The cell phone effect on pedestrian fatalities

Peter D. Loeb, William A. Clarke

Article info
Article history:
Received 10 April 2008
Received in revised form 6 July 2008
Accepted 3 August 2008

Keywords:
Pedestrian fatalities
Cell phones
Motor vehicle accidents

Abstract
This paper examines the impact of cell phone usage on pedestrian fatalities in the United States using econometric models and specification error tests. The model makes use of a polynomial specification so as to allow for potential life-saving and life-taking effects of cell phones. The results indicate that when cell phones were first introduced they had an adverse effect on pedestrian safety, but after a critical number of cell phones was reached, the life-saving effect dominated over the life-taking effect. However, as the number of phones continued to increase, the life-taking effect once again dominated over the life-saving effects.

1. Introduction

Motor vehicle accidents continue to be responsible for many lost lives in the United States. In the year 2005, over forty-three thousand lives were lost due to such accidents. As such, the study of the determinants of motor vehicle accidents continues to be of major interest to economists, safety officials, and public policy makers. To date, numerous studies have been conducted evaluating the impact of various factors on motor vehicle fatalities such as: vehicle speed, speed variance, unemployment rates, alcohol consumption, population characteristics, seat belt regulations, the deregulatory climate of the 1980's, income, technology advances, miles driven, age of the fleet, among many others. Only recently has there been any research conducted regarding the effect of cell phones on motor vehicle related accidents. These studies have centered on the impact of cell phones on victims of the vehicles themselves or on property damage. No published research to date has investigated the potential effect of cell phones on pedestrian fatalities. This paper addresses this omission using econometric methods and a time series data set.

2. Background

The interest in the contributing effect of cell phones on motor vehicle accidents is a relatively new area of concern for safety researchers and public policy makers. Researchers initially investigated the effect of cell phones on motor vehicle accidents using models similar in design to those suggested by Peltzman (1975). Using regression analysis and time series as well as cross-sectional data, Peltzman examined the effect of automobile regulations on safety and suggested that there may be offsetting behavior on the part of drivers as they attempt to adjust their driving behavior in the face of regulations, such as the requirement that cars be equipped with seat belts. Among other things, he suggests that while drivers may
experience a reduction in fatalities due to safety advances, pedestrians may experience greater risks as drivers adjust their driving behavior to the new safety environment. This study led to a whole host of additional studies which either supported or rejected the Peltzman claim.2

As mentioned above, statistical studies have been forthcoming over the last several decades which examined many driving related variables such as alcohol consumption, speed limits, seat belt laws, income, and wealth factors, among many others. As cell phones became more common, a concern arose that they were contributing to accidents. It may be argued that cell phone use by drivers increases the probability of motor vehicle accidents, but it may not be as obvious that cell phones increase the probability of fatalities. Cell phone use by drivers may increase accident rates due to an inability of drivers to both use such a device and drive at the same time (much like not being able to chew gum and talk at the same time) as well as the potential distracting effects of cell phone conversations. In addition and perhaps related to this, is the possibility that cell phones may reduce a driver’s attention span and reaction time. The concern for the effect of cell phone use on accidents grew with the number of cell phones in use. This has resulted in five states (New York, New Jersey, Connecticut, California, and Washington) as well as Washington D.C. banning the use of hand-held cell phones by drivers.3

Cell phone use is only a recent phenomenon in the United States. In 1985 there were only slightly more than 340,000 cell phone subscribers in the United States. Since then, the number of subscribers has grown exponentially. By 2008 there were over 255 million subscribers.4 However, it is not just the sheer number of cell phones available that concerned researchers, but also the number of drivers who combine driving while talking on a cell phone. Glassbrenner (2005) in a National Highway Traffic Safety Administration Study (NHTSA) estimated that in 2005, ten percent of all drivers at any moment in time during daylight hours were using a hand-held or hands-free phone. Furthermore, there is statistical evidence that the proportion of drivers using cell phones is increasing over time.5 As such, not only are the number of cell phones and subscribers increasing, but driver usage of these phones is increasing as well, and at what appears to be an increasing rate. It is only natural that economists and safety experts would be inclined to examine what part of the forty thousand plus traffic fatalities per year since 1985 might be attributed to cell phone usage.

