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Understanding the cell phone effect on vehicle fatalities: a Bayesian view

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This article examines the potential effect of various factors on motor vehicle fatality rates using a rich set of panel data and classical regression analysis combined with Bayesian Extreme Bounds Analysis, Bayesian Model Averaging and Stochastic Search Variable Selection procedures. The variables examined in the models include traditional motor vehicle and socioeconomic factors. In addition, the models address the effects of cell phone usage on such accidents. The use of both classical and Bayesian techniques diminish the model and parameter uncertainties which afflict more conventional modelling methods which rely on only one of the two methods.

Keywords: motor vehicle fatality rates; cellphones; applied Bayesian methods

JEL Classification: L92; C11; I18

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] 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 determine the causes of motor vehicle accidents. The factors leading to such accidents are attributed 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 and 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. Inconsistent results have appeared across these studies. Differing results may be due to the use of different data sets, different estimation techniques, as well as differences in the general model specifications. We present in this article econometric models using a rich set of panel data covering the period 1980 to 2005 by state and the District of Columbia.

Modelling the determinants of motor vehicle fatality rates is done in several ways in this study.

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[1] National Highway Traffic Safety Administration (NHTSA, 2008).

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First, a model is developed using linear regression modelling techniques based on the work of Loeb *et al.* (forthcoming). This model serves as the reference prior to the research. We recognize that linear modelling, which relies on a known and well-behaved sampling distribution, may be prone to error due to fundamental uncertainty regarding model specification. In this article we address issues related to both parameter and to model uncertainty via three Bayesian techniques.

In what follows, Section II 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. The next section describes the data and defines the variables used in this article. Section III estimates this model using fixed effects regression. The next section explores global model fragility using Extreme Bounds Analysis (EBA). The next sections present results from Bayesian Model Averaging (BMA) and Stochastic Search Variable Selection (SSVS) procedures which direct attention to the most probable models. The next section compares the four estimation approaches. Section IV provides some concluding comments including highlights on how the frequentist and Bayesian methods agree and differ across model specifications and suggests ways in which these data may be further examined.

II. Background

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 the offsetting effects of driver responses to improvements in the safety of vehicles over time and the imposition of safety regulations. For example, in the 1980s seatbelt laws were being passed in the US to reduce fatalities and injuries to occupants of cars involved in accidents. 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 behaviour. In addition, risk may be transferred from the drivers to pedestrians.

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,[2] the effect of speed and speed variance on such accidents,[3] the effect of seatbelts and seatbelt laws on accidents[4] and the effect of alcohol and related taxing policies on accidents.[5] Loeb *et al.* (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 US became relevant, from a practical point of view, starting in the 1980s. There were only about 340 thousand cell phone subscribers in the US in 1985. Since then, the number of subscribers of cell phones has grown exponentially. By the year 2007, there were over 255 million subscribers.[6] 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. First, cell phone usage may have a distracting effect on the driver and may impede a driver's ability to operate a vehicle due to an inability to do more than one thing at a time. In addition, cell phone use may reduce attention spans and increase reaction times (for both drivers and pedestrians). 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.[7] 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.[8]

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 10% of all drivers at any moment of time during daylight hours are using either hand-held or hands-free phones. Furthermore there is evidence that this percentage is increasing over time as well.[9]

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

[3] See, for example, Lave (1985), Levy and Asch (1989), Fowles and Loeb (1989), among others.

[4] See, for example, Cohen and Einav (2003), Evans (1996), Dee (1998) and Loeb (1993, 1995, 2001).

[5] See, for example, Fowles and Loeb (1989) and Chaloupka *et al*. (1993).

[6] See Cellular Telecommunications and Internet Association, CTIA (2007, Available at http://www.ctia.org).

[7] In addition, both New Jersey and California banned text messaging by drivers in 2008.

[8] See, for example, Consiglio *et al*. (2003).

