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The Cell Phone Effect on Motor Vehicle Fatality Rates:

A Bayesian and Classical Econometric Evaluation

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Abstract

This paper examines the potential effect of cell phones on motor vehicle fatality rates normalized for other driving related and socioeconomic factors. The model used is nonlinear so as to address both life-taking and life-saving attributes of cell phones. The model is evaluated using classical methods along with Bayesian Extreme Bounds Analysis (EBA). The use of both classical and Bayesian methods diminishes the model and parameter uncertainties which afflict more conventional modeling methods which rely on only one of the two methods. The results indicate the presence of both life-taking and life-saving attributes of cell phones on motor vehicle fatality rates depending on the volume of cell phone subscribers in existence.

Keywords: motor vehicle fatality rates, cell phones, Bayesian econometric models

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I. Introduction

The attempt to reduce motor vehicle related fatalities in the United States has been a major public health endeavor for the last several decades. Nonetheless, the number of fatalities is still quite large. In 2005, for example, there were over forty-three thousand lives lost on our roads and highways.[1] To date numerous studies have been conducted to examine the determinants of such accidents and what could be done to ameliorate the losses. These studies considered factors associated with vehicles, roadways, and drivers. More specifically, they have examined the effect of alcohol consumption, speed, speed variance, the type of highways, income, types of vehicles on the roadways, inspection of vehicles, miles driven, unemployment rates, speed limits, the deregulatory climate, among many other factors. Just recently some of these studies have included the effect of cell phones on accidents. The effects of these factors do not necessarily remain static over time which only compounds the difficulty in examining the marginal effects of each one of them.[2]

Peltzman (1975) can be credited with initiating the modern econometric modeling approach to investigating the determinants of motor vehicle accidents. One of the important contributions of the Peltzman study was the attempt to examine potential offsetting behavior on the part of drivers as they adjusted their driving behavior as regulations were imposed, such as the requirement that automobiles be equipped with

[1] See U.S. Census Bureau (2008).
[2] For example, it was estimated that motor vehicle inspection had a life-saving effect initially, but its effect diminished over time. See, for example, Keeler (1994).

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seatbelts. Since his classic paper, numerous studies have been conducted on such topics using various econometric techniques and data sets. For example, there were many studies looking at the effect of motor vehicle inspection on automobile accidents[3], the effect of speed and speed variance on such accidents[4], the effect of seatbelts and seatbelt laws on accidents[5], the effect of alcohol and taxing policies on accidents[6], among other factors which might have offsetting effects. Loeb, Talley, and Zlatoper (1994) evaluate the evidence on many of these potential determinants of accidents. However, these early studies obviously did not consider the impact of cell phones on motor vehicle accidents since cell phone use in the United States only became relevant starting approximately in the 1980s. For example, there were only about 340 thousand cell phone subscribers in the United States in 1985. The growth of cell phone usage and number of subscribers has been explosive since then. By the year 2004 there were over 182 million subscribers in the United States.[7] Given this rapid increase in cell phone usage, economists, safety experts, and policy makers increased their attention to the effect it may have on motor vehicle related accidents.

Cell phone use by drivers may increase accident rates due to the distracting effect of telephone conversations, an inability to do more than two things at the same time, i.e., drive a vehicle and talk on a cell phone, as well as reduce attention spans and adversely affect reaction times. To date, five states (Connecticut, New Jersey, New York, California, and Washington) and the District of Columbia have banned the use of hand-

[3] See, for example, Keeler (1994), Loeb (1985, 1990), Loeb and Gilad (1984), and Garbacz and Kelly (1987).
[4] See, for example, Lave (1985), Levy and Asch (1989), Fowles and Loeb (1989), among others.
[5] See, for example, Evans (1996), Dee (1998), Loeb (1993, 1995, 2001), and Cohen and Einav (2003).
[6] See, for example, Fowles and Loeb (1989) and Chaloupka, et al (1993).
[7] See Cellular Telecommunication and Internet Association (2005).