The statistical studies conducted tend to show a positive relationship between cell phones and automobile accidents. However, the results among the studies are not consistent, i.e., there are results which show no significant association between these variables. The most well known study by Redelmeier and Tibshirani (1997) using cross-over analysis finds the risk of a property – only accident increased fourfold when cell phones are used. However, they also find that 39% of drivers involved in these accidents use their cell phones after an accident to summon assistance. McEvoy et al. (2005) find a similar increase in risk of an accident when examining crashes resulting in hospital visits. Consiglio et al. (2003), simulating driving conditions in a laboratory environment, found that reaction time was reduced in a braking situation when cell phones were in use, regardless of whether they were hands-free or hand-held devices. However, Laberge-Nadeau et al. (2003) using survey data and logistic regression models found that the sensitivity of accidents to cell phones diminished as the models estimated became more extensive, i.e., included more and more variables. Sulliman and Baas (2003), using survey data and cross-over analysis did not find a correlation between cell phone use and crash involvement once demographic factors and other variables were accounted for. Finally, Loeb et al. (2004) using regression techniques with a polynomial model found that the effect of cell phones on fatalities was dependent upon the number of cell phones in use. The Loeb et al. (2007) study argued that cell phones had both a life-saving and a life-taking attribute. Cell phone use by drivers can lead to accidents. However, given an accident, cell phone availability increases the likelihood of obtaining medical help promptly and, as such may save lives. The net effect of the life-saving versus life-taking attributes of cell phones is examined and the statistical results indicate the life-taking effects overwhelm the life-saving effects when cell phone subscription rates reach around 100 million.

Pedestrian fatalities have not been explored to the extent that over-all motor vehicle fatalities, truck fatalities, and other motor vehicle type fatalities have been.6 Little or no research has been reported in the academic journals regarding the effect of cell phones on pedestrian fatalities, where pedestrian fatalities comprise about 12 to 15 percent of auto related fatalities in the US. Cell phones may contribute to pedestrian fatalities not only due to driver use, but pedestrian use of these devices as well. As such, a state senator from New York is proposing a bill to ban the use of cell phones and other electronic devises by pedestrians when crossing streets in New York City and Buffalo. The present paper addresses the omission of a rigorous statistical analysis of the effect of cell phones on pedestrian fatalities by specifying a model similar to that estimated by Loeb et al. (2007) for total motor vehicle related fatalities which allows for life-taking and life-saving effects of cell phones.

More specifically, the current paper evaluates the determinants of pedestrian fatalities with specific attention given to the effect of cell phones. An econometric model is developed and estimated using time series data covering the period 1975–2002. The model makes use of a polynomial function so as to address turning points and controls for traditional factors found in accident models, e.g., population attributes, income, unemployment rates, etc. The models are evaluated by a set of specification error tests to reduce the probability that they suffer from omission of variables, misspecification of the structural

---

2 See Loeb et al. (1994) for examples.
5 Glassbrenner (2005) estimated that driver use of hand-held phones alone increased from 5% in 2004 to 6% in 2005.
6 See Loeb et al. (1994) on this.
form, or simultaneous equation bias (which may result in biased estimates of the parameters) along with non-normality of the error structure and serial correlation. Only models which are not rejected by any of the specification error tests are used in the analysis which follows. As such, a stringent set of criteria are imposed on the modeling process so as to add statistical reliability to the results.