[9] Glassbrenner (2005) has estimated that driver use of just hand-held phones increased from 5% in 2004 to 6% in 2005.

Redelmeier and Tibshirani (1997) is the most well-known study of the effects of cell phones on automobile accidents. 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) find an increase in the risk of an accident due to cell phones. Violanti (1998) attributes an approximate ninefold increase in fatalities when cell phones are in use as opposed to when they are not.[10] 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 increased when cell phones were in use and this increase 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 found that hands-free devices adversely effected driving performance.

Not all research has supported the claim that cell phones are associated with accidents and fatalities. 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. This risk was diminished as their basic models were extended, however, suggesting that their results were fragile with respect to model specification. This suggests that results from modelling 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 Schofield found that, 'Over one in eight current mobile phone users have used their phones to report a road accident.'[11] 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.[12] Similarly, Poysti *et al.* (2005) claim that, 'phone-related accidents have not increased in line with the growth of the mobile phone industry.'[13]

More recently, Loeb *et al.* (forthcoming) addresses the fragile results reported across various research endeavors examining the positive and negative effects of cell phone use. A nonlinear model is posited and the statistical results demonstrate a nonmonotonic relationship between cell phone availability and motor vehicle fatalities, suggesting both a positive and negative effect due to cell phone use. 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.[14]

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, DC over the period 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 travelled.[15] 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.[16] Another major change observed in the data allowed states to modify the 55 mile per hour speed limit on

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[10] SeeViolanti (1998, p. 522).

[11] See Chapman and Schofield (1998, p. 5).

[12] See Chapman and Schofield (1998, p. 6).

[13] See Poysti (2005, p. 50).

[14] 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 EBA.

[15] 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.

[16] Newly available data on actual phone subscribers for the last 5 years have a correlation with the imputed data of 0.9943.

Table 1. Explanatory variables[a]

Name	Description	Expected sign (priors)
YEAR	Year	−
PERSELAW	Dummy variable indicating the existence of a law defining intoxication of a driver in terms of 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 interstate highways	+
BELT	Indictor for presence of a legislated seat belt law	−
BEER	Per capita beer consumption (in gal) per year	+
MLDA	Minimum legal drinking age	−
YOUNG	Percentage of males (16–24) relative to population of age 16 and over	+
CELLPOP	Number of cell phone subscribers per capita	+
POVERTY	Poverty rate (percentage)	+
UNEMPLOY	Unemployment rate (percentage)	−
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 (reported crimes per 100 000 population)	?
SUICIDE	Suicide rate (suicides per 100 000 population)	?

Notes: Cross sectional-time series analysis of traffic fatality rates for 50 states and DC from 1980 to 2005.
[a]For data sources, see Appendix B.

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 0.08 BAC illegal per se law.[17] Seat belt legislation varies widely across states. Our data record 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 11 regions.[18] The variables are defined and described in Table 1 along with their expected effects (priors) on fatality rates.

III. Econometric Models

The classical fixed effects model[19]

We begin by specifying a linear relationship between the fatality rate – FATAL – (vehicle fatalities per 100 million miles travelled) and the set of explanatory variables listed in Table 1 for the jth state and for the ith year. The model is estimated using regional dummy variables and includes the year as a trend variable. Ordinary least squares results 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.

There is considerable sign agreement in terms of expected and estimated effects. Three variables are estimated with sign differences – INSPECT, BELT and MLDA. 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 of statistical significance testing), we directly address model and parameter uncertainty using three Bayesian econometric methods. They are EBA, BMA and 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

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[17] The per se law refers to a legislation that makes it illegal to drive a vehicle with a blood alcohol level at or above the specified BAC level. BAC is measured in grams per deciliter.
[18] The regions are defined in Appendix B.
[19] The fixed effects model is selected over a random effects model based on a Hausman test with a chi-square value of 639.44.

