most important statistical problems today is the task of inference in the context of model uncertainty.[33] Dealing with both parameter and model uncertainty is a challenging endeavor due to the sheer magnitude of the number of models that need to be considered. In this paper we have looked at intuitive Bayesian methods along with ordinary least squares. With our data, there are millions of possible model specifications. Bayesian procedures are nicely suited to explore this high dimensional model space. These procedures are not model mining, but are based on solid probability and statistical theory and provide researchers with inferential tools that are not a part of the non-Bayesian toolkit.

Table 7 summarizes and compares results from our classical and Bayesian methods.[34] OLS estimates, t-values, and standard significance stars are shown in columns 2, 3, and 4; BMA inclusion probabilities are shown in column 5; EBA bounds that are non-fragile (NF) when all variables are considered doubtful are shaded in column 6 (from Table 5); and EBA non-fragile bounds (data-favored and global) when the five focus variables are considered free are shaded as non-fragile (NF) in columns 7 and 8 (from Table 6).

[33] See Breiman (2001).

[34] A constant and the regional variables were included, but results are not shown.

Table 7
Summary of OLS, BMA, and EBA Results for
Motorcycle Fatality Rate Models for US States from 1980 to 2010

	OLS	t-value	sig	BMA	EBA1	EBA2	EBA2 Global
YEAR	-0.1055	-13.225	***	100	NF	NF	
PERSELAW	0.0270	0.489		0.8			
SPEED	-0.0039	-1.051		1.9			
BEER	0.4086	5.156	***	100		NF	
MLDA21	-0.2616	-4.574	***	100			
YOUNG	-0.0351	-0.048		1.3			
CELLPOP	0.0287	15.944	***	100	NF	NF	
POVERTY	-0.0131	-2.191	*	10.9			
UNPLOY	-0.0077	-0.932		2.3			
INCOME	0.0001	-1.282		1.7			
ED_HS	-0.0161	-2.985	**	24.6			
ED_COL	-0.0331	-5.198	***	100			
CRIME	0.0001	2.809	**	88.6			
SUICIDE	0.0228	2.838	**	47.9			
GINI	4.8990	5.321	***	100			
UNIVERSAL	-0.8118	-14.171	***	100	NF	NF	NF
PARTIAL	-0.2752	-5.108	***	100		NF	

Signif. codes: 0 '***', 0.001 '**' , 0.01 '*'

The classical and Bayesian Model Average results, as mentioned above, are in strong agreement with one-another. Estimated marginal effects from all procedures are very similar. When p-values are less than .001, BMA inclusion is 100%; there are eight variables that pass this criteria: YEAR, BEER, MLDA21, CELLPOP, ED_COL, GINI, and both UNIVERSAL and PARTIAL helmet laws. For EBA when all variables are doubtful, non-fragile data-favored bounds are indicated for only three variables: YEAR, CELLPOP, and for the UNIVERSAL helmet law (column 6 -- EBA1). When our five focus variables are not set as being doubtful, EBA data-favored bounds are non-fragile for YEAR, BEER, CELLPOP, and both UNIVERSAL and PARTIAL helmet laws (column 7 -- EBA2). The final column in Table 7 highlights the unique characteristic of the UNIVERSAL helmet law – it is the only variable that has non-fragile global bounds in addition to being data-favored, always included in BMA, and statistically significant.

The variable, YEAR, i.e., the time trend, is found to be highly significant, always included by BMA. Furthermore, it proves to be non-fragile in two of the three EBA specifications. YEAR picks up the influence of potentially omitted factors in the model as well as serving as a proxy for technology advances and possibly permanent income.[35]

There is an impressive cellphone effect (CELLPOP) as shown by its significant outcome depicted by the classical methods and 100 percent inclusion by BMA. It also proves to be non-fragile in two of the three EBA specifications which entail between 2^{17} to 2^{23} different models. These results are consistent with that found by Loeb et al. (2009), Fowles et al. (2010) and Blattenberger et al. (2012, 2013) for motor vehicle fatalities in general. One can conclude that the distracting effect of cell phones impinges on motorcyclists directly or through their interaction with other vehicles, or both. This would lead to a recommendation that cell phone bans be extended beyond the fourteen states and DC which have currently enacted such laws. In addition, such laws might be expanded to include hands-free devices and that stricter policing of the laws and more viable fine structures be put in place for violation of the law.

