"Understanding the Cell Phone Effect on Motor Vehicle Fatalities Using Classical & Bayesian Methods"

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I. Introduction

Motor vehicle accidents continue to result in large numbers of fatalities each year. In 2006, for example, there were over 42,700 fatalities associated with these accidents.[1] As such, the determinants of these accidents and methods to reduce them continue to be of great interest to economists, public health officials, and policy makers.

To date, numerous studies have been conducted to attempt to determine the causes of motor vehicle accidents. The factors leading to such accidents are attributed generally to the vehicles themselves, the roadways, or to drivers. More specifically, the studies have examined the effects of speed limits, types of highways, vehicle speed, speed variance, motor vehicle inspection, seat belt laws, minimum legal drinking age, alcohol consumption, income, population characteristics, among many others. Just recently, some studies have directed their attention to the impact of cell phones on motor vehicle accidents and fatalities. Cell phones have become an issue in the literature given the growth of their widespread use in the general public and by drivers as well. The effects of these factors do not necessarily remain static over time which compounds the difficulty of evaluating the marginal impact of them on fatality rates.[2]

Fragile and inconsistent results across studies may be due to different data sets (either survey or non-survey data), different estimation techniques used, e.g., cross-over analysis versus logistic analysis or OLS, as well as differences in the general model specifications. We present in this paper econometric models using a rich set of panel data covering the period 1980 to 2005 by state and the District of Columbia. In addition, the panel data set allows for measurement of changes in federal speed limit laws which have changed in 1987 and again in 1995.

Modeling the determinants of motor vehicle fatality rates is done several ways in this study. First, a linear model is developed using classical linear regression modeling techniques based on the work of Loeb et al. (forthcoming). This classically specified model serves as the reference prior of the research. We recognize that classical linear modeling, which relies on a known and well-behaved sampling distribution, may be

[1] See NHTSA (2008).
[2] See, for example, Keeler, who estimated that motor vehicle inspection had a life-saving effect initially, but its effect diminished over time.

prone to error due to fundamental uncertainty regarding model specification. In this paper we then address issues related to both parameter and to model uncertainty via three Bayesian techniques.

In what follows, Section II.A develops an econometric reference model to articulate the anticipated effects of explanatory variables on traffic fatalities. In a Bayesian context, this serves to reference prior beliefs regarding the effects of variables. Section II. B describes the data and defines the variables used in this paper. Section III.A estimates this model using a classical fixed effects regression. Section III.B explores global model fragility using Extreme Bounds Analysis. Sections III.C and III.D present results from Bayesian Model Average and Stochastic Search Variable Selection procedures which direct attention to the most probable models. Section III. E compares the four estimation approaches. Section IV. provides some concluding comments including highlights on how the classical and Bayesian methods agree and differ across model specifications and suggests ways these data may be further examined.

II. A. The Reference Prior

Econometric models of the determinants of motor vehicle accidents often follow the approach suggested by Peltzman (1975). One of the important contributions of Peltzman was to examine potential offsetting behavior on the part of drivers as they adjust their driving behavior in the face of improved safety of vehicles over time and the imposition of safety regulations. For example, in the 1980's seatbelt laws were being passed in the U.S. to reduce fatalities and injuries of occupants of cars involved in accidents. However, although there may be a benefit to the seatbelt user should there be an accident, the probability of an accident may be increased as drivers take on riskier driving behavior which may, among other things, put pedestrians at greater risk.

Peltzman's paper initiated numerous studies on the determinants of automobile accidents using various econometric techniques and data sets. There were many studies on the effect of motor vehicle inspection on automobile accidents[3], the effect of speed

[3] See, for example, Keeler (1994), Loeb (1985, 1990), Loeb and Gilad (1984), and Garbacz and Kelly (1987).

and speed variance on such accidents[4], the effect of seatbelts and seatbelt laws on accidents[5], the effect of alcohol and related taxing policies on accidents[6], among other factors which might have countervailing effects. Loeb, Talley, and Zlatoper (1994) review and evaluate the impact of many of these potential determinants of accidents. Until recently, however, most studies did not consider the impact of cell phones on motor vehicle accidents since cell phone use in the United States became relevant, from a practical point of view, starting in the 1980s. There were only about 340 thousand cell phone subscribers in the United States in 1985. Since then, the number of subscribers of cell phones has grown exponentially. By the year 2007, there were over 255 million subscribers.[7] Given this fast and large increase in cellular phone subscribership, economists, safety experts, and policy makers have recently increased their attention to the effect cell phones may have on motor vehicle accident rates.

Cell phone use by drivers may result in an increase in accidents and fatalities for several reasons. Firstly, cell phone usage may have a distracting effect on the driver (as well as pedestrians) and may impede a driver's ability to operate a vehicle due to an inability to do more than one thing at a time, i.e., drive a car and talk on a cell phone. In addition, cell phone use may reduce attention spans and reaction times. With this in mind, five states (Connecticut, New Jersey, California, New York, and Washington) along with the District of Columbia have banned the use of hand-held phones by drivers.[8] Strangely, the bans do not affect the use of hands-free devices in spite of research indicating that such devices have a similar adverse effect on safety as do the hand-held devices.[9]

It is not merely the sheer number of cell phones available to the public which has safety researchers concerned, but also the propensity of drivers to use them. Glassbrenner (2005) has estimated that ten percent of all drivers at any moment of time during daylight hours were using either hand-held or hands-free phones. Furthermore, there is indication

[4] See, for example, Lave (1985), Levy and Asch (1989), Fowles and Loeb (1989), among others.
[5] See, for example, Cohen and Einav (2003), Evans (1996), Dee (1998), and Loeb (1993,1995,2001).
[6] See, for example, Fowles and Loeb (1989), and Chaloupka et al. (1993).
[7] See Cellular Telecommunications and Internet Association (2007).
[8] In addition, both New Jersey and California banned text messaging by drivers in 2008.
[9] See, for example, Consiglio et al. (2003).

that the percentage of drivers using these devices is increasing over time as well.[10] Not only are cell phones and subscribers increasing over time, but driver usage is increasing as well and apparently at an increasing rate.