3. The model and data

3.1. The general model

A model of the form:

\[
\text{Pedestrian fatalities} = \beta_0 + \beta_1 \text{CELLS} + \mathbf{X} \delta + \mu
\]

is posited where \(\text{CELLS}\) is a measure of cell phone usage or availability whose influence on the dependent variable is to be examined. \(\mathbf{X}\) is a matrix of socioeconomic and driving related variables also thought to be determinants of pedestrian fatalities (PEDFAT) and \(\delta\) is the associated vector of coefficients. So as to allow for the nonlinear effect(s) of cell phones on pedestrian fatalities, this variable may enter the model in a polynomial manner. More precisely, CELLS is entered so that the model appears as a polynomial of degree three. (This use of a polynomial conforms to models found in the Industrial Organization literature examining the determinants of Research and Development as well as a recent model in the transportation safety literature.) Cell phone usage is proxied by the number of cell phone subscribers. As such, it includes both the effect of usage by both drivers and pedestrians and the general population at large. \(\mu\) is a random error term assumed to comply with the full ideal conditions (FIC) underlying the classical linear regression model which would provide best linear unbiased estimates (BLUE) of the coefficients when the model is estimated by ordinary least squares.

The variables considered for possible inclusion in \(\mathbf{X}\) are:

- UNEMP – the civilian unemployment rate.
- ETHOTOTAL – apparent total per capita ethanol consumption (in gallons) based on population aged 14 and over.
- VEHMI – vehicle miles driven (billions).
- TOTALMI – total highway mileage (in thousands).
- INTERMI – interstate highway mileage (in thousands).
- URBANMI – urban highway mileage (in thousands).
- RURALMI – rural highway mileage (in thousands).
- POP – total population (in thousands).
- BAC – a weighted or annualized dummy variable indicating the blood alcohol threshold associated with driving under the influence of alcohol. State laws vary over time requiring the dummy variable to be weighted. At the extremes, a BAC of “1” indicates either a 0.1 or 0.08 BAC threshold is in effect while a BAC of “0” indicates no such legal threshold exists.
- SPEED95 – a dummy variable indicating the repeal of the maximum speed limit by the National Highway System Designation Act of 1995 in December 1995 which allowed states to set their own limits for the first time since 1974.
- YEAR – a time trend.
- CELLS – estimated number of cell phone subscribers (in millions).

We anticipate a negative effect on the dependent variable by BAC. The effect of UNEMP on pedestrian fatalities is to be determined empirically. Unemployment rates have been shown to be inversely related to motor vehicle accidents. One anticipates that higher unemployment rates are associated with less economic activity and a reduction in the use of motor vehicles which would result in fewer fatalities. However, there may be an increase in pedestrian traffic with a downturn in the economy as individuals substitute walking for driving. This may result in an increase in pedestrian fatalities. We expect a positive

---

7 See Scherer (1965a,b) and Loeb and Lin (1977).
8 See Loeb et al. (2007).
9 Again, this is important so as to account for both the potential life-saving and life-taking effects of cell phones. To repeat, as cell phone usage increases by drivers and pedestrians, there may be an increase in pedestrian fatalities as cell phones may distract both drivers and pedestrians. However, an increase in the number of cell phones among the general population may increase the speed which medical assistance may be acquired, which may result in life savings.
10 Alternative measures of population were examined as well where the entire population was decomposed into various age groups, i.e. those aged 16–19, 20–24, 25–44, 45–64, and 65 and older. This allowed for examining whether different parts of the population contributed more to accidents than others. Results using POP were generally superior to the alternative population measures. The alternative results are available from the authors.
11 The BAC data are by state and over time. An annualized value is obtained by weighting each state’s BAC threshold for a given year by its relative share of the population for the year. We are grateful to Michael Grossman for the data and the weighting mechanism used to generate this variable.
12 An alternative dummy variable to account for the speed limit (Speed87) was also evaluated. SPEED87 indicated the years Congress allowed states to increase speed limits to 65 mph on rural interstates. The regressions using this variable instead of SPEED95 did not provide improved results. The results are available from the authors.
13 A time trend may serve as a proxy for permanent income, changes in technology, and other omitted factors. See Loeb (1993, 2001) and Peltzman (1975).
15 We are indebted to two anonymous referees for bringing this to our attention.
effect by ETHOTOTAL, the ratio of rural mileage to urban mileage (RURALMI/URBANMI), and CELLS on pedestrian fatalities. We do not have strong a priori expectations regarding the effects of INTERMI and POP, and the other factors listed above. In addition, there is a strong correlation between several of the variables listed. For example, population (POP), real GDP (RGDP), and YEAR are highly correlated with correlation coefficients of 0.99 or higher. A strong correlation exists as well between both the Real GDP and VEHMI as well as between POP and VEHMI with correlation coefficients of approximately 0.995 in both cases. As such, the choice of some of the regressors included in the estimated models is restricted so as to avoid multicollinearity.

