# State Variation in the Determinants of Motor Vehicle Fatalities

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*Research on motor vehicle safety has involved virtually all modes of transportation. Most of these have been national in scope with relatively few studies focused on the determinants of motor vehicle fatalities at the state level. This paper investigates the determinants of motor vehicle fatalities across the states of California, Illinois, Louisiana, Pennsylvania, and Texas, which collectively account for 27% of U.S. motor vehicle fatalities in 2006. An important finding is that fatalities vary significantly by state even after controlling for commonly cited fatality determinants.*

## INTRODUCTION

The causes of transportation accidents and fatalities have been and continue to be a major concern of economists and policymakers. Research on motor vehicle safety has involved virtually all modes of transportation, including motor vehicles, railroads, and airlines. Many of these studies have been national in scope with relatively fewer examinations focused on the determinants of motor vehicle fatalities at the state level. This study partially addresses this research gap by empirically estimating the determinants of motor vehicle fatalities in the states of California, Illinois, Louisiana, Pennsylvania, and Texas. These five states were not selected by any other scientific criteria but for the fact that they are in different regions of the country and account for a relatively large amount (27%) of the motor vehicle fatalities in the United States in 2006.

There are several reasons to suspect state variation in the determinants of motor vehicle fatalities. For example, in 2006, California led the nation with 4,236 fatalities, while North Dakota had only 111. There is also state variation in the fatality rate (fatalities per 100 million vehicle miles) as South Dakota has a 2006 rate of 2.22 while Connecticut's rate is 0.87. Fatalities are positively related to total vehicle miles. California had 327,478 million vehicle miles in 2006 while Wyoming had 9,415 million. Research has also shown that fatalities are positively related to the ratio of rural to urban vehicle miles. Montana had the highest 2006 ratio in the nation (3.29) while Massachusetts had the lowest ratio (0.08). The maximum speed limit on rural interstate highways, seat belt laws, and police enforcement of highway safety laws also vary by state. While the results of this study are unique to the five states, the methodology employed in this study can be adopted by researchers to study the determinants of motor vehicle fatalities in other states. The results of such studies help inform state transportation policy.

The objectives of the paper are as follows:

- Conduct a literature review of motor vehicle safety studies
- Formulate an empirical model of the determinants of motor vehicle traffic fatalities
- Estimate the statistical significance of the various determinants of fatalities across the five states
- Analyze variation in state motor vehicle traffic fatalities across the five states

The objectives are accomplished by using various econometric models – log linear regression, Poisson regression, and Negative Binomial regression – of the determinants of state fatalities from 1970-2006.

In what follows, the second section discusses trends in motor vehicle fatalities across the five states. The literature is reviewed in the third section. The model is presented in the fourth section. Sources and characteristics of the data are discussed in the next section. Empirical results are discussed in the sixth section and concluding remarks offered in the last section.

## TRENDS IN STATE MOTOR VEHICLE FATALITIES

Figure 1 displays the motor vehicle deaths for the five states from 1970-2006. With the exception of Pennsylvania, where motor vehicle fatalities declined more or less continuously from 1970-2006, the other states in the sample exhibited a "rollercoaster" pattern of increases and decreases.