Redelmeier and Tibshirani (1997) is the most well-known study of the effects of cell phones on automobile accidents. Using cross-over analysis, they conclude that property-only accidents increase four-fold when cell phones are involved. They also find that 39% of all drivers involved in these accidents make use of their cell phones to call for assistance after the accident. McEvoy et al. (2005) also find an increase in the risk of an accident due to cell phones using data on crashes resulting in hospital visits. Violanti (1998) attributes an approximate nine-fold increase in fatalities when cell phones are in use as opposed to when they are not.[11] Neyens and Boyle (2007) examining teenage drivers, found that cell phones increased the likelihood of rear-end collisions relative to fixed-object collisions. From a different perspective, Consiglio et al. (2003), using a laboratory environment, simulated driving conditions and found that brake reaction time was reduced when cell phones were in use and this reduction occurred regardless of whether the cell phones were hand-held or hands-free devices. Similarly, Beede and Kaas (2006) using a sample of 36 college students and simulating driving conditions in a laboratory environment also found that hands-free devices adversely effected driving performance.

As noted above, not all research has supported the claim that cell phones are associated with accidents and fatalities. Rather, there are studies indicating that cell phones do not have a significant impact on motor vehicle accidents. Laberge-Nadeau et al. (2003) using logistic-normal regression models and Canadian survey data initially found an association between cell phone use and accidents. However, this risk was diminished as their basic models were extended, suggesting that their results were fragile with respect to model specification. This suggests that results from modeling may be questioned due to issues of both model and parameter uncertainty. The life-taking effect of cell phones was further countered by Chapman and Schofield (1998) who argue that cell phones should be credited with saving lives as opposed to taking them. Chapman and

[10] Glassbrenner (2005) has estimated that driver use of just hand-held phones increased from 5% in 2004 to 6% in 2005.
[11] See Violanti (1998, p. 522).

Schofield found that, "Over one in eight current mobile phone users have used their phones to report a road accident."[12] Referring to the "golden hour," – the period of time crucial for survivorship from various medical emergencies and accidents – they claim that it is highly likely that many lives were saved due to cell phones.[13] Similarly, Poysti, et al. (2005) claim that, "phone-related accidents have not increased in line with the growth of the mobile phone industry."[14]

More recently, Loeb et al. (forthcoming) addresses the fragile results reported across the various research endeavors by using econometric methods and specification error tests to examine the potential interacting-effect of life-saving and life-taking attributes of cell phones with regard to motor vehicle fatalities. A non-linear model is posited and the statistical results suggest a non-monotonic relationship between cell phone availability and motor vehicle fatalities. Initially, with low cell phone subscriber rates, cell phones are found to be associated with net life-taking effects. As the number of subscribers increase, the life-saving effect overwhelms the life-taking effect. This life-saving effect may be due to sufficient numbers of cell phones being available so that a quick response to an accident by witnesses is likely and their expeditious call for medical help avails the victims to the benefit of the golden hour rule. Starting in the 1990s, however, when subscribers numbered 100 million and more, the life-taking effect overwhelmed the life-saving effect once again.[15] These results were found to be statistically significant and stable. The results are considered reliable given the outcome of the specification error tests which paid particular attention to the structural form of the models.[16]

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[12] See Chapman and Schofield (1998, p. 5).
[13] See Chapman and Schofield (1998, p. 6).
[14] See Poysti (2005, p. 50).
[15] These results allow for not only driver usage of cell phones to impact on automobile related fatalities, but for a potential beneficial externality associated with the general population having cell phones. Usage by both drivers and the general public may offset or more than offset each other with regard to safety effects.
[16] The models presented by Loeb et al. (forthcoming) were evaluated for their conformity to the Full Ideal Conditions associated with the error term, i.e., $\mu \sim N(0,\sigma^2 I)$. To examine this, a set of specification error tests were applied to the models, i.e., the Regression Specification Error Test (RESET), the Jarque-Bera Test, and the Durbin-Watson Test. Rejection of the null hypothesis of no specification errors by one or more of these tests resulted in the elimination of the models from consideration. These results were supported as well by Fowles et al. (2008) using Bayesian Extreme Bounds Analysis.

II. B. The Data

In order to better understand the effects of socio-economic and policy related variables on traffic fatality rates we utilize a newly compiled, rich set of data that were collected on 50 states and Washington, D.C. over the period from 1980 to 2005.

The choice of the measure of the dependent variable was of prime importance. Data are available on the number of fatalities, and on four different fatality rates. Here we examine the most commonly reported dependent variable, fatalities per 100 million vehicle miles traveled.[17] During our coverage period there were significant changes in a host of variables. Our data cover the time of the explosive growth in cell phone subscriptions from effectively zero to over 270 million. Because annual subscription data are only available at the national level we imputed state level subscriptions to be proportional to state population proportions for each year. Another major variable change related to Federal legislation that allowed states to modify the 55 mile per hour speed limit on 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.[18] Seat belt legislation varies widely across states. Our data records the years in which a state mandatory primary or secondary seat belt law came into effect. The data are organized by geographical coding of states into eleven regions. The variables are defined and described in Table 1 along with their expected effects (priors) on fatality rates.

[17] The other fatality rate measures are fatalities per capita, fatalities per vehicle registrations, and fatalities per licensed drivers. All measures exhibit, at the national level, a downward trend.