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held cell phones by drivers.[8] Strangely, the bans do not include the use of hands-free devices as of yet in spite of research indicating that these devices are likely to have similar adverse effects on safety as do hand-held devices.[9] As such, there is indeed concern that accidents are related to the volume of cell phones. But it is not only the sheer number of cell phones that concern researchers but also the propensity of drivers to use these devices. 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. In addition, there is indication that the percentage of drivers using these devices is increasing over time.[10] Hence, not only are cell phones and subscribers increasing over time, but so is driver usage of these devices and apparently at an increasing rate.

A. Background

While statistical studies do seem to indicate a possible association between cell phones and automobile accidents, the results are not consistent, with some studies indicating no significant relationship between cell phones and automobile accidents and others indicating a relationship. The most well-known study regarding cell phone effects on automobile accidents is by Redelmeier and Tibshirani (1997) using cross-over analysis and examining property-only accidents in Toronto, Canada for the period 1994 to 1995. They conclude that property-only accidents increase four-fold when cell phones

[8] These states and the District of Columbia have primary laws banning hand-held cell phone use while driving with the exception of Washington, which has a secondary law. In addition, Utah has, what is in effect, a secondary law banning hand-held cell phone use and Oregon will impose a primary law banning hand-held cell phone use by drivers on January 1, 2010. Furthermore, by January 2010, seventeen states and the District of Columbia will have banned text messaging by all drivers (either via a primary or secondary law). See Insurance Institute for Highway Safety (November 2009).
[9] See, for example, Consiglio et al. (2003).
[10] Glassbrenner (2005) has estimated that driver use of just hand-held phones increased from 5% in 2004 to 6% in 2005.

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are involved. They also find that 39% of drivers involved in these accidents use their cell phones to call for assistance after the accident. McEvoy et al. (2005), using Australian data between April 2002 and July 2004, also find an increase in the risk of an accident using data on crashes resulting in hospital visits. Using a laboratory environment, with 22 research participants from Miami University, Consiglio et al. (2003) simulated driving conditions and found that the reaction time in a brake producing situation was slowed when cell phones were in use and this reduction occurred regardless of whether the cell phones were hand-held or hands-free devices. Violanti (1998), using Oklahoma data for the period 1992 to 1995 and regression analysis, found a strong association between cell phone use and motor vehicle fatalities. More specifically, Violanti attributes an approximate nine-fold increase in fatalities when cell phones are in use as opposed to when they are not.[11]

As mentioned above, not all research has supported the claim that cell phones were associated with accidents. Rather, there is research evidence that cell phones do not have such a significant impact on motor vehicle accidents. Laberge-Nadeau et al. (2003) using logistic-normal regression models and Canadian survey data for the period January 1996 to August 2000, 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. 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. Using a random national telephone survey in Australia in November 1997, Chapman and Schofield found that, “Over one in eight

[11] See Violanti (1998, p. 522).

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current mobile phone users have used their phones to report a road accident."[12] Making reference 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), using Finish data, claim that, "phone-related accidents have not increased in line with the growth of the mobile phone industry."[14]

More recently, Loeb et al. (2009) addresses the fragile results reported across the various research endeavors by using econometric methods and specification error tests, with U.S. data for the years 1975 to 2003, 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 suggested 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. However, starting in the 1990s, when subscribers numbered 100 million and more, the life-taking effect overwhelmed the life-saving effect once again.[15] These results are found to be statistically significant and stable. The results are considered reliable given

[12] See Chapman and Schofield (1998, p.817).
[13] See Chapman and Schofield (1998, p. 818).
[14] See Poysti (2005, p. 50).
[15] This paper only looks at the effect the number of cell phone subscribers have on fatality rates. The increase in the number of cell phones and cell phone subscribers over time may be due to numerous factors including the pricing of phone service, availability of service, income, and tastes as well as other socioeconomic, gender, technology, and population age factors. Such issues would be fruitful avenues for future research, e.g., the estimation of the demand function for cell phones and cell phone service.

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the outcome of the specification error tests which paid particular attention to the structural form of the models.[16] Yet the above mentioned models have only been examined from a classical perspective leaving concern pertaining to both model and parameter uncertainty. This paper addresses this concern.