Universal Helmet Laws are found to be statistically significant and are always included in the models by BMA. The Partial Helmet Law is also always significant by classical analysis and always included in the BMA analysis. However, of great interest are the EBA results which add particularly strong reason to recognize the importance of the Universal Helmet Law in reducing motorcycle fatality rates over that of the Partial

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35 See Loeb (1993, 2001) and Peltzman (1975).

Helmet Law given the non-fragile results associated with all three EBA criteria. This draconian procedure considers up to 2^{23} specifications, all non-fragile. This is a very strong policy finding that supports legislation for universal helmet laws as opposed to either partial or no helmet laws.

Alcohol has been generally found to be a significant cause of motor vehicle fatalities and accidents in general. The results found here with respect to motorcycle fatality rates are consistent with those found in general. Both BEER and MLDA21 are indicative of the risk imposed on motorcyclists from a classical perspective as well as from a Bayesian Model Average perspective. In addition, the BEER effect proves non-fragile with our data-favored EBA analysis when using our focus variables as free. These results suggest that imposing stricter sanctions against driving while under the influence along with stricter policing and perhaps the use of expenditures on substance abuse treatment centers are worthy of further investigation.[36]

The SUICIDE effect is similar to that found by Blattenberger et al. (2013). Although this factor is included in only 47.9 percent of the models via BMA, it proves always to be statistically significant from a classical perspective. It should be noted that high suicide states are also high motor vehicle fatality states.[37] 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.[38] Interestingly, suicides have also been found to be an area of concern with other modes of transportation, in particular with railroads.[39] It may be that suicidal propensities are measuring changes in risk taking propensities by

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[36] See Chaloupka et al. (1993) and Freeborn and McManus (2007).
[37] See Blattenberger et al. (2013).
[38] See Centers for Disease Control and Prevention (2012).
[39] See, for example, Savage (2007).

individuals or society in general. A potential avenue of future research may be investigating 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.[40] However, it seems that suicidal propensities are not as pronounced for motorcycle fatalities as they are for automobile fatalities.

Crime rates may also be measuring the effects of economic wellbeing along with differing tolerances for risk in society over time. Although the coefficient associated with crime is always significant (although small in absolute value) and included by BMA in 88.6% of the time, it is considered fragile from an EBA perspective.

The effect of the maximum speed limit on urban interstate highways was never significant in the classical analysis and was never included by Bayesian Model Averaging and was found fragile by EBA. As such, the results here are similar to those reported by French et al. (2009).

The effects of education and income distribution are what we expect a priori. Investment in a college education is an investment in human capital and might be expected to lead to higher income over the life of the individual. With a higher life-time income, safety while driving may be preferred over the utility from the thrills of speed.[41] The GINI coefficient is always significant and included in all models by BMA. As one would expect, greater income inequality is associated with higher fatality rates all else

[40] See Savage (2007) and Conner et al. (2001).

[41] The effect of permanent income might be picked up by the trend variable as suggested by Peltzman (1975).

equal. This may argue for greater income equality. Of course the policy for achieving this is often a political one, i.e., taxing one group for the benefit of another versus enhancing the ability of citizens to find well-paying jobs as opposed to low paying jobs or none at all. Such policy suggestions are not in the purview of this paper.