[18] 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.

Table 1
Explanatory Variables [a]
Cross Sectional - Time Series Analysis of Traffic Fatality Rates
For 50 States and DC from 1980 to 2005

Name	Description	Expected Sign (Priors)
YEAR	Year	-
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.)	-
INSPECT	Indicator for annual safety inspection	-
SPEED	Maximum posted speed limit, urban highways	+
BELT	Indictor for presence of a legislated seat belt law	-
BEER	Per capita beer consumption (in gal)	+
MLDA	Minimum legal drinking age	-
YOUNG	Percentage of males (16-24) relative to population of age 16 and over	+
CELLPOP	Imputed number of cell phone subscribers per capita	+
POVERTY	Poverty rate	+
UNEMPLOY	Unemployment rate	-
REALINC	Real per household income in 2000 dollars	?
ED_HS	Percent of persons with high school diploma	-
ED_COL	Percent of persons with a college degree	-
CRIME	Crime rate	?
SUICIDE	Suicide rate	?

[a] For data sources, see Appendix 1

III. A. The Classical Fixed Effects Model

We begin by specifying a linear relationship between the fatality rate – FATAL – (vehicle fatalities per 100 million miles traveled) for the j^{th} state and for the i^{th} year. The base model is estimated using regional dummy variables and includes the year as a trend variable. Ordinary least squares results for the basic model are presented in Table 2. In order to compare the effects of the variables on fatality rates among estimation methods, all data are standardized to have mean zero and range 1. As mentioned, the regression included regional dummy variables, but those estimated coefficients are omitted from the table.[19]

Table 2
OLS Estimates for the Fatality Rate Model*

Variable	Estimate	Standard Error	t value
YEAR	-.466	.0334	-13.961
PERSELAW	-.0331	.00697	-4.754
INSPECT	.00775	.00544	1.425
SPEED	.0333	.011	3.023
BELT	.000318	.00753	0.042
BEER	.0935	.0163	5.752
MLDA	.0104	.00903	1.148
YOUNG	.0619	.0197	3.133
CELLPOP	.196	.0225	8.731
POVERTY	.175	.0211	8.321
UNEMPLOY	-.0561	.0232	-2.414
REALINC	.154	.0384	4.01
ED_HS	-.0361	.0283	-1.274
ED_COL	-.269	.0311	-8.632
CRIME	-.0000337	.0231	-0.001
SUICIDE	.127	.0286	4.439

* Residual standard error: 0.06843 on 1300 degrees of freedom
Multiple R-squared: 0.807, Adjusted R-squared: 0.8031
F-statistic: 209.1 on 26 and 1300 DF, p-value: < 2.2e-16

There is considerable sign agreement in terms of expected and estimated effects. Three variables are estimated with sign differences -- INSPECT, BELT, and MLDA. Classical estimation addresses the issue of parameter uncertainty and statistical significance in relation to the sampling distribution induced by assumptions in the linear regression model. It may be noted that the three variables estimated with the "wrong" sign are not statistically significant at conventional testing levels. Instead of changing the model specification by adding or removing variables (and thus violating the principle

[19] We selected the model presented in this paper for expository clarity. Additional models were estimated which exclude some of the regressors presented and include others, such as what is referred to as a "companion variable." Companion variables attempt to account for factors not addressed by the time trend and are discussed in Loeb (1995, 2001). In this case, both the crime rate and suicide rate may serve as companion variables. Alternatively, the suicide rate may proxy to some extent the self-evaluation of the value of life. Regardless, results remain stable and similar to those reported in Table 2 and these additional models are available from the authors.

of statistical significance testing), we directly address model and parameter uncertainty using three Bayesian econometric methods. They are Extreme Bounds Analysis (EBA), Bayesian Model Averaging (BMA), and Stochastic Search Variable Selection (SSVS). All three of the methods recognize that differing parameter estimates can be obtained under varying specifications, in particular, when subsets of the 2^K regressions (with K potential explanatory variables) are considered. The next sections examine the extent to which changes in model specifications lead to different conclusions regarding the influences of particular explanatory variables, and to discover classes of model specifications that have high posterior probabilities. Given that 2^K is in the order of 250 million for these data, specification is non-trivial and yet is mathematically tractable for these procedures.

III. B. Extreme Bounds Analysis

Extreme Bounds Analysis was developed by Leamer in a series of articles beginning in 1978 (Leamer 1978, 1982, 1983, 1985, 1997). 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. The extreme values are those that could be estimated via maximum likelihood estimation when all possible linear combinations of the explanatory variables are considered under all possible model specifications. This method is rather draconian in the sense that all possible specifications are considered and that very few hypotheses survive a full EBA analysis (Mayer, 2007). Lack of survivability is seen in ranges of posterior estimates for model parameters that cover zero. Such variables are called fragile even though associated parameter estimates obtained via classical estimation might be seen to be statistically significant. Fowles and Loeb (1989, 1995), and Fowles et al. (forthcoming) have repeatedly used EBA analysis in models analyzing aggregate U.S. cross section and time series models of traffic fatality rates.[20]

[20] Calculations of EBA were computed in Gauss using MICRO-EBA (Fowles, 1988). The Gauss code is available free on request.