The Loeb et al. paper is the basis for the current study. The reliability of the results suggested in the Loeb et al. paper is examined here using a large and newly created set of panel data and making use of both classical and Bayesian estimation techniques. One would expect that the true relationship between motor vehicle fatalities and cell phones should be observed using either classical or Bayesian techniques. Confidence regarding the results should be enhanced if similar results are forthcoming from both the classical and Bayesian techniques.

To be more precise, one of the most widely used and familiar methods to understand the marginal effects of the various potential factors on traffic fatalities is multiple regression using ordinary least squares (OLS). In this paper we utilize OLS using cross sectional, time series data and then we apply Bayesian Extreme Bounds Analysis. Our methods are designed to explore both parameter uncertainty and model uncertainty.

In Section II we describe the data, develop a fixed effects model, and discuss parameter estimates. Section III further explores estimation using Bayesian sensitivity analysis. In particular we see whether or not the data can support reliable parameter estimates over subsets of models. Our concluding section (IV) highlights how classical

[16] The models presented by Loeb et al. 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 error by one or more of these tests resulted in the elimination of those models from consideration.

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and Bayesian methods agree and differ across model specifications and suggests ways these data might be further examined.

II. The Classical Model

In order to understand the effects of socio-economic and policy related variables on traffic fatality rates we utilize data on 50 states and Washington, D.C. over the period from 1980 to 2004. We specify 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 and the variables described in Table 1. The base model is estimated using 50 dummy variables and includes the year as a trend variable.[17] As such, we can specify the basic model as:

(1) $\text{FATAL} = X\beta + \mu$

where: FATAL is the fatality rate,

X is a set of regressors made up of those listed in Table 1 (which includes a measure of cell phone use)

and μ is the error term.

This set of variables form the basis for a fairly standard specification that is not particularly complex. One novel feature is the use of the square and cube of the number

[17] The results in this paper are not sensitive to other specifications such as fixed effects or random effects estimation. 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 a "companion variable." Companion variables attempt to account for factors not addressed by the time trend and are discussed in Loeb (1995, 2001). In addition, models were estimated using regional dummies instead of state dummies. Regardless, the results remain stable and similar to those reported. These additional models are available from the authors. Additional variables to those listed in Table 1 were also considered. These included measures of income and law enforcement. The correlation between these factors and the time trend (based on aggregate time series data) were greater than 0.98. Hence they were not included so as to avoid multicollinearity. Climatological conditions are assumed to be captured by the state dummy variables.

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of cell phone subscribers.[18] As discussed in Loeb et al. (2009), the number of cell phone subscribers and the square and cube of this variable are included to account for the possibilities of externalities associated with increasing cell phone usage that would allow quicker emergency resources to be available at a crash site.

Ordinary least squares results for the basic model are presented in Table 2. This regression included 50 state dummy variables and a constant term, but those estimated coefficients are omitted from the table. The results conform with the conventional wisdom. Of major interest are the non-monotonic and significant results associated with cell phones on motor vehicle fatality rates. This model provides the prior for the Bayesian analysis to follow.

III. Bayesian Extreme Bounds Analysis

Classical estimation addresses the issue of parameter uncertainty conditional on the validity of the model. As shown in Section II, statistically significant estimates were associated with the majority of the variables included in the model and the signs of the estimates conformed to prior beliefs about what the marginal effects of the variables should be. In this section we address the issue of parameter stability across model specifications using Extreme Bounds Analysis (EBA) as introduced in Leamer (1982). For more detailed examples of EBA theory and applications see Fowles and Loeb (1995) or Fowles and Loeb (1989). The spirit in which EBA is used in this paper is to provide a picture as to the extent to which changes in fundamental model specification (inclusion or

[18] Because annual subscription data on cell phones are only uniformly available at the national level, we imputed state level subscriptions to be proportional to state population proportions for each year. As such, we assume all states are equally impacted by cell phone availability over time. Annual subscription data were available at the state level beginning in the year 2000. Our method of imputing cell phone data subscriptions correlates with the actual data with a correlation coefficient of 0.9943. (Once again, we assume that cell phone innovation and the receptiveness of the population to cell phones spreads uniformly by proportion of people who live in the states through the 1990s as cell phones became more widespread.)

