A Bayesian and Classical Econometric Evaluation of the Effect of Cell Phones on Motor Vehicle Fatality Rates

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Richard Fowles, Peter D. Loeb, and Wm. A. Clarke*

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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 models are 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.

Key Words: Motor Vehicle Fatality Rates, Cell Phones, Bayesian Econometric Methods, Extreme Bounds Analysis, Classical Econometric Methods

JEL Classification: L92

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. 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.[1]

        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

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

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[1] 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).

studies looking at 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], the effect of alcohol and taxing policies on accidents[5], among other factors which might have countervailing 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.[6] Given this rapid increase in cell phone usage, economists, safety experts, and policy makers increased their attention to the effect they 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 reduce 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-held cell phones by drivers.[7] Strangely, the bans do not impact on the use of hands-free devices as of yet in spite of research indicating that these devices are likely to have similar adverse effects

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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, Evans (1996), Dee (1998), Loeb (1993, 1995, 2001), and Cohen and Einav (2003).
[5] See, for example, Fowles and Loeb (1989) and Chaloupka, et al (1993).
[6] See Cellular Telecommunication and Internet Association (2005).
[7] Furthermore, both New Jersey and California banned text messaging by drivers in the year 2008.

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on safety as do hand-held devices.[8] 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.[9]

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. They conclude that property-only

accidents increase four-fold when cell phones 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) also find an increase in the risk of an accident using data

on crashes resulting in hospital visits. Using a laboratory environment, 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

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[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.

of whether the cell phones were hand-held or hands-free devices. Violanti (1998), using 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.[10]

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 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. Chapman and Schofield found that, "Over one in eight current mobile phone users have used their phones to report a road accident."[11] 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.[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 the various research endeavors by using econometric methods and specification error tests to examine the potential interacting effect of life-saving and life-taking

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[10] See Violanti (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).

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. These results are 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 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 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.

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[14] 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.

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 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 jth state and for the ith year and the variables described in Table 1. The base model is estimated using 50 state dummy variables and includes the year as a trend variable.[15]

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[15] 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.

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 of cell phone subscribers.[16] As discussed in Loeb et al. (forthcoming), 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.

III.   Bayesian Extreme Bounds Analysis

Classical estimation addresses the issue of parameter uncertainty in relation to the sampling distribution induced by normality assumptions in the linear regression 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 exclusion of variables)

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[16] 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.

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. 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.

There are two results presented here. First, all variables were treated as doubtful with prior means set at zero 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%, 95%, 99%, and 100% confidence ellipsoids. Table 3 presents 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 we

imposed vague priors on YEAR, BACLAW, ANNUAL, SPEEDRU, BELT, BEER, MLDA, and YOUNG. The 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.[17] EBA exposes fragility that is inherent when data are multicollinear. Remarkably, this data do not suffer much from this econometric problem.[18]

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[17] See, for example, Granger and Uhlig (1990) or Cassell and Fowles (1998).
[18] 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.

IV.   Concluding Comments

This paper uses classical regression methods along with Bayesian Extreme Bounds Analysis (EBA) to addresses 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. (forthcoming). 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.

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. (forthcoming). 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 involve 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 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 have an adverse affect 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.

References

Cassell, Paul G. and Richard Fowles, "Handcuffing the Cops? A Thirty-Year Perspective on Miranda's Harmful Effects on Law Enforcement," *Stanford Law Review*, 1998, 50(4), 1055-1146.

Cellular Telecommunications and Internet Association (CITA) (2005). http://www.ctia/org/

Chaloupka, F.J., H. Saffer, and M. Grossman, "Alcohol-Control Policies and Motor Vehicle Fatalities," *Journal of Legal Studies*, 1993, 22 (1), 161-186.

Chapman, S. and W.N. Schofield, "Lifesavers and Samaritans: Emergency Use of Cellular (Mobile) Phones in Australia," *Accident Analysis and Prevention*, 1998, 30 (6), 815-819.

Cohen, A. and L. Einav, "The Effects of Mandatory Seat Belt Laws on Driving Behavior and Traffic Fatalities," *The Review of Economics and Statistics*, 2003, 84 (4), 828-843.

Consiglio, Wm., P. Driscoll, M. Witte, and Wm. P. Berg, "Effect of Cellular Telephone Conversations and Other Potential Interference on Reaction Time in Braking Responses." *Accident Analysis and Prevention*, 2003, 35, 495-500.

Dee, T.S., "Reconsidering the Enforcement of Seat Belt Laws and their Enforcement Status," *Accident Analysis and Prevention*, 1998, 30 (1), 1-10.

Evans, L., "Safety-belt Effectiveness: the Influence of Crash Severity and Selective Recruitment," *Accident Analysis and Prevention*, 1996, 28 (4), 423-433.

Fowles, Richard and Peter D. Loeb, "Speeding, Coordination, and the 55-MPH Limit: Comment," *The American Economic Review*, 1989, vol. 79, issue 4, pages 916-21.

Fowles, Richard and Peter D. Loeb, "Effects of Policy-Related Variables on Traffic Fatalities: an Extreme Bounds Analysis Using Time Series Data," *The Southern Economic Journal*, 1995, 62, 359-366.

Garbacz, C. and J.G. Kelly, "Automobile Safety Inspection: New Econometric and Benefit/Cost Estimates," *Applied Economics*, 1987, 19, 763-771.