A major advantage in using EBA is that prior distributions only have to be specified for certain sets of variables, yet bounds can be computed for all variables in the model. Following Leamer (1982) we specify a natural conjugate prior for a set of p doubtful variables, or those variables which could plausibly be dropped from a specification.[21] In this paper, those are the regional binary variables, the remaining variables, called free variables, are not linked to a proper prior specification. Free variables are associated with a diffuse prior. For the normal linear regression model

$$Y \sim N(X\beta,\sigma^2 I)$$

the prior mean on the p doubtful variables is also normal, centered at zero, with variance matrix H^{*-1}. This is written as

$$R\beta \sim N(0, H^{*-1})$$

where R is a pxK matrix of constants, β is a kx1 vector of parameters, 0 is a px1 zero vector, and H* is a pxp positive definite symmetric precision matrix (the inverse of the variance/covariance matrix). EBA obtains posterior information of dimension K based on specification of dimension p (p < K). In particular, the extreme values of linear functions of the posterior mean, b**, for the full Kx1 vector τ,[22]

$$\tau' b^{**} = \tau'(H + R'H^*R)^{-1}Hb$$

are given by

$$a + \tau^{*\prime} f \pm (\tau^{*\prime} A^{-1} \tau^{*} c)^{.5}$$

when H^{*-1} is constrained to fall between positive definite matrices V_L and V_H and

[21] Dropping a variable forces a very strong prior belief that the coefficient is exactly equal to zero with perfect precision.
[22] In this paper, τ is a vector with one 1 and k-1 zeros that corresponds with the i^{th} parameter of interest.

$$a = \tau'b - \tau'H^{-1}R'(RH^{-1}R')^{-1}Rb,$$

$$\tau^{*\prime} = \tau'H^{-1}R'(RH^{-1}R')^{-1},$$

$$f = (h + V_L^{-1})^{-1}(hRb + (V_L^{-1} - V_H^{-1}) * (h + V_H^{-1})^{-1}hRb/2),$$

$$A = (h + V_H^{-1})(V_L^{-1} - V_H^{-1})^{-1}(h + V_H^{-1}) + (h + V_H^{-1}),$$

$$c = (Rb)'h(h + V_H^{-1})^{-1}(V_L^{-1} - V_H^{-1})(h + V_L^{-1})^{-1}hRb/4,$$

$$h = (RH^{-1}R')^{-1},$$

$$b = (X'X)^{-1}X'Y,$$

$$H = s^{-2}X'X,$$

$$s = ((Y-Xb)'(Y-Xb)/(n-K))^{.5}.$$

Table 3 reports the maximum and minimum bounds for the posterior means for the non-doubtful variables with the widest possible bounds corresponding with $V_L = 0H^{*-1}$ and $V_H = \infty H^{*-1}$. Column 1 reports the Maximum Likelihood Estimates for the entire model. Columns 2 and 3 report the EBA minimum and maximum values for the posterior mean when the regional variables are specified as doubtful variables. The last two columns show the EBA minimum and maximum values that lie within a 95% confidence ellipsoid with all variables specified as doubtful. Bounds within the 95% ellipsoid are referred to as being data favored. This specification (zero prior mean) corresponds with the prior specifications used for BMA and SSVS specifications that follow in the next two sections. Using EBA, priors are minimally specified since H*, the prior precision matrix, is only required to be positive definite symmetric.[23] Results are

[23] In MICRO-EBA, H* was set equal to the identity matrix, so the priors are spherically symmetric, centered at zero.

only sensitive to the free-doubtful mix via the R matrix which reduces the dimensionality for the prior space from K to p.

Table 3
Maximum Likelihood & Extreme Bounds Analysis for the Fatality Model Specification

Variable Name	Maximum Likelihood Estimate	EBA Minimum Regional Doubtful	EBA Maximum Regional Doubtful	EBA Minimum 95% Likelihood All Doubtful	EBA Maximum 95% Likelihood All Doubtful
YEAR	-0.519	-0.5707	-0.3998	-0.7317	-0.2973
PERSELAW	-0.0324	-0.0467	-0.0274	-0.0758	0.01149
INSPECT	0.0086	-0.0116	0.0318	-0.0256	0.0427
SPEED	0.0358	0.0124	0.0678	-0.0334	0.1045
BELT	0.0064	-0.0086	0.0246	-0.0414	0.0541
BEER	0.0886	0.0408	0.1271	-0.0138	0.1897
MLDA	0.015	-0.0005	0.0209	-0.042	0.0719
YOUNG	0.0498	0.0288	0.1376	-0.0753	0.1743
CELLPOP	0.2255	0.1785	0.2443	0.0788	0.3687
POVERTY	0.1851	0.1556	0.2561	0.0518	0.3157
UNEMPLOY	-0.0628	-0.1329	-0.005	-0.2083	0.0836
REALINC	0.1704	0.0267	0.2761	-0.0722	0.4106
ED_HS	-0.0154	-0.1266	0.075	-0.1949	0.1641
ED_COLLEGE	-0.2837	-0.3698	-0.1685	-0.4759	-0.0872
CRIME	-0.0069	-0.0436	0.1183	-0.1524	0.1386
SUICIDE	0.1228	0.0764	0.352	-0.0577	0.3016

When the regional variables are considered doubtful, non-fragile inferences are obtained for all the explanatory variables except five: inspection (INSPECT), seat belts (BELT), minimum legal drinking age (MLDA), high school education (ED_HS), and crime (CRIME). When all variables are doubtful, EBA bounds necessarily cover zero. However, the data favored extreme bounds are non-fragile for four variables: year

(YEAR), cell phone subscriptions (CELLPOP), poverty (POVERTY), and college education (ED_COLLEGE).

Although EBA as discussed in this paper provides insight into the range of values that the posterior means can take, it does not pay direct attention to the posterior probabilities of the corresponding models. The next two procedures address this issue.

III. C. Bayesian Model Averaging

Bayesian Model Averaging was addressed extensively by Raftery, Madigan, and Hoetling (1993) following a suggestion by Leamer (1978). By averaging across many model specifications, especially among those with high posterior probability, BMA is able to explicitly account for model uncertainty as it relates to parameter estimation. As presented in Hoetling, Madigan, Raftery, and Volinsky (1999), BMA provides a straightforward method to summarize the effects of explanatory variables as measured by their regression coefficients as they are manifest in assorted models. In what follows, one should keep in mind that two primary sources of uncertainty are addressed: of models and of parameters.