3.2. The data

Data cover the period 1975–2002. The dependent variable (PEDFAT) is measured as the number of pedestrian fatalities and is reported in NHTSA (2005). Vehicle miles driven (VEHMI), measured in billions of miles, are reported in NHTSA (2005) also. The unemployment rate (UNEMP) and population data (POP) are reported in the Economic Report of the President (2005). Total apparent per capita ethanol consumption (ETHOTOTAL) is reported by the National Institute on Alcohol Abuse and Alcoholism and is found at: http://www.niaa.nih.gov/Resources/DatabaseResources/QuickFacts. Data on highway mileage, i.e. total mileage (TOTALMI), interstate mileage (INTERMI), rural mileage (RURALMI), and urban mileage (URBANMI) are reported in the US Bureau of the Census (2006). The speed limit variable (SPEED95) was generated as a dummy variable taking on the value of “1” for the years in which the National Highway System Designation Act of 1995 was in effect and “0” otherwise. The value for SPEED95 was set equal to 0.083333 for the year 1995 to reflect the proportion of that year the act was in effect. Data associated with the BAC laws were provided by MADD (http://www.madd.org/laws/) and the US Bureau of the Census (2000). Data for the number of cell phone subscribers (CELLS) are in millions and are reported by CTIA (2008) for the years 1985–2004. CTIA does not report data on cell phones prior to 1985 and one could infer that none existed. However, in 1977 AT&T put in place a marketing experiment involving 2000 customers. As such, rather than assuming there were no cell phones available between 1977 and 1985, we extrapolated the number of potential subscribers for that period.

4. Model selection and regression results

4.1. Model selection

Eq. (1) is respecified so as to allow for a polynomial effect of CELLS on the dependent variable. The revised model is of the form:

\[
PEDFAT = \beta_0 + \beta_1 CELLS + \beta_2 CELLS^2 + \beta_3 CELLS^3 + X\delta + \mu
\]

and \(X\) includes various combinations of the other regressors discussed above. Variations of Eq. (2) are estimated by OLS. Under the full ideal conditions, OLS results in best linear unbiased estimates. Concern arises that the model may be affected by various specification errors including not only serial correlation, given the use of time series data, and non-normality of the error term, but also biased estimates which could arise from the potential omission of variables, simultaneous equation problems, and misspecification of the structural form of the model. Misspecification of the structural form of the model is of particular concern given the polynomial form of the equation employed. Consequently, the various specifications estimated are subject to a set of specification error tests to detect the violation of the full ideal conditions. These tests include the regression specification error test (RESET) developed by Ramsey (1974), the Jarque–Bera test (JB) for normality, and the Durbin–Watson test (DW) for serial correlation. RESET examines the residuals of a given regression for the possibility of omission of variables, simultaneous equation bias and misspecification of the structural form of the regressors, any of which may result in biased estimates. Any given estimated specification is rejected if one or more of the specification tests reject the hypothesis of the presence of the full ideal conditions. This is a severe model selection criterion as compared to relying on more traditional evaluations of student-t-statistics or R^2's. The specifications which are not rejected by the tests provide reasonable estimates to evaluate from a single equation perspective.

---

16 Prior studies have found a positive relationship between income and accidents when using time series data and a negative relationship when using cross-sectional data. See Loeb et al. (1994) for a discussion on this as well as on the expected effects of the various variables.

17 Various measures of mileage traveled were included in the models to adjust for exposure. All measures of the mileage variables provided similar regression results with respect to coefficients associated with cell phones and other variables. However, the correlation between INTERMI and variables which trend over time (for example POP, YEAR, and RGDP) was much lower, with a correlation coefficient around 0.77–0.82, than with other measures of mileage such as URBANMI/RURALMI or VEHMI, etc. Hence, INTERMI was used in the models found in Table 2. Regressions with other mileage variables are available from the authors.