**Figure 1: Motor Vehicle Traffic Fatalities (1970-2006)**

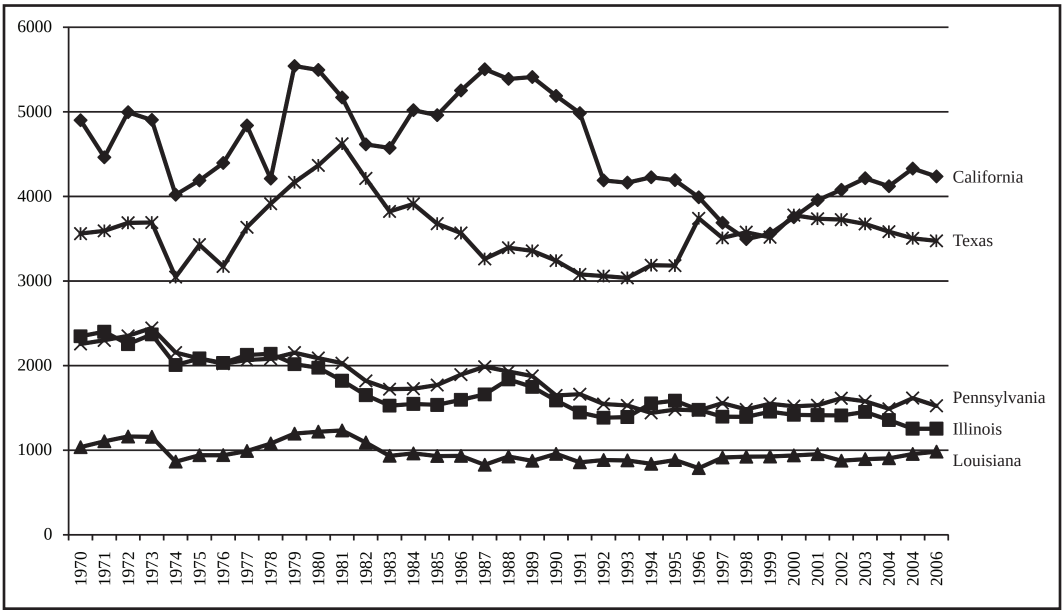


Table 1 reports motor vehicle fatalities from 1970 to 2006 and the percentage decrease in fatalities between 1970 and 2006 for the five states. As the data indicate, Illinois and Pennsylvania had the largest percentage declines in fatalities; Louisiana and Texas had the smallest decreases; and California was in the middle with a 13.6% decrease.

**Table 1: Overview of Road Fatalities at the Beginning and End of the Sample Period**

| State | 1970 Fatalities | 2006 Fatalities | Percent Change |
|---|---|---|---|
| California | 4,901 | 4,236 | -13.6 |
| Illinois | 2,346 | 1,254 | -46.5 |
| Louisiana | 1,035 | 982 | -5.1 |
| Pennsylvania | 2,225 | 1,505 | -32.4 |
| Texas | 3,560 | 3,475 | -2.4 |

## LITERATURE REVIEW

As suggested by Loeb and Clarke (2007) many determinants of motor vehicle accidents and fatalities have been investigated in previous studies. These include population characteristics, such as age, race, and gender; roadway characteristics, such as the rates of rural to urban vehicle miles, interstate highway travel, degree of congestion, speed limits, average speed, speed variation, and vehicle miles driven; economic factors, such as the unemployment rate and real gross domestic product (GDP); and other factors, such as weather, traffic law enforcement, motor vehicle safety improvements, and alcohol consumption.

The amount of driving and exposure to potential accidents is directly related to the state of the economy. There is less driving during recessions, resulting in fewer accidents and deaths. Robertson (1984), Partyka (1984), Evans and Graham (1988), Fowles and Loeb (1995), and Welki and Zlatoper (2007) found evidence of a negative relationship between the unemployment rate and highway fatalities. Loeb and Clarke (2007) point out that the impact of income on fatalities is theoretically indeterminate. As income decreases, driving decreases, which results in fewer fatalities. Also, an increase in the unemployment rate will decrease income and fatalities. However, as income falls the demand for safety declines, resulting in an increase in fatalities. Thus the net effect of income on fatalities has to be determined empirically.

Motor vehicle fatalities are directly related to vehicle miles traveled. Loeb et al. (1994, 25-26) cited several studies that found a significantly positive relationship between travel volume variables and highway fatalities.

Driver characteristics also influence highway fatalities. Loeb et al. (1994, 20-21), Welki and Zlatoper (2007), Fowles and Loeb (1989), and Babcock et al. (2008) found that greater alcohol consumption (assumed to be directly related to alcohol consumption while driving) leads to more highway accidents and deaths. Fatal accident rates in the United States are highest for young drivers, decline with age, and then rise for the oldest drivers (Loeb et al. 1994, Fowles and Loeb 1995, Welki and Zlatoper 2007, and Babcock et al. 2008). This pattern of accident rates may be due to young drivers' risk taking and older motorists' loss of driving-related physical skills, such as vision and speed of reflexes (Evans 1991). According to Loeb et al. (1994, 23-25), the empirical evidence is mixed on the hypothesized positive relationship between fatalities and the number of the youngest and oldest drivers. However, Welki and Zlatoper (2007) and Babcock et al. (2008) found a highly significant positive relationship in the states of Ohio and Kansas respectively. Empirical evidence also found that male drivers are more likely to be involved in motor vehicle accidents (Levy and Asch 1989).