Table 2. OLS estimates for the fatality rate model[a]

Variable	Estimate	SE	*t*-value	Expected sign
YEAR	−0.466	0.0334	−13.961	−
PERSELAW	−0.0331	0.00697	−4.754	−
INSPECT	0.00775	0.00544	1.425	−
SPEED	0.0333	0.011	3.023	+
BELT	0.000318	0.00753	0.042	−
BEER	0.0935	0.0163	5.752	+
MLDA	0.0104	0.00903	1.148	−
YOUNG	0.0619	0.0197	3.133	+
CELLPOP	0.196	0.0225	8.731	+
POVERTY	0.175	0.0211	8.321	+
UNEMPLOY	−0.0561	0.0232	−2.414	−
REALINC	0.154	0.0384	4.01	?
ED_HS	−0.0361	0.0283	−1.274	−
ED_COL	−0.269	0.0311	−8.632	−
CRIME	−0.0000337	0.0231	−0.001	?
SUICIDE	0.127	0.0286	4.439	?

[a] Residual SE: 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: $<2.2\mathrm{e}-16$.

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 nontrivial and yet is mathematically tractable for these procedures.

Extreme bounds analysis

EBA was developed by Learner in a series of articles beginning in 1978 (Learner, 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.* (2008) have repeatedly used EBA analysis in models analysing aggregate US cross section and time series models of traffic fatality rates.[20]

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 Learner (1982) we specify a natural conjugate prior for a set of doubtful variables, or those variables which could plausibly be dropped from a specification.[21] In this article, 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.

Table 3 reports the maximum and minimum bounds for the posterior means for the nondoubtful variables with the widest possible bounds. 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 favoured. This specification (zero prior mean) corresponds with the prior

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

[21] Dropping a variable forces a very strong prior belief that the coefficient is exactly equal to zero with perfect precision.

Table 3. Maximum likelihood and EBA 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

specifications used for BMA and SSVS specifications that follow in the next two sections. Using EBA, priors are minimally specified since the prior precision matrix is only required to be positive definite symmetric and results are only sensitive to the free-doubtful choice.[22]

When the regional variables are considered doubtful, nonfragile 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 favoured extreme bounds are nonfragile for four variables: year (YEAR), cell phone subscriptions (CELLPOP), poverty (POVERTY) and college education (ED_COLLEGE).

Although EBA as discussed in this article 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.

Bayesian model averaging

BMA was addressed extensively by Raftery *et al.* (1993) following a suggestion by Learner (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 *et al.* (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.

Table 4 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. The column headed ‘Probability Inclusion’ gives the posterior probability that the particular variable is included in the model. The ‘Posterior Mean’ column shows the average posterior mean for the variable for the BMA runs and ‘Posterior Standard Deviation’ is the average posterior SD for the variable. The best performing model included 16 explanatory variables with a posterior probability of 0.279. In that model, INSPECT, BELT, MLDA, UNEMPLOY, ED_HS and CRIME were not 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 nonfragile under EBA when the regional dummy variables are considered doubtful. SPEED is the tenth explanatory variable that was nonfragile under EBA. BMA selects this

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[22] In MICRO-EBA, the prior precision matrix was set equal to the identity matrix, so the priors are spherically symmetric, centred at zero.

Table 4. BMA for the fatality rate model specification

Variable	Probability inclusion	Posterior mean	Posterior SD
YEAR	1.00	−0.445	0.0262
PERSELAW	1.00	−0.0350	0.00677
INSPECT	0.015	0.0000735	0.00081
SPEED	0.666	0.0203	0.0168
BELT	0.00	0.00	0.00
BEER	1.00	0.0934	0.0157
MLDA	0.014	0.000138	0.00157
YOUNG	1.00	0.0784	0.0197
CELLPOP	1.00	0.179	0.02096
POVERTY	1.00	0.184	0.0205
UNEMPLOY	0.368	−0.0198	0.0291
REALINC	1.00	0.161	0.0339
ED_HS	0.022	−0.000827	0.00676
ED_COL	1.00	−0.0282	0.0247
CRIME	0.00	0.00	0.00
SUICIDE	1.00	0.115	0.025

variable two-thirds of the time. There is a considerable agreement between EBA and BMA model choice.