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exclusion of variables) lead to changes in the signs of estimated parameters associated with fatality rate regressors. At first there could be 2^{61} possible subset regressions if we considered adding or dropping individual state dummy variables. Although EBA could easily produce credible bounds for parameter estimates over this wide a variety of specifications we decided to constrain the search over just a subset of possible models by forcing state dummy variables to always be included. In order to tractably manage the fifty state binary variables, EBA was performed on a modified model that was developed in two stages. First, fatality rates were regressed on the fifty state binary variables and then the residuals from this regression were analyzed based on the classical model discussed above.[19] The cubic and square effects of the number of cell phones were attenuated by transforming cell phone usage and the polynomial transformations by several orders of magnitude for computational ease and readability.[20]

There are two results presented here. First, all variables were treated as doubtful with prior means set at zero and with a prior variance/covariance matrix set to the identity matrix. Posterior bounds are calculated by then sweeping a scalar multiple of the prior variance/covariance matrix from zero to infinity. With this Bayesian specification, the extreme upper and lower bounds always allow for a zero posterior mean (corresponding to infinite prior precision). From a traditional perspective, setting the prior mean to zero represents the tacit belief that these variables could plausibly be dropped from a regression specification. Results are reflective of the posterior bounds within 0%, 75%,

[19] More specifically, this is a traditional fixed effects adjustment. In the first stage, the fatality rate is regressed against the state dummy variables and the residuals are retained. These residuals are then analyzed using EBA in the second stage where the residuals are now the dependent variable, i.e., may be considered as the fatality rate cleansed of the effects measured by the state dummy variables.
[20] The cell phone data were rescaled by several orders of magnitude in order to reduce problems in the many matrix inversions necessary within EBA. This rescaling accounts for the differences associated with the coefficients of the various CELL variables when comparing EBA results with OLS results.

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95%, 99%, and 100% confidence ellipsoids. Table 3 presents these EBA upper and lower bounds for 100% (extreme), 75%, and 95% likelihood ellipsoids. The 75% and 95% bounds are data favored, or what Leamer (1983) calls credible bounds.

In Table 4, the variables YEAR, BACLAW, ANNUAL, SPEEDRU, BELT, BEER, MLDA, and YOUNG are considered doubtful with a prior mean at zero. This second model places no restrictions on the intercept term, nor on CELL, CELLSQ, and CELLCUBE. Thus they are considered "free" variables without a defined conjugate prior. From a frequentist perspective, these variables would not be variables that would plausibly be dropped from a regression specification.

The shaded cells in Tables 3 and 4 represent non-fragile estimates where the bounds for the posterior mean do not cover zero. Data clearly suggest that YEAR, BACLAW, BEER, YOUNG, and CELL estimates are insensitive to model specification changes and that the posterior mean estimates fall within regions that are anticipated. Notice that EBA results from Table 3 generally conform with OLS estimates presented in Table 2. Non-fragile estimates certainly are associated with estimates that are statistically significant at a 5% level. This is especially true for YEAR, BACLAW, YOUNG, and CELL. When comparing EBA and OLS results from Table 4, the only inferential differences occur in the estimation of the effect of BELT which is conventionally statistically significant, but fragile from a Bayesian perspective.

It is somewhat unusual to see this much agreement between OLS and EBA results because of the draconian nature of the EBA procedure.[21] EBA exposes fragility that is

[21] See, for example, Granger and Uhlig (1990) or Cassell and Fowles (1998).