18 See, for example, About.com:Inventors (http://inventors.about.com/library/weekly/aa070899.htm) for the early history of cell phone use.

19 RESET basically evaluates the classical assumptions that \(E(\mu) = 0\) and \(E(X\mu) = 0\) where \(X\) in this case includes all regressors. Once again, this is of particular interest given the test’s ability to detect misspecification of the structural form of the model. See Ramsey (1974) and Ramsey and Zarembka (1971) for a detailed discussion.

20 Models in terms of pedestrian fatality rates measured as PEDFAT/VEHMI, PEDFAT/POP, and models in log form were also estimated. These models tend to be rejected for specification errors.
4.2. Empirical Results

Models based on Eq. (2) were estimated by ordinary least squares and examined for specification errors. Table 1 provides summary statistics for the variables used in the equations which were not rejected for the specification errors mentioned above or for multicollinearity. Table 2 provides estimates of models of PEDFAT which were not rejected for specification errors.

Our primary interest is the effect of cell phones on pedestrian fatalities. In addition, we are interested, for policy purposes, on the effects of alcohol consumption and the effect of more stringent BAC standards on defining driving under the influence of alcohol. These variables, as well as the unemployment rate, to address economic conditions will be referred to as our focus variables.

The estimated coefficients associated with these variables in Table 2 tend to be stable (non-fragile) across the various specifications. Again, the results reported are associated with models which are not rejected due to specification errors. The $R^2$s associated with these models are between 0.976 and 0.991 (with adjusted $R^2$s between 0.971 and 0.988). The estimated coefficient associated with alcohol consumption is consistently positive and statistically significant at the 0.005 level or better. The coefficient associated with the unemployment rate is consistently negative and highly significant across the specifications. As anticipated, the BAC coefficient was negative and highly significant, indicating that imposing more stringent BAC limits results in fewer pedestrian fatalities.

The major variables of interest in this study are variants of CELLS which indicate the potential effect of cell phone usage on pedestrian fatalities. The coefficients associated with these variables are always stable and significant although the signs depend on whether we are examining CELLS and CELLS$^3$ which always have positive coefficients or CELLS$^2$ which have negative coefficients. The model, therefore, suggests that cell phones have an effect on pedestrian fatalities which is nonlinear. The effect on these fatalities increases at a decreasing rate as noted by the coefficients associated with CELLS and CELLS$^2$, but the effect of cell phones on pedestrian fatalities is impacted by CELLS$^3$. At some point, the effect of cell phones may decrease the number of fatalities. Using specification (1) from Table 2, for example, we can see that the marginal effect of CELLS on fatalities depends on the level of CELLS. Evaluated at the mean of CELLS indicates a value of 7.892 and evaluated at the value of CELLS for the year 2002 indicates a value of 24.820. In either case, the marginal effect of CELLS is positive. However, examining specification (1) for the volume of cells associated with a maximum or minimum number of pedestrian fatalities requires that we examine the partial derivative of PEDFAT with respect to CELLS. Setting $\frac{\partial PEDFAT}{\partial CELLS} = 0$ gives rise to a quadratic with the two roots being 33.292 and 121.542. Evaluating the second derivative results in CELLS > 77.417 is associated with a minimum and CELLS < 77.417 is associated with a maximum. More precisely, evaluating the specification in question for the effect of CELLS on PEDFAT, holding all else equal, reveals an initial maximum at 33.292 CELLS and a minimum at 121.542 CELLS. As such, the effect of cell phones initially exacerbates fatalities and then fatalities decline with additional phone subscribers. However, the analysis must continue, for the above maximum and minimum values are local maxima and minima. The function then increases without end after reaching the minimum.