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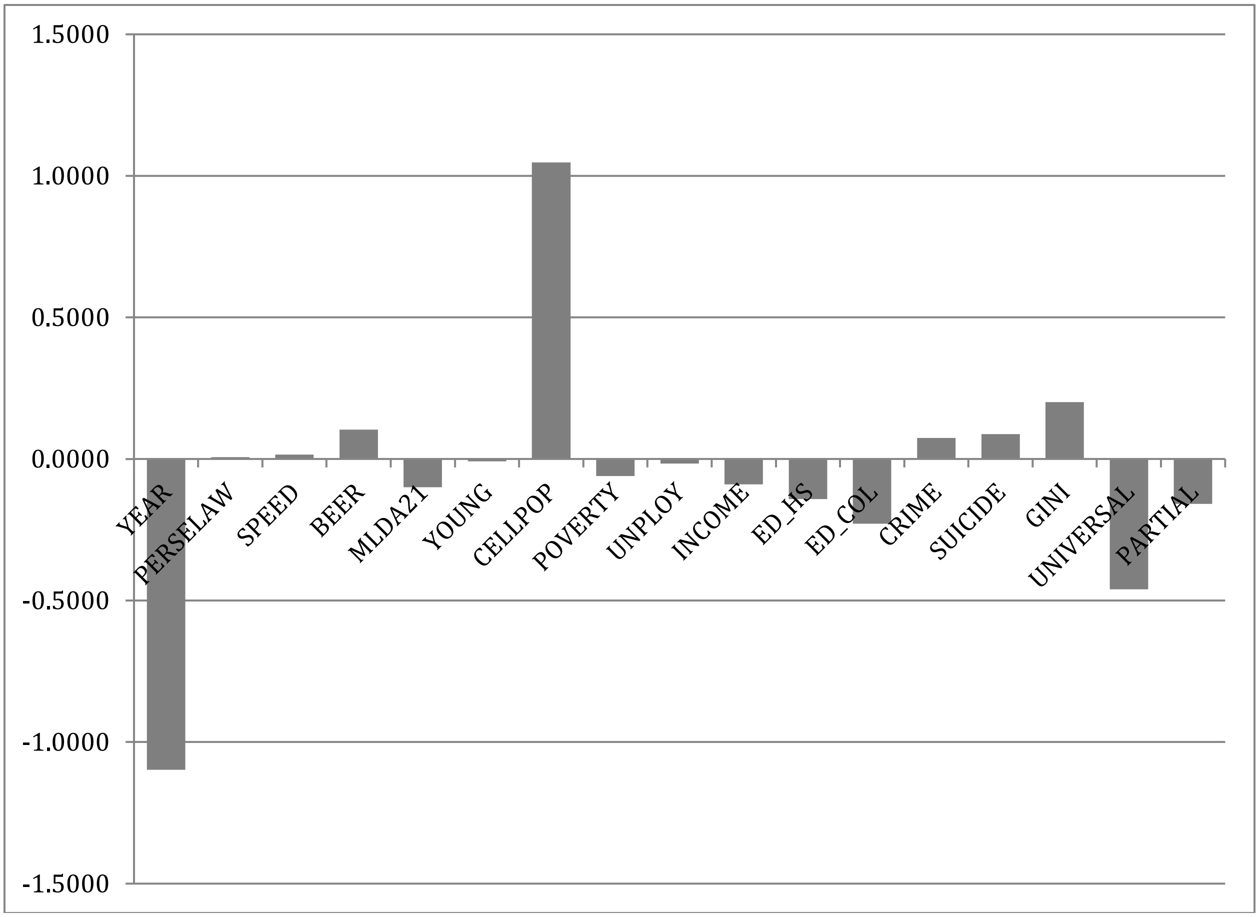
Appendix 1: Data Sources

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

Appendix 2: Plot of Standardized OLS Regression Coefficients for the Fatality Model Specification

Figure A1

Standardized OLS Regression Coefficients for the Fatality Model Specification[42]



[42] See Table 3, Full Model, for the basis for this specification using raw data. All variables are standardized to mean 0 and variance 1 so as to allow unit-free comparisons.

Appendix 3: Plot of US State Motorcycle Fatality Rates

Figure A2