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inherent when data are multicollinear. Remarkably, this data do not suffer much from this econometric problem.[22]

IV. Concluding Comments

This paper uses classical regression methods along with Bayesian Extreme Bounds Analysis (EBA) to address the effect of cell phones on motor vehicle fatality rates so as to examine the potential of net life-taking and life-saving effects. The models adjust for a time trend (YEAR), the blood alcohol concentration legislation (BACLAW) required for drunk driving arrests, annual inspection (ANNUAL), the maximum posted rural speed limit (SPEEDRU), a dummy variable indicating the presence of a seat belt law (BELT), per capita consumption of beer (BEER), the minimum legal drinking age (MLDA), the percentage of males aged 16-24 relative to the population of age 16 and over (YOUNG), and various measures of cell phone subscribers (CELL, CELLSQ, CELLCUBE). The measures of cell phones are allowed to enter the model in a non-linear manner so as to examine the potential of non-monotonic effects of cell phones on motor vehicle fatality rates as suggested by Loeb et al. (2009). The models are estimated using panel data for all fifty states and the District of Columbia for the years 1980 to 2004. The classical and Bayesian estimates correspond well with each other. The classical results presented in Table 2 correspond in sign with the expected values suggested in Table 1. Most interestingly, the Bayesian analysis corresponds well with the classical analysis.

[22] The correlation matrix for FATAL and the primary explanatory variables is provided in Appendix 2. Note, EBA does not suggest multicollinearity even with the presence of higher order polynomials associated with cell phones.

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Using the Bayesian results reported in Table 4 and comparing them with the classical results of Table 2, we find the following:

The coefficient of YEAR is significant in the classical model and is stable using both a 75% and 95% ellipsoid using EBA. The same is true for BACLAW. The coefficient of BEER in the classical case corresponds well with the Bayesian case with the 75% ellipsoid. The correspondence between the classical estimates and the Bayesian ones remain intact for ANNUAL, SPEEDRU, and MLDA. In the classical model, the coefficients associated with these variables prove statistically insignificant at usual levels and the EBA estimates are fragile. The coefficient associated with BELT is just about significant in the classical case but is fragile using EBA. This may not be surprising, given the marginal significance of this coefficient in the classical case. Most interestingly from our perspective, the coefficients associated with the various CELL variables prove statistically significant and with signs expected based on Loeb et al. (2009). These results are consistent with the EBA results which remain stable at both the 75% and 95% likelihood ellipsoids. This once again indicates that there are life-taking and life-saving effects associated with cell phones as they relate to motor vehicle fatality rates. Initially, cell phones contribute to motor vehicle fatality rates. This may be due to the inability of drivers to use phones and drive, a diminution of a driver's attention span, among other reasons. Later the net effect of cell phones is associated with a reduction of the fatality rate. This may be due to the necessity of having a critical mass of cell phones available among the public so that the likelihood of those not involved in an accident calling for assistance is high. As such, the victims may be afforded a greater probability of taking advantage of the "golden hour." However, after yet another critical amount of

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cell phones enter use, the life-taking effect overwhelms the life-saving effect. This may be due to the rapid pace by which cell phones are entering usage and the growth rate of cell phone use by drivers. As a stylization, Figure 1 plots fatality rates against cell phone subscriptions using the parameter estimates from Table 2. Although more research is needed on the exact timing of when cell phone use becomes problematic, the overall picture is clear.

The bottom line is that cell phones now have an adverse effect on motor vehicle fatality rates. Policy makers may encourage their legislatures to prohibit the use of cell phones by drivers. These bans might be associated with fines/penalties so as to influence driver behavior. In addition, thought should be given to extending these bans from secondary enforcement to primary enforcement. Future research can entertain these possibilities so as to lower motor vehicle fatality rates.

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Table 1
Explanatory Variables [a]
Cross Sectional - Time Series Analysis of Traffic Fatality Rates
For 50 States and DC from 1980 to 2004

Name	Description	Mean	Std Dev	Expected Sign
YEAR	Year	1992	7.214	-
BACLAW	Dummy variable indicating the existence of a law defining intoxication of a driver in terms of Blood Alcohol Concentration (BAC). BACLAW=1 indicates the existence of such a law and BACLAW=0 indicates the absence of such a law.	.0842	.0426	-
ANNUAL	Indicator for annual safety inspection	.430	.495	-
SPEEDRU	Maximum posted speed limit, rural highways	63.211	6.325	+
BELT	Indicator for presence of a legislated seat belt law	.658	.474	-
BEER	Per capita beer consumption (in gal)	1.322	.229	+
MLDA	Minimum legal drinking age	20.631	.883	-
YOUNG	Percentage of males (16-24) relative to population of age 16 and over	.184	.0289	+
CELL	Imputed number of cell phone subscribers	971316.8	2161472	+
CELLSQ	Square of CELL	5.61e+12	3.15e+13	-
CELLCUBE	Cube of CELL	6.39e+19	6.33e+20	+