Let Δ represent a measure of interest, for example, the effect of speed laws on motor vehicle fatality rates. The posterior distribution of Δ, conditional on data D, is a weighted average of posterior distributions over models:

$$P(\Delta \mid D) = \sum_N P(\Delta \mid M_N, D)\, P(M_N \mid D)$$

where $M_1, M_2, \ldots, M_N$ are the N models under consideration. In order to calculate this, the posterior distribution of model M_N is required and is given by Bayes' theorem as

$$P(M_N \mid D) = P(D \mid M_N)P(M_N)/\sum_N P(D \mid M_N)P(M_N).$$

In the numerator, $P(D|M_N)$ represents the integrated likelihood of model M_N and is calculated as

$$P(D \mid M_N) = \int P(D \mid \theta_N, M_N)P(\theta_N \mid M_N)d\theta_N$$

where θ_N is the vector of parameters of model M_N. For linear regressions in this paper, θ is the vector comprised of the β's and σ^2. The posterior mean and variance for Δ are calculated based on Raftery (1995) as:

$$E(\Delta \mid D) = \sum_N d_N\, P(M_N \mid D) \text{ and}$$

$$V(\Delta \mid D) = \sum_N (\mathrm{Var}[\Delta \mid D, M_N] + d_N^2)P(M_N \mid D) - E(\Delta \mid D)^2$$

for $d_N = E(\Delta \mid D, M_N)$, the estimated, or fitted, effect under model M_N.

Note that the effects of Δ are measured by averaging over many models with weights that correspond to the models' posterior probabilities. Posterior variance is comprised of sampling and model variation. In this paper, the formidable task of calculating the integrated likelihood function is mitigated by utilizing the fact that this likelihood function is well-approximated by the Bayesian Information Criterion (BIC).[24] Non-informative priors (uniform over models, M_N) and diffuse over parameters within models (θ_N) were utilized.

The following table summarizes BMA analysis for the same model presented above (in Table 3), regressing fatality rates on the core set of explanatory variables. Regional binary variables were included in the analysis but are not reported 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 posterior mean for the variable for the BMA runs and "SD" is the posterior standard deviation for the variable. The best performing model included 16 explanatory variables with a posterior probability of .279. In that model, INSPECT, BELT, UNEMPLOY, ED_HS, MLDA, and CRIME were not

[24] For this paper, BMA results are computed in R using the BMA package with bicreg. BMA procedures were based on finding alternatives to stepwise methods based on p-value style searches. BMA calculations can be performed using monte carlo (MC) integration to compute the integrated likelihood function. The leaps method of selection is a fast alternative (George M. Furnival and Robert W. Wilson, 1974). The relationship between the integrated likelihood function and the BIC score is developed in Raftery (1995). MC methods are utilized in SSVS calculations in this paper.

present. BMA never chooses to include BELT or CRIME, and always includes YEAR, PERSELAW, BEER, YOUNG, CELLPOP, POVERTY, REALINC, ED_COL, and SUICIDE. Of these nine variables, all are non-fragile under EBA when the regional dummy variables are considered doubtful. SPEED is the tenth explanatory variable that was non-fragile under EBA. BMA selects this variable two-thirds of the time. As such, there is a considerable agreement between EBA and BMA model choice.

Table 4
Bayesian Model Averages for the Fatality Rate Model Specification

Variable	p!=0	EV	SD
YEAR	100	-.445	0.0262
PERSELAW	100	-.0350	0.00677
INSPECT	1.5	.0000735	0.00081
SPEED	66.6	.0203	0.0168
BELT	0	0.00	0
BEER	100	.0934	0.0157
MLDA	1.4	.000138	0.00157
YOUNG	100	.0784	0.0197
CELLPOP	100	.179	0.02096
POVERTY	100	.184	0.0205
UNEMPLOY	36.8	-.0198	0.0291
REALINC	100	.161	0.0339
ED_HS	2.2	-.000827	0.00676
ED_COL	100	-.0282	0.0247
CRIME	0	0	0
SUICIDE	100	.115	0.025

III. D. Stochastic Search Variable Selection

Stochastic Search Variable Selection was introduced by George and McCulloch (1993). Because it is computationally burdensome, it is one of the more recent procedures in Bayesian analysis that takes advantage of the ability to integrate over multidimensional spaces using Markov Chain Monte Carlo (MCMC) methods typically found when dealing with analyses of the posterior density. This is done with a Gibbs sampler.

All K of the explanatory variables are included at each iteration of the Markov chain to take advantage of the application of the Gibbs sampler to a hierarchical Bayesian model. The variable selection choice is imposed by means of a latent variable, γ. Each model is represented by a binary vector $\gamma = (\gamma_1, \gamma_2, \ldots, \gamma_K)$ with $\gamma_i = 1$ if the explanatory variable is to be effectively included in the model and $\gamma_i = 0$ if the variable is to be effectively excluded from the model. The prior distributions on the slope parameters (β's) for the explanatory variables are distributed normally with mean zero and variance $c_i^2\tau_i^2$ when $\gamma_i = 1$, $N(0, c_i^2\tau_i^2)$, and normally with mean zero and variance τ_i^2, $N(0, \tau_i^2)$ when $\gamma_i = 0$ with c greater than 1.

$$\beta_i|\gamma_i \sim (1-\gamma_i)\, N(0, \tau_i^2) + \gamma_i\, N(0, c_i^2\tau_i^2)$$