Stochastic search variable selection

SSVS 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, y. 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 $\gamma=0$ 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. This is written as

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

The effective exclusion of the ith variable 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 effectively excluded in a model compared with a more diffuse prior when a variable is effectively included.[23]

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 probability. Initial values of 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.[24] In particular, the Gibbs sampler begins with initialized parameters $\gamma^{(0)}$, $\beta^{(0)}$, $\sigma^{2(0)}$ and generates the sequence $\gamma^{(1)}$, $\beta^{(1)}$, $\sigma^{2(1)}$, $\gamma^{(2)}$, $\beta^{(2)}$, $\sigma^{2(2)}, \ldots$. 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.[25] The first column (Mean Beta) gives the weighted average for the sequence of slope coefficients, weighted by the probability of inclusion. The second column (Mean SD) is the mean value of the weighted SDs 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. Table 5 can easily be compared with the column labelled 'Probability Inclusion' 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

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

[24] In this article, SSVS was implemented via MCMC methods using *R*. This code is available on request.

[25] The first 500 iterations were deleted as a break-in period so there were a total of 9500 iterations employed in the results reported.

Table 5. SSVS for the fatality rate model specification

Variable	Mean beta	Mean SD	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

categorized them for exclusion.[26] The five variables with the highest values for inclusion (probability of inclusion >0.95) in the model correspond with the four EBA non-fragile variables (YEAR, POVERTY, CELLPOP and ED_COLLEGE) as presented in the final two columns of Table 3. SSVS chooses BEER almost always, and is nonfragile under EBA when the prior specification includes BEER as a nondoubtful variable and the regional variables as doubtful.

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 Fig. 1.[27]

Figure 1 compares EBA, BMA and SSVS results. 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 nonfragile. 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

Table 6 below compares the results of the three Bayesian procedures and Ordinary Least Squares (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 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 '0.666' 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 0.95 or greater). This allows for the comparison of results similar to Fig. 1. In what follows we make use of the criterion established above in Table 6 and then supported by Fig. 1. That is, we consider a variable more certain to impact the fatality rate based on a combination of nonfragile EBA results and inclusion of the variable by BMA and/or SSVS as well as statistical 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 nor by SSVS. Figure 1 shows the Bayesian results centring 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.[28]

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[26] The average value of p for this set was 0.12.

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

[28] See, for example, Loeb (1995, 2001).