Table 1

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Mean</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>PEDFAT</td>
<td>6407.821</td>
<td>1087.209</td>
</tr>
<tr>
<td>UNEMP</td>
<td>6.425</td>
<td>1.466</td>
</tr>
<tr>
<td>ETHOTOTAL</td>
<td>2.445</td>
<td>0.24</td>
</tr>
<tr>
<td>VEHMI</td>
<td>2049.464</td>
<td>478.032</td>
</tr>
<tr>
<td>INTERMI</td>
<td>44.050</td>
<td>3.43</td>
</tr>
<tr>
<td>URBANMI</td>
<td>746.464</td>
<td>83.49</td>
</tr>
<tr>
<td>RURALMI</td>
<td>3147.250</td>
<td>57.12</td>
</tr>
<tr>
<td>POP</td>
<td>2493.345</td>
<td>2211.498</td>
</tr>
<tr>
<td>SPEED95</td>
<td>0.233</td>
<td>0.049</td>
</tr>
<tr>
<td>CELLS</td>
<td>26.401</td>
<td>42.235</td>
</tr>
<tr>
<td>RURALMI/URBANMI</td>
<td>4.275</td>
<td>0.551</td>
</tr>
<tr>
<td>URBANMI/RURALMI</td>
<td>0.238</td>
<td>0.031</td>
</tr>
<tr>
<td>BAC</td>
<td>0.725</td>
<td>0.31</td>
</tr>
<tr>
<td>RGDP</td>
<td>6910.329</td>
<td>1759.707</td>
</tr>
</tbody>
</table>

21 Specification error tests were evaluated at the 5% significance level. In addition, a correlation matrix is available from the authors.

22 The coefficient associated with the population variable was always negative and highly significant. Population is highly correlated with both a time trend and RGDP. The correlation between these variables is over 0.99 and as such, population may be serving as a proxy for the time trend. The coefficient associated with INTERMI is fragile and never significant when included in the model.

23 The number of cell phone subscribers in 2002 was 140.7668 million.

24 $\frac{\partial PEDFAT}{\partial CELLS} = 48.581 - 1.858 CELLS + 0.012 CELLS^2$.

25 Similar results are obtained when evaluating alternative specifications from Table 2. For example, specification (5) had a positive marginal effect associated with CELLS when evaluating at either the mean of CELLS or the value of CELLS in the year 2002. Furthermore, the values of CELLS associated with a minimum and maximum number of pedestrian fatalities is 22.62 and 108.35, respectively (considering only the local maxima and minima).
As such, we first notice a contributing effect of cell phones on pedestrian fatalities. This may be due to several factors including the distracting effect of cell phone use on pedestrians as well as the distracting effect of cell phone use on drivers. In addition, with a small number of cell phones among the public initially, a fast response time to an accident (possible with cell phones) may have been less likely. A faster response rate to an accident might have countered the negative effects of cell phone use. After a critical amount of subscribers is reached, the life-saving effect of cell phones may have increased the likelihood of survivorship in an accident due to the ability to acquire medical assistance quickly. Hence, the life-saving effect of cell phones may have outweighed the life-taking effect after some point. However, beyond a certain level of cell phone usage, the life-taking effect overwhelms the life-saving effect once again. Given the exponential growth of cell phones among the public, it is not surprising to find more and more pedestrians as well as drivers using cell phones. This may reflect a change in attitudes and habits of society regarding cell phone use over time. As noted previously, NHTSA reports a 50% increase in drivers using cell phones in daylight hours since 2002 which puts both themselves and pedestrians at additional risk.

5. Concluding comments

This study examines the effect of cell phone usage on pedestrian fatalities using econometric models and specification error tests. The models adjust for alcohol consumption, the unemployment rate, blood alcohol legislation, and other factors as well as cell phone usage. Data are obtained for the years 1975–2002 and models are estimated by ordinary least squares. Only models which fail to be rejected for specification errors are considered in the analysis. As anticipated, the estimated coefficients associated with alcohol consumption are consistently positive and statistically significant across all specifications. This lends support for public policies which might result in reduced alcohol consumption. Such policies may include increased taxes on alcohol or possibly raising the minimum legal drinking age. Such policies may prove quite appropriate given the high incidence of alcohol involvement in fatal motor vehicle related accidents. The unemployment rate has a negative and statistically significant effect on pedestrian fatalities. Furthermore, more stringent BAC laws to define driving while under the influence of alcohol also reduce fatalities. Hence, reducing the blood alcohol limit indicating when driving under the influence may prove to be a valuable policy for reducing pedestrian fatalities. Most notably, cell phones are found to have a significant adverse effect on pedestrian safety. Initially, as cell phones become more readily available, pedestrian fatalities increase. After reaching a certain critical mass of cell phones [33.292 million based on specification (1)] the life-saving effects of cell phones overtake the life-taking effects. However, with cell phone subscribers reaching about 121 million or more, the life-taking effect overtakes the potential life-saving effect once again. These results are non-fragile across specifications and are statistically significant. Given that there are over 255 million cell phone users in the United States, this suggests that cell phones may be contributing to an increase in pedestrian fatalities.