The effective exclusion of variable i is imposed by forcing β_i to be close to zero. This framework results in sets of posterior distributions for all vectors γ of dimension K and pays attention to the relatively sharp prior distribution around zero when a variable is not effectively included in a model compared with a more diffuse prior when a variable is effectively included.[25]

Each variable is examined in random order at the end of each iteration of the Gibbs sampler to evaluate the marginal effect of effectively including/excluding that variable in the model. Based on this a probability of including the variable is computed and the value of γ_i for the next iteration is computed stochastically based on this

[25] c_i and τ_i are choice variables. In this paper the reported results are for $c_i = 10$ and τ_i=(2 log(c) $(c^2/(1-c^2))^{-.5}\sigma_{\beta i}$ where the parameter $\sigma_{\beta i}$ is the OLS coefficient standard deviation. This choice is consistent with George and McCulloch (1993) and follows their notation.

probability. Initial values of the γ_i are all set at 1 and the initial probabilities of inclusion are set at 0.5. Then a stochastic iteration scheme is implemented using Gibbs sampling to search for the models with the highest posterior densities.[26] In particular, the Gibbs sampler begins with initialized parameters $\gamma^{(0)}$, $\beta^{(0)}$, $\sigma^{2(0)}$ and generates the sequence $\gamma^{(1)}$, $\beta^{(1)}$, $\sigma^{2(1)}$, $\gamma^{(2)}$, $\beta^{(2)}$, $\sigma^{2(2)}$, …. This sequence converges to a posterior distribution which supplies the complete posterior $P(\beta, \sigma^2, \gamma \mid Y)$. Concurrent with the iterative values of the vector γ are iterative values of the vector p, the probability of variable inclusion, enabling us to compute an expected value of the vector β at each iteration.

Table 5 summarizes the findings for SSVS for the linear fatality model based on 10,000 iterations.[27] The first column (Mean Beta) gives the weighted average for the sequence of slope coefficients, weighted by the probability of inclusion. The second column (Standard Deviation) is the mean value of the weighted standard deviations of the sequence of slope coefficients. The third column (Probability Inclusion) is the mean value of the probability of a variable's inclusion in the model. Column 3 of Table 5 can easily be compared with the column labeled "p!=0" in Table 4. It should be noted that the regional dummies were treated like any other variable. They were not singled out a priori as being doubtful; nonetheless SSVS categorized them for exclusion.[28] The five variables with the highest values for inclusion (probability of inclusion > .95) in the model correspond with the four EBA non-fragile variables (YEAR, POVERTY, CELLPOP, and ED_COLLEGE) as presented in Table 3. SSVS chooses BEER almost always, and is non-fragile under EBA when the prior specification includes BEER as a non-doubtful variable and the regional variables as doubtful.

[26] In this paper, SSVS was implemented via Markov chain Monte Carlo methods using R. This code is available on request.
[27] The first 500 iterations were deleted as a break-in period so there were a total of 9500 iterations employed in the results reported
[28] The average value of p for this set was .12.

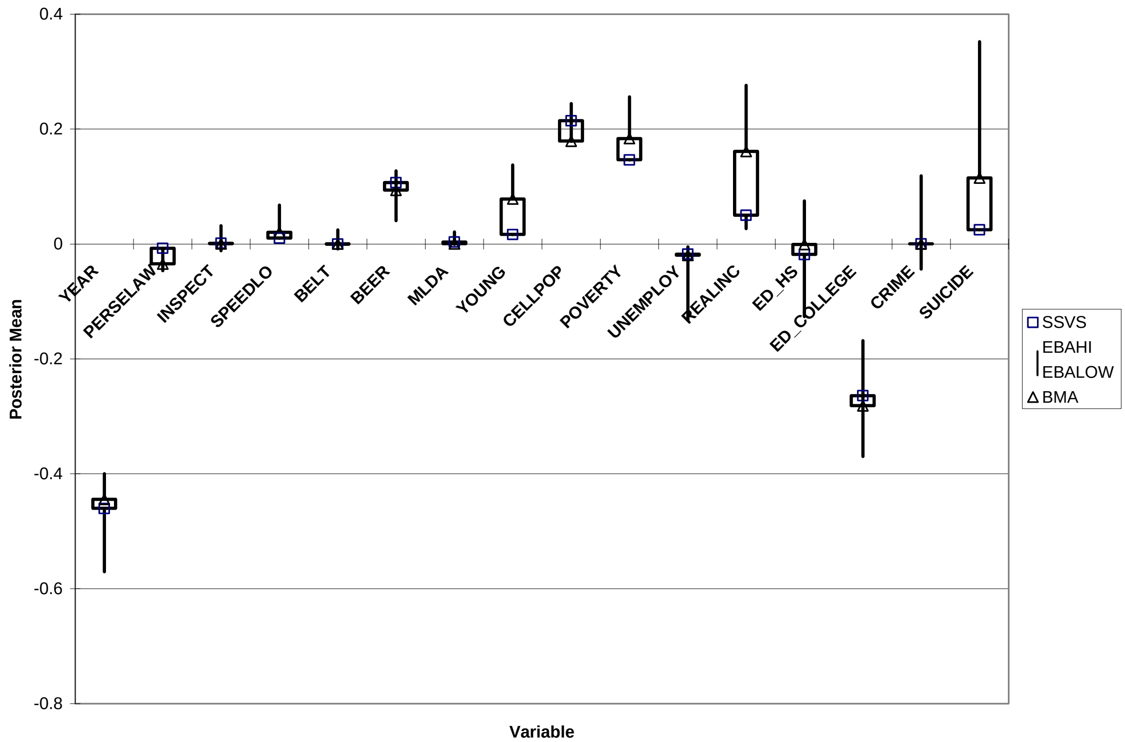
Table 5
Stochastic Search Variable Selection for the Fatality Rate Model Specification