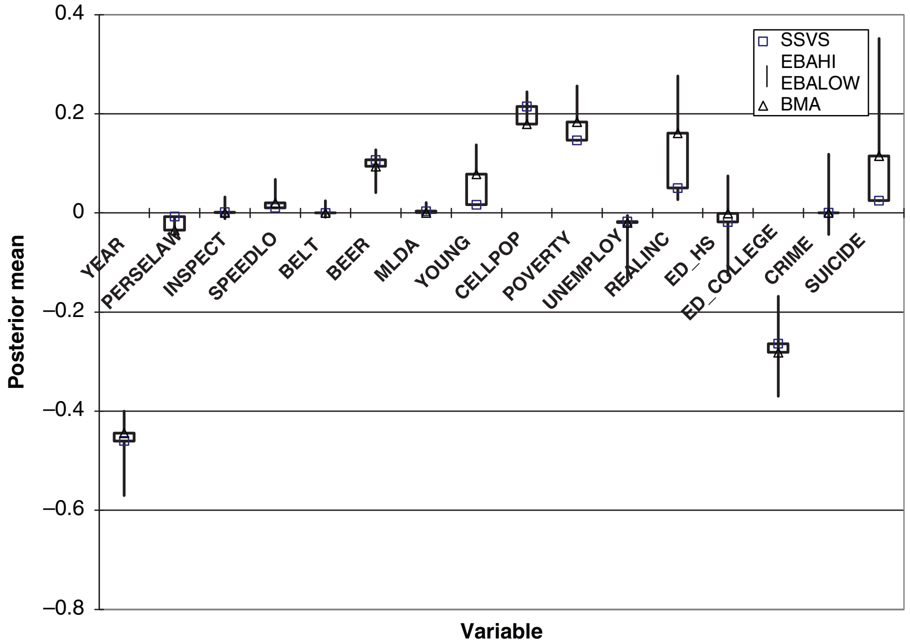

Fig. 1. **Posterior means for the fatality rate model EBA extreme bounds, BMA and SSVS average values regional variables doubtful**

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	−0.466*	−	−0.445/1	−0.4604/1
PERSELAW	−0.0331*	−	−0.035/1	
INSPECT	0.00775	Fragile		
SPEED	0.0333*	+	0.0203/0.66	
BELT	0.000318	Fragile		
BEER	0.0935*	+	0.0934/1	0.1069/0.9999
MLDA	0.0104	Fragile		
YOUNG	0.0619*	+	0.0785/1	
CELLPOP	0.196*	+	0.179/1	0.2146/1
POVERTY	0.175	+	0.184/1	0.1463/0.9999
UNEMPLOY	−0.0561*	−		
REALINC	0.154*	+	0.161/1	
ED_HS	−0.0361	Fragile		
ED_COLLEGE	−0.269*	−	−0.282/1	−0.2642/0.9999
CRIME	−0.000037	Fragile		
SUICIDE	0.127*	+	0.115/1	

Note: *indicate statistical significance of 2.00 or more (in absolute value).

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 nonfragile 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 nonfragile by Fowles *et al.* (forthcoming) as well as by Loeb *et al.* (forthcoming). However, the later study found that the significance of the coefficient associated with BAC 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 discussed by Loeb *et al*. (1994).[29]

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 Fig. 1. Clearly the percentage of males between 16 and 24 years of age has 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 included as a 'companion variable' to measure the potential effect of excluded variables not addressed by the time trend (YEAR). It has a strong positive influence on motor vehicle fatality rates.[30]

The most consistently strong results across all methods of estimation (based again on the criteria in Table 6 and nested in Fig. 1) pertain to the variables: YEAR, BEER, CELLPOP, POVERTY and ED_COLLEGE. All these variables have signs consistent with *a priori* expectations. YEAR proxies time trend and technological changes over time. We expect safety to increase over time hence lower fatality rates, assuming that drivers do not compensate by taking on additional risks. 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.[31] College education is an investment in human capital and might enhance the value of life or the knowledge of risk. This may then result in life-protecting behaviour, given the higher potential opportunity costs associated with risky driving (and other risky activities). The strong result associated with SUICIDE merits further research. 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 life-taking effect when considering motor vehicle fatality rates.

IV. Concluding Comments

This study evaluated the effect of various driving related and socioeconomic factors on motor vehicle fatality rates using four estimation techniques. 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. 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 modelling 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, effective penalties for driving while under the influence of alcohol and taxes on alcohol.[32]

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[29] 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 US Department of Transportation (USDOT) and as such speed and speed variance could not be investigated in the current study.

[30] Suicide may reflect measures of self worth and thus be associated with risk taking behaviours.

[31] See Loeb *et al*. (1994).

[32] See Chaloupka *et al*. (1993) on the effect of alcohol control policies.