[a] For data sources, see Appendix 1

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Table 2
Ordinary Least Squares Estimates [a]
Standard Errors, t-Statistics, P values, and Confidence Intervals
Cross Sectional - Time Series Analysis of Traffic Fatality Rates
For 50 States and DC from 1980 to 2004

	Estimated Coefficient	Standard Error	t-Stat	P>|t|	95% Lower	95%Upper
YEAR	-0.06537	0.003262	-20.04	0.000	-0.0717	-0.0589
BACLAW	-1.37518	0.223152	-6.16	0.000	-1.812	-0.9373
ANNUAL	-0.02375	0.047246	-0.50	0.615	-0.1164	0.06894
SPEEDRU	0.003277	0.002775	1.18	0.238	-0.0021	0.0087
BELT	-0.06479	0.03247	-2.00	0.046	-0.1284	-0.0010
BEER	0.766971	0.105354	7.28	0.000	0.5602	0.97366
MLDA	-0.00208	0.013218	-0.16	0.875	-0.0280	0.02385
YOUNG	3.984259	0.400289	9.95	0.000	3.198	4.76959
CELL	7.80E-08	2.41E-08	3.24	0.001	3.08E-08	1.25E-07
CELLSQ	-1.05E-14	3.53E-15	-2.99	0.003	-1.75E-14	-3.61E-15
CELLCUBE	3.53E-22	1.30E-22	2.71	0.007	9.74E-23	6.09E-22

[a] Estimated coefficients for state variable dummies were included in the model specification, but the estimates for these and the constant term are omitted from Table 2. Adjusted R^2= .8580; Root MSE= .28642; F(61,1213)= 127.23

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Table 3
Extreme, 75%, and 95% Likelihood Bounds
Estimates of Posterior Means with All Variables Doubtful

Variable	Extreme Minimum	Extreme Maximum	75% Minimum	75% Maximum	95% Minimum	95% Maximum
YEAR	-.114	.0451	-.0771	-.0597	-.0786	-.0579
BACLAW	-7.155	6.088	-1.833	-.292	-1.977	-.145
ANNUAL	-.555	.566	-.0536	.0773	-.0660	.0896
SPEEDRU	-.0558	.0534	-.0087	.0040	-.0099	.0052
BELT	-.925	.857	-.171	.0363	-.191	.0560
BEER	-1.165	1.332	.0207	.311	-.0069	.339
MLDA	-.396	.389	-.0524	.0393	-.0611	.0480
YOUNG	-9.177	12.588	2.137	4.654	1.896	4.885
CELL	-.593	.697	.0283	.178	.0140	.192
CELLSQ	-.112	.0984	-.0258	-.0013	-.0281	.0010
CELLCUBE	-3.816	4.259	-.0298	.911	-.119	.999

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Table 4
Extreme, 75%, and 95% Likelihood Bounds
Estimates of Posterior Means with
Intercept, CELL, CELLSQ, and CELLCUBE as Free Variables

Variable	Extreme Minimum	Extreme Maximum	75% Minimum	75% Maximum	95% Minimum	95% Maximum
YEAR	-.103	.0340	-.0767	-.0597	-.0781	-.0579
BACLAW	-6.234	5.167	-1.831	-.291	-1.973	-.145
ANNUAL	-.477	.488	-.0536	.0772	-.0660	.0895
SPEEDRU	-.0482	.0458	-.0087	.0040	-.0099	.0052
BELT	-.801	.733	-.171	.0363	-.191	.0560
BEER	-.992	1.158	.0207	.311	-.0069	.338
MLDA	-.341	.335	-.0524	.0393	-.0610	.0479
YOUNG	-7.663	11.073	2.137	4.643	1.896	4.872
CELL	-.550	.327	.0442	.153	.0330	.162
CELLSQ	-.0430	.0702	-.0201	-.0059	-.0212	-.0044
CELLCUBE	-2.270	1.414	.192	.654	.144	.692