6. Additional models

Additional models were estimated using alternative combinations of regressors which included URBANMI/RURALMI, VEHMI, RGDP, SPEED95, and YEAR. Results are consistent with those reported for the focus variables. Additional models were estimated using alternative specifications which included URBANMI/RURALMI, VEHMI, RGDP, SPEED95, and YEAR. Results are consistent with those reported for the focus variables.

Table 2
Regression results for models of PedFat

<table>
<thead>
<tr>
<th>Equation #</th>
<th>independent variable name</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-6420.678 (-5.276)</td>
<td>2565.343 (1.023)</td>
<td>3010.533 (1.148)</td>
<td>-4438.264 (-2.593)</td>
<td>-1133.735 (-0.933)</td>
<td></td>
</tr>
<tr>
<td>ETHOTOTAL</td>
<td>5680.221 (11.688)</td>
<td>4176.087 (7.685)</td>
<td>4096.246 (7.279)</td>
<td>5359.997 (10.491)</td>
<td>3852.501 (8.467)</td>
<td></td>
</tr>
<tr>
<td>UNEMP</td>
<td>187.484 (-4.881)</td>
<td>-185.331 (-6.170)</td>
<td>-184.453 (-6.057)</td>
<td>-188.692 (-5.081)</td>
<td>-177.9 (-7.191)</td>
<td></td>
</tr>
<tr>
<td>CELLS</td>
<td>48.581 (3.387)</td>
<td>47.687 (4.251)</td>
<td>46.951 (4.113)</td>
<td>49.894 (3.592)</td>
<td>20.089 (1.914)</td>
<td></td>
</tr>
<tr>
<td>CELLS²</td>
<td>-0.929 (-3.927)</td>
<td>-0.857 (-4.607)</td>
<td>-0.829 (-4.295)</td>
<td>-0.967 (-4.204)</td>
<td>-0.537 (-3.215)</td>
<td></td>
</tr>
<tr>
<td>CELLS³</td>
<td>0.004 (3.835)</td>
<td>0.004 (4.555)</td>
<td>0.004 (4.232)</td>
<td>0.004 (4.128)</td>
<td>0.003 (3.491)</td>
<td></td>
</tr>
<tr>
<td>POP</td>
<td>-0.022 (-3.872)</td>
<td>-0.025 (-3.359)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>INTERMI</td>
<td>12.374 (0.682)</td>
<td></td>
<td></td>
<td>-26.981 (-1.594)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BAC</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-823.635 (-5.681)</td>
<td></td>
</tr>
</tbody>
</table>

Adjusted R²  0.971 0.982 0.982 0.973 0.988
DW          1.771 2.190 2.126 2.223 2.802
JB          2.612 1.168 1.044 1.756 0.508
RESET       0.795 0.374 0.378 1.667 1.186
phone subscribers in the United States (in 2008) leads one to believe that the life-taking effect of cell phones on pedestrian fatalities is greater than the life-saving effect. Based on the current research, one cannot attribute the life-taking effect purely to pedestrian use of cell phones (and other electronic devices which may have a distracting effect on the pedestrian) since driver use also puts pedestrians at risk. Nonetheless, policies which would reduce cell phone use by pedestrians while crossing streets and by drivers may be warranted. This might be accomplished through fines combined with active enforcement.

Acknowledgement

Loeb gratefully acknowledges the research support of a Rutgers University Research Council Grant.

References


33 See NHTSA (2003).