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Appendix A. EBA

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, centred at zero, with variance matrix H^{*-1}. This is written as

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

where R is a $p \times K$ matrix of constants, β is a $k \times 1$ vector of parameters, 0 is a $p \times 1$ zero vector, and H^* is a $p \times p$ 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 $K \times 1$ vector τ,[33]

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

are given by

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

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

$$\begin{aligned}
a &= \tau' b - \tau' H^{-1} R'(RH^{-1}R')^{-1}\, Rb \\
\tau*' &= \tau' H^{-1} R'(RH^{-1}R')^{-1} \\
f &= (h + V_{\mathrm{L}}^{-1})^{-1}(hRb + (V_{\mathrm{L}}^{-1} - V_{H}^{-1}) \\
&\qquad * (h + V_{\mathrm{H}}^{-1})^{-1} hRb/2) \\
A &= (h + V_{\mathrm{L}}^{-1})^{-1}(V_{\mathrm{L}}^{-1} - V_{\mathrm{H}}^{-1})^{-1}(h + V_{\mathrm{H}}^{-1}) + (h + V_{\mathrm{H}}^{-1}) \\
c &= (Rb)' h(h + V_{\mathrm{H}}^{-1})^{-1}(V_{\mathrm{L}}^{-1} - V_{\mathrm{H}}^{-1})(h + V_{\mathrm{L}}^{-1}) hRb/4 \\
h &= (RH^{-1}R')^{-1}, \\
b &= (X'X)^{-1} X'Y \\
H &= s^{-2} X'X \\
s &= ((Y - Xb)'(Y - Xb)/(n - K))^{-5}
\end{aligned}$$

Appendix B. 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	US 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, US Census Bureau
YOUNG	State Population Estimates (various years), US 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), US Census Bureau website http://www.census.gov/hhes/poverty/histpov19.html
UNEMPLOY	Statistical Abstract of the United States (various years), US Census Bureau

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[33] In this article, τ is a vector with one 1 and $k - 1$ zeros that corresponds with the ith parameter of interest.

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), US Census Bureau
ED_COL	Digest of Education Statistics (various years), National Center for Education Statistics, Educational Attainment in the United States (various years), US Census Bureau
CRIME	Statistical Abstract of the United States (various years), US Census Bureau
SUICIDE	Statistical Abstract of the United States (various years), US Census Bureau
REGIONS	The 11 regions include the following 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 C. Alternative Presentation of Bayesian Models

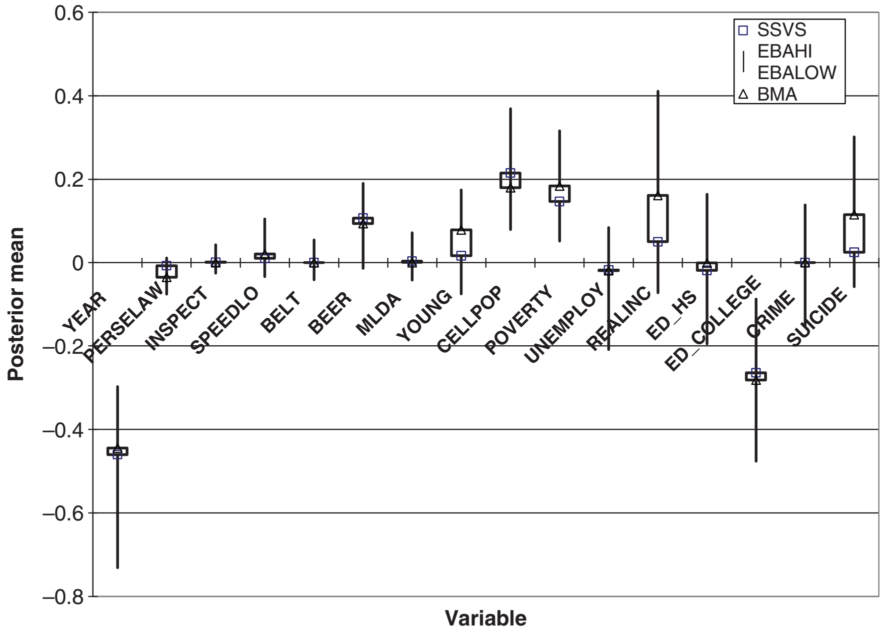

Fig. 2. Posterior means for the fatality rate model EBA extreme bounds, BMA and SSVS average values