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The Determinants of Motor Vehicle Fatalities Using Classical Specification Testing and Bayesian Sensitivity Methods

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ABSTRACT

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 maximum blood alcohol concentration legislation (BAC) required for drunk driving arrests, annual inspection (ANNUAL), the maximum posted rural speed limit (SPEED_RU),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 nonlinear 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.

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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. 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

[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, four states (Connecticut, New Jersey, New York, and Utah) 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 on safety

[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), and Loeb (1993, 1995, 2001).
[5] See, for example, Fowles and Loeb (1989) and Chaloupka, et al (1993).
[6] See Cellular Telecommunication and Internet Association (2005).
[7] Both California and Washington will ban the use of cell phones by drivers on July 1, 2008. Furthermore, both New Jersey and California will ban text messaging by drivers in the year 2008.

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 accident 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 reduced when cell phones were in use and this reduction occurred

[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.

regardless 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

[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. However, starting in the 1990s, when subscribers number 100 million and more, the life-taking effect overwhelms 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.

The Loeb et al. paper is the basis for the current study. The reliability of the results suggested is examined 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.

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 suggest ways this 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 (vehicle fatalities per 100 million miles traveled) for the j^{th} state and for the i^{th} year and the variables described in Table I. The base model is estimated using 50 state dummy variables and includes the year as a trend variable.[14]

[14] 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.

Table I
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
PERSE	Blood alcohol concentration (BAC) required for drunk driving arrest with zero coded as an indicator of no PERSE law	.0842	.0426	-
ANNUAL	Indicator for annual safety inspection	.430	.495	-
SPEED_RU	Maximum posted speed limit, rural highways	63.211	6.325	+
BELT	Indictor for presence 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

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. As discussed in Loeb (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 II. This regression included 50 state dummy variables and a constant term, but those estimated coefficients are omitted from the table.

Table II
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
PERSE	-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
SPEED_RU	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 II. Adjusted R^2: .8580; Root MSE: .28642. F(61,1213): 127.23

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) 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 III presents EBA upper and lower bounds for 100% (extreme), 75%, and 95% likelihood ellipsoids. The maximum likelihood point estimate is within the 0% confidence ellipsoid (the upper and lower bounds are equal). 75% and 95% bounds are data favored, or what Leamer (1983) calls credible bounds. In Table IV we imposed vague priors on YEAR, PERSE, 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.

Table III
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
PERSE	-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 IV
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
PERSE	-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

The shaded cells in Tables III and IV represent non-fragile estimates where the bounds for the posterior mean do not cover zero. Data clearly suggest that YEAR, PERSE, 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 III generally conform with OLS estimates presented in Table II. Non-fragile estimates certainly are associated with estimates that are statistically significant at a 5% level. This is especially true for YEAR, PERSE, YOUNG, and CELL. When comparing EBA and OLS results from Table IV, 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.[15] EBA exposes fragility that is inherent when data are multicollinear. Remarkably, this data do not suffer much from this econometric problem.[16]

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 maximum blood alcohol concentration legislation (BAC) required for drunk driving arrests, annual inspection (ANNUAL), the maximum posted rural speed limit (SPEED_RU),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 II correspond in sign with the expected values

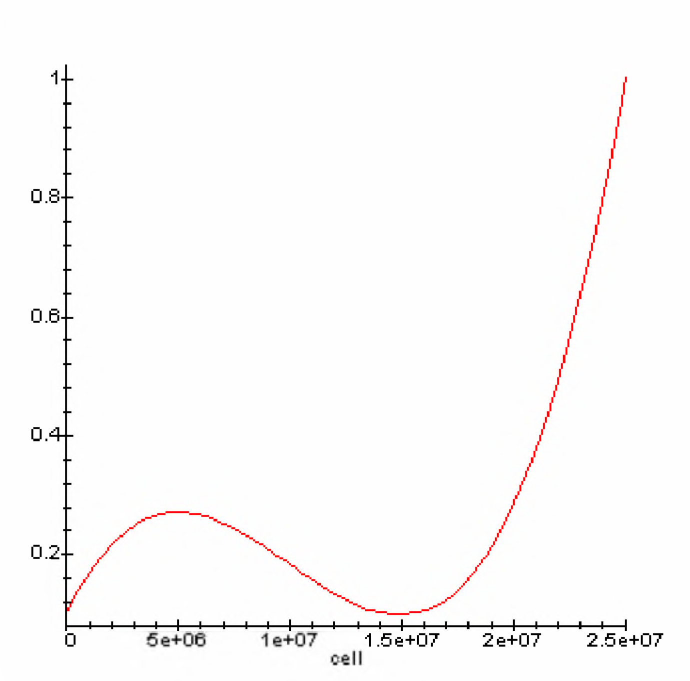
[15] See, for example, Granger and Uhlig (1990) or Cassell and Fowles (1998).
[16] The correlation matrix for FATAL and the primary explanatory variables is provided in Appendix 2.

suggested in Table I. Most interestingly, the Bayesian analysis corresponds well with the classical analysis.

Using the Bayesian results reported in Table IV and comparing them with the classical results of Table II, 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 PERSE. 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, SPEED_RU, 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 II. Although more research is needed on the exact timing of when cell phone use becomes problematic, the overall picture is clear.

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



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.

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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.
PERSE	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.
SPEED_RU	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	perse	annual	speed_ru	belt	beer	mlda	young	cellphone
fatal	1.0000									
years	-0.6832	1.0000								
perse	-0.2546	0.2187	1.0000							
annual	-0.0627	0.0097	-0.0328	1.0000						
speed_ru	-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