Glassbrenner, D., ""Driver Cell Phone Use in 2005 – Overall Results," *Traffic Safety Facts: Research Note*, 2005, NJTSA, DOT HS 809967. <http://www.nrd.nhtsa.dot.gov/pdf/nrd-30/NCSA/RNotes/2005/809967.pdf>

Granger, Clive W.J. and Harald F. Uhlig, "Reasonable Extreme-Bounds Analysis," *Journal of Econometrics*, 1990, 44(1-2), 159-170.

Keeler, Theodore, E., "Highway Safety, Economic Behavior, and Driving Environment," *The American Economic Review*, June 1994, 84(3), pp. 684-693.

Laberge-Nadeau, C.U. Maag, F. Bellavance, S.D. Lapiere, D. Desjardins, S. Messier, and A. Saidi, "Wireless Telephones and Risk of Road Crashes," 2003, <doi:10:1016/S0001-4575(02)00043-X>

Lave, C.A., "Speeding, Coordination and the 55 MPH Limit," *American Economic Review*, 1985, 75, 1159-1164.

Levy, D.T. and P. Asch, "Speeding, Coordination, and the 55 MPH Limit: Comment," *American Economic Review*, 1989, 79 (4), 913-915.

Leamer, Edward E., "Sets of Posterior Means with Bounded Variance Priors." *Econometrica*, May 1982, 725-36.

Leamer, Edward E., "Let's Take the Con Out of Econometrics," *The American Economic Review*, 1983, Vol. 73, No. 1, 31-43.

Loeb, Peter D., "The Efficacy and Cost-Effectiveness of Motor Vehicle Inspection Using Cross-Sectional Data – An Econometric Analysis," *Southern Economic Journal*, 1985, 52, 500-509.

Loeb, Peter D., "Automobile Safety Inspection: Further Econometric Evidence," *Applied Economics*, 1990, 22, 1697-1704.

Loeb, Peter D., "The Effectiveness of Seat-Belt Legislation in Reducing Various Driver-Involved Injury Rates in California," *Accident Analysis and Prevention*, 1993, 25 (2), 189-197.

Loeb, Peter D., "The Effectiveness of Seat-Belt Legislation in Reducing Injury Rates in Texas," *American Economic Review – Papers and Proceedings*, 1995, 88 (2), 81-84.

Loeb, Peter D., "The Effectiveness of Seat Belt Legislation in Reducing Driver-Involved Injury Rates in Maryland," *Transportation Research: Part E*, 2001, 37 (4), 297-310.

Loeb, Peter D. and B. Gilad, "The Efficacy and Cost-Effectiveness of Vehicle Inspection – A State Specific Analysis Using Time Series Data," *Journal of Transport Economics and Policy*, 1984, 18, 145-164.

Loeb, P.D., Wm. Clarke, and R. Anderson, "The Impact of Cell Phones on Motor Vehicle Fatalities," *Applied Economics*, forthcoming.

Loeb, P.D., W.K. Talley, and T.J. Zlatoper, Causes and Deterrents of Transportation Accidents: An Analysis by Mode, 1994, Westport, CT, Quorum Books.

McEvoy, S.P., M.R. Stevenson, A.T. McCartt, M. Woodward, C. Haworth, P. Palamara, and R. Cercarelli, "Role of Mobile Phones in Motor Vehicle Crashes Resulting in Hospital Attendance: A Case-Crossover Study," *British Medical Journal*, July 12, 2005, <BMJ:doi: 10.1136/bmj.38537.397512.55>

Peltzman, S., "The Effects of Automobile Regulation," *Journal of Political Economy*, 1975, 93 (4), 677-725.

Poysti, L., S. Rajalin, and H. Summala, "Factors Influencing the Use of Cellular (Mobile) Phone During Driving and Hazards While Using It," *Accident analysis and Prevention*, 2005, 37 (1), 47-51.

Redelmeier, D.A. and R.J. Tibshirani, "Association Between Cellular-Telephone Calls and Motor Vehicle Collisions," *The New England Journal of Medicine*, 1997, 336 (7), 453-458.

Violanti, J.M., "Cellular Phones and Fatal Traffic Collisions," *Accident Analysis and Prevention*, 1998, 30 (4), 519-524.

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
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	Indictor 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	+
YEAR	Year	1992	7.214	-

[a] For data sources, see Appendix 1

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

Table 3
Extreme, 75%, and 90% 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

Table 4
Extreme, 75%, and 90% 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

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
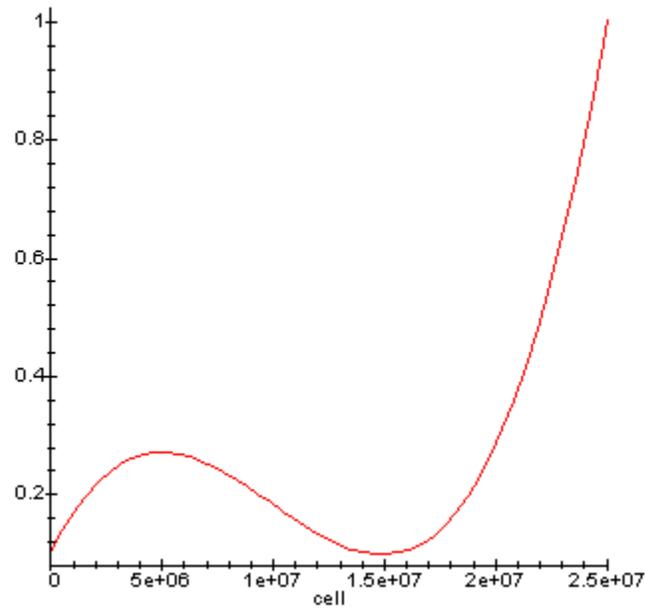
Appendix 1 -- Data Sources

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
```