Variable	Mean Beta	Standard Deviation	Probability Inclusion
YEAR	-0.4604	0.0258	1
PERSELAW	-0.0076	0.0134	0.2485
INSPECT	0.0012	0.0029	0.3696
SPEED	0.0102	0.0149	0.3386
BELT	-0.0001	0.0032	0.4208
BEER	0.1069	0.0123	0.9999
MLDA	0.0034	0.0056	0.4081
YOUNG	0.0163	0.0278	0.2685
CELLPOP	0.2146	0.0186	1
POVERTY	0.1463	0.0174	0.9999
UNEMPLOY	-0.0177	0.0265	0.3313
REALINC	0.0498	0.0643	0.3891
ED_HS	-0.0185	0.0269	0.3732
ED_COLLEGE	-0.2642	0.0299	0.9999
CRIME	0.0002	0.0108	0.4642
SUICIDE	0.0244	0.0441	0.2436

III. E. Comparing OLS, EBA, BMA, and SSVS Estimation

The four procedures discussed above shed insight on the relative importance of a variable's contribution in explaining fatality rates. Not surprisingly, there are agreements between OLS, EBA, BMA, and SSVS findings. This section highlights the results which are summarized graphically in Figure 1.[29]

Figure 1
Posterior Means for the Fatality Rate Model
EBA Extreme Bounds, BMA and SSVS Average Values
Regional Variables Doubtful



[29] Figure 2 in Appendix 2 highlights the findings when all variables are doubtful and presents data favored EBA bounds.

Figure 1 compares EBA, BMA, and SSVS results in a graphical way. The solid lines (like whiskers in a box and whisker plot) plot the high and low values for the posterior mean for each explanatory variable as computed by EBA. If these lines do not cross zero, these variables are considered non-fragile. The BMA slope coefficient averages are plotted as triangles, "Δ," and the SSVS averages are plotted as squares, "□." Box width reveals the difference between the BMA and SSVS means. For example, there is almost no disparity between the BMA and SSVS means for variables such as inspection (INSPECT) or minimum legal drinking age (MLDA) and some differences for real income (REALINC), and the suicide rate (SUICIDE). There is sign agreement between BMA and SSVS for all variables in the model.

Because the data are standardized we can assess the relative importance of each explanatory variable. The foremost variable is YEAR; clearly there has been a downward trend in motor vehicle fatality rates over time. College education is the second most important variable followed by cell phone per capita and the poverty rate. It is interesting to note that the OLS results provide the same results.

Table 6 below compares the results of the three Bayesian procedures and OLS. With respect to the OLS column, we indicate the estimated coefficient with an asterisk (*) indicating significance with a t-statistic of 2.00 or more (in absolute value). The EBA column reflects the sign of the coefficients associated with columns 2 and 3 of Table 3 where the regional variables are doubtful and when the coefficients are non-fragile, i.e. robust. In addition it indicates if the variable coefficient is fragile. The BMA column indicates the posterior mean for the variable followed by a "1" if the variable is always selected by BMA and ".666" if it is selected two-thirds of the time. Hence, this column reflects the basic results of Table 4. The SSVS column reflects the basic results of Table 5, indicating the "Mean Beta" for the five variables with the highest probability for inclusion (with probability of .95 or greater). This allows for the comparison of results similar to Figure 1 and can be viewed together. However, in what follows, we make use of the criterion established above in Table 6 and then supported by Figure 1. That is, we consider a variable more certain to impact the fatality rate based on a combination of non-fragile EBA results and inclusion of the variable by BMA and/or SSVS as well as classical significance.

The variables which appear not to have an effect by any of the estimation techniques include: INSPECT, BELT, MLDA, ED_HS, and CRIME. From the Bayesian perspective, the results are fragile using EBA and not included via the BMA criterion or by SSVS. Figure 1 shows the Bayesian results centering consistently on the zero line. The OLS results dovetail with these results, given that they provide statistically insignificant results. These findings are consistent with other studies. For example, Keeler (1994) has found the effect of seatbelt laws has diminished over time. Other studies dealing with seatbelt laws have generally suggested that seat belt laws provide net benefits, but the results have been mixed. For example, Loeb (1995) found that seatbelt laws were effective in reducing fatality and injury rates in Texas. However, when examining seatbelt laws in Maryland, Loeb (2001) found the results varied in significance depending on single vehicle versus multiple vehicle accidents.

What might be called a weak effect is noted with: PERSELAW, SPEED, and UNEMPLOY. None of these were selected by SSVS. However, they were found non-fragile by EBA and selected by BMA except for UNEMPLOY. The results once again dovetail with the OLS results. In addition, most of these results are consistent with the literature. PERSELAW was found to be significant and non-fragile by Fowles et al. (forthcoming) as well as by Loeb et al. (forthcoming). However, the later study found the significance of the coefficient associated with BACLAW using time-series data was dependent on model specification. SPEED, like others in this group, does not have a large associated coefficient, but is consistent with a good deal of the literature which argues that higher speed limits are associated with motor vehicle accidents. Some counter arguments are to be found in the literature as well as discussed by Loeb et al. (1994).[30]

Both YOUNG, REALINC, and SUICIDE have relatively strong results with all methods of estimation but are somewhat attenuated by SSVS based on the criterion used in Table 6 and supported by Figure 1. Clearly the percentage of males aged between 16-24 have an increasing effect on motor vehicle fatality rates. Part of this may be attributed to inexperience in decision making, including decisions pertaining to driving situations, along with potentially higher risk taking associated with youth. SUICIDE has been

[30] Lave (1985), Fowles and Loeb (1989), and Levy and Asch (1989), among others, have examined the effect of speed versus speed variance as well. Data on average speed and the 85% speed are no longer collected by USDOT and as such speed and speed variance could not be investigated in the current study.

included as a "companion variable" to measure the potential effect of excluded variables not addressed by the time trend (YEAR). However, it has a strong positive influence on motor vehicle fatality rates. One speculates that SUICIDE may proxy a measure of self worth in society. As such, if self worth diminishes, suicides may increase as well as behavior associated with additional risk taking.