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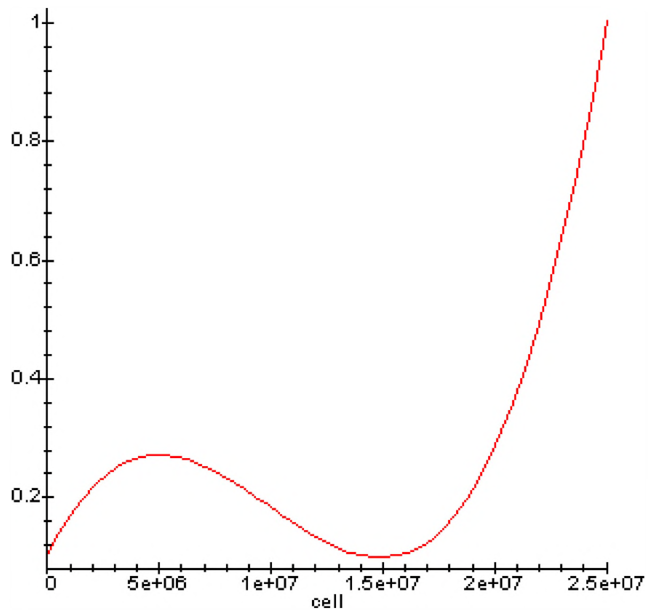
Figure 1
Fatality Rates Plotted Against Cell Phones
Using Parameter Estimates from Table 2
Fatal = .1+.78e-7*cell-.105e-13*cell^2+.353e-21*cell^3



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Appendix 1 -- Data Sources

Variable	Source
FATAL	National Transportation Statistics (various years), Federal Highway Administration, National Highway and Traffic Safety Administration.
BACLAW	Digest of State Alcohol Highway Safety Related Legislation (various years). Traffic Safety Facts, National Highway and Traffic Safety Administration.
ANNUAL	Digest of Motor Laws (various years), American Automobile Association.
SPEEDRU	Highway Statistics (various years), Federal Highway Administration, National Highway and Traffic Safety Administration.
BELT	Traffic Safety Facts (various years), National Highway and Traffic Safety Administration.
BEER	Statistical Abstract of the United States, U.S. Census Bureau.
MLDA	Digest of State Alcohol Highway Safety Related Legislation (various years). Traffic Safety Facts, National Highway and Traffic Safety Administration.
YOUNG	State Population Estimates (various years), U.S. Census Bureau.
CELL	Cellular Telecommunication and Internet Association Wireless Industry Survey, International Association for the Wireless Telecommunications Industry.

Appendix 2 – Correlation matrix of FATAL and primary explanatory variables

	FATAL	YEAR	BACLAW	ANNUAL	SPEEDRU	BELT	BEER	MLDA	YOUNG	CELLPHONE
FATAL	1.0000									
YEARS	-0.6832	1.0000								
BACLAW	-0.2546	0.2187	1.0000							
ANNUAL	-0.0627	0.0097	-0.0328	1.0000						
SPEEDRU	-0.1751	0.5303	0.1674	-0.1286	1.0000					
BELT	-0.5520	0.7311	0.2663	-0.0257	0.3184	1.0000				
BEER	0.3084	-0.2181	0.0202	-0.1589	-0.0719	-0.2202	1.0000			
MLDA	-0.4589	0.5539	0.2137	-0.0388	0.2748	0.5280	-0.1617	1.0000		
YOUNG	0.3896	-0.1786	-0.1386	-0.0499	0.2012	-0.3189	0.0146	-0.3273	1.0000	
CELLPHONE	-0.3489	0.5115	0.0494	-0.0176	0.2869	0.3120	-0.1886	0.1854	0.0272	1.000