The most consistently strong results across all methods of estimation (based again on the criteria in Table 6 and nested in Figure 1) pertain to the variables: YEAR, BEER, CELLPOP, POVERTY, and ED_COLLEGE. All these variables have signs consistent with a priori expectations. YEAR may proxy technological changes over time and permanent income[31]. We expect safety to increase with technology and hence lower fatality rates, assuming that drivers don't compensate by taking on additional risks. In addition, to the extent that YEAR serves as a proxy for permanent income, one would expect fatality rates to diminish with increases in such income should it be a measure of long-run income.[32] The effect of alcohol has been long studied and has been found to have an increasing effect on fatality rates. This has led to policy recommendations of increasing the minimum legal drinking age as well as tax policies so as to reduce demand for alcohol, especially among youths.[33] Poverty is expected to potentially have an increasing effect on fatality rates, given that individuals with low incomes have lower opportunity costs associated with risky driving. Similarly, college education is an investment in human capital and as such would enhance the value of life. This may then result in life-protecting behavior, given the higher potential opportunity costs associated with risky driving (and other risky activities). Finally, the strong results associated with CELLPOP are consistent with the findings of Fowles et al. (forthcoming) and Loeb et al. (forthcoming) as opposed to Chapman and Shofield (1998), Poysti et al. (2005), and to some extent by Laberge-Nadeau et al. (2003). Clearly, cell phones have a net life-taking effect when considering motor vehicle fatality rates.

[31] As suggested by Peltzman (1975).
[32] See Loeb et al. (1994) for a discussion.
[33] See Loeb et al. (1994).

Table 6
Comparison of OLS, EBA, BMA, and SSVS Results

Variable Name	OLS Estimate	EBA Result Regional Doubtful	BMA /P(Inclusion)	SSVS /P(Inclusion)
YEAR	-.466*	-	-.445/1	-.4604/1
PERSELAW	-.0331*	-	-.035/1	
INSPECT	.00775	Fragile		
SPEED	.0333*	+	.0203/.66	
BELT	.000318	Fragile		
BEER	.0935*	+	.0934/1	0.1069/.9999
MLDA	.0104	Fragile		
YOUNG	.0619*	+	.0785/1	
CELLPOP	.196*	+	.179/1	0.2146/1
POVERTY	.175	+	.184/1	0.1463/.9999
UNEMPLOY	-.0561*	-		
REALINC	.154*	+	.161/1	
ED_HS	-.0361	Fragile		
ED_COLLEGE	-.269*	-	-.282/1	-.2642/.9999
CRIME	-.000037	Fragile		
SUICIDE	.127*	+	.115/1	

IV. Concluding Comments

This study evaluated the effect of various driving related and socioeconomic factors on motor vehicle fatality rates using four estimation techniques. Three Bayesian results were compared with a simple classical OLS model which may be considered as a bench-mark. Of particular interest is the effect of cell phones on motor vehicle fatalities. Cell phones were found to increase fatality rates regardless of the estimation technique used. All the Bayesian methods as well as the classical regression method suggest this outcome when making use of a large and fertile panel data set covering the period 1980 to 2005. This suggests that efforts to diminish the use of cell phones by drivers are warranted. It supports the decision by those states which have outlawed the use of hand-held cell phones by drivers (in five states and the District of Columbia) and suggests that other states may want to consider such legislation as well. These results are consistent with those of Fowles et al. (forthcoming) and Loeb et al. (forthcoming) using different modeling approaches and data sets. Banning the use of cell phones by drivers might be accomplished through fines and penalties. Given that experiments have concluded that both hand-held and hands-free cell phones are risky, additional studies might be considered to determine if legislation banning hands-free devices might be warranted.

Alcohol continues to be a major contributing factor in automobile accidents. This fact is supported by the current study. States may reduce the effect of alcohol by education, fines and effective penalties for driving while under the influence of alcohol, and taxes on alcohol.[34]

It should be noted that the above potential policy recommendations would require active enforcement as well. In addition, suicides have been found to track automobile fatalities. We have used suicides as a companion variable to account for excluded factors which have not been picked up by the time trend.[35] However, from a policy perspective, investment in public health/mental health facilities may be warranted to reduce fatalities. This would be food for thought for future research.

[34] See Chaloupka et al. (1993) on the effect of alcohol control policies.
[35] See Loeb (1995, 2001) for a discussion of companion variables.

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Appendix 1**:** Data Sources

Name	Data Source
FATAL	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
INSPECT	Highway Statistics (various years), Federal Highway Administration
SPEED	Highway Statistics (various years), Federal Highway Administration
BELT	Traffic Safety Facts (various years), National Highway and Traffic Safety Administration
BEER	U.S. Census Bureau, National Institute on Alcohol Abuse and Alcoholism
MLDA	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
UNEMPLOY	Statistical Abstract of the United States (various years), U.S. Census Bureau
REALINC	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	Statistical Abstract of the United States (various years), U.S. Census Bureau
SUICIDE	Statistical Abstract of the United States (various years), U.S. Census Bureau

Appendix 2: Alternative Presentation of Bayesian Models

Figure 2
Posterior Means for the Fatality Rate Model
EBA Extreme Bounds, BMA and SSVS Average Values