Highway characteristics, such as interstate highway travel, ratio of rural to urban vehicle miles, speed limits, speed, and speed variation, affect motor vehicle accidents and fatalities. There is some empirical evidence that both higher speed and speed variance increase highway deaths (Loeb et al. 1994, Lave 1985, Fowles and Loeb 1989, 1995, Levy and Asch 1989, Welki and Zlatoper 2007, and Babcock et al. 2008). Loeb et al. (1994, 65-67) cited research confirming the negative effect on fatalities during the reduction of the national speed limit to 55 mph in 1973, and the increase in fatalities related to increasing the limit to 65 mph on certain roads. The opposing view is that a higher speed limit reduces the probability of a fatigue-related accident. Fatal accidents occur more often in rural areas than urban areas (NHSTA 2002, 52). Several studies found a significant positive relationship between motor vehicle fatality measures and the ratio of rural to urban vehicle miles (Loeb et al. 1994, 52, Welki and Zlatoper 2007, and Babcock et al. 2008).

Highway safety regulation enforcement helps create safer driving conditions by enforcing speed limits, seat belt laws, and intoxicated driver laws. Alexander (1992) found that the number of police officers per mile of road had a statistically significant negative relationship with various truck accident rates. Zlatoper (1991) found a significant inverse relationship between per capita motor vehicle fatalities and per capita expenditures on highway law enforcement and safety. Welki and Zlatoper (2007) found a negative relationship between fatalities and arrests for drunk driving in Ohio. Babcock et al. (2008) found an inverse relationship between Kansas highway fatalities and police per 10,000 population, police per 100 miles of road, and real per capita expenditures for police protection.

Motor vehicle inspections could make driving safer by removing unsafe vehicles from the road if vehicle safety defects triggered by inspections are remedied, resulting in fewer accidents and deaths. Kraas (1993) found a statistically significant negative relationship between truck-at-fault accidents per vehicle mile and roadside inspections per vehicle mile. Loeb (1990) reported evidence that motor vehicle inspections have a statistically significant life-saving effect. In contrast, Merrell et al. (1999) found no evidence that state automobile safety inspections reduce fatality or injury rates. Keeler (1994) found that vehicle inspection programs reduced motor vehicle fatalities in 1970, but not 1980. This result may be due to changes in the age of the automobile stock.

To encourage seat belt use, states have enacted mandatory usage laws. According to the U.S. General Accounting Office (1992) and Loeb (1995), state seat belt laws decrease highway accidents, injuries, and deaths. Loeb (1993) and Loeb (2001) found that the effectiveness of the California and Maryland seat belt laws varied with the type of injury. Babcock et al. (2008) found a statistically significant negative relationship between the Kansas seat belt law and fatalities. In contrast, Welki and Zlatoper (2007) found no evidence that Ohio's secondary seat belt law saves lives.

Motor carrier deregulation occurred in 1980 with the passage of the Motor Carrier Act of 1980. The empirical evidence regarding the impact of motor carrier deregulation on trucking accidents is mixed. Adams (1989), Daicoff (1988), and Kraas (1993) found evidence that deregulation reduced safety in the trucking industry. In contrast, Moore (1989), Viscusi (1989), and Alexander (1992) found that motor carrier deregulation did not result in a decline in various measures of motor carrier safety. Loeb and Clarke (2007) did not find evidence that deregulation resulted in an increase in truck accidents.

**MODEL**

The model in this paper is based on empirical findings of prior studies of motor vehicle safety, and it incorporates some of the explanatory variables discussed above. The model is estimated for the five states as a group. Following the approach of Welki and Zlatoper (2007), the general form of the model is as follows:

(1) *Motor vehicle fatalities= f(economic conditions, driver characteristics, traffic regulations, location of driving, traffic law enforcement, other variables).*

Formally, we use the following log linear specification of the model:

(2) $$\log y_{it} = \beta_0 + \sum_{k=1}^{K} \beta_k \log x_{kit} + \mu_i + \tau + \varepsilon_{it} \ ,$$

where $y_{it}$ is the number of deaths in state $i$ during time period $t$, $x_{1it}$, $x_{2it}$,…, $x_{Kit}$ are determinants of motor vehicle deaths that we subsequently describe, $\beta_0$, $\beta_1$,…, $\beta_K$ are parameters to be estimated, $\mu_i$ controls for state fixed effects, τ is a time trend, and $\varepsilon_{it}$ is a random error term.

Since $y_{it}$ only takes on non-negative integer values, it is appropriate to explore the following Poisson regression specification (see Cameron and Trivedi (1986) and Gourieroux et al., 1984):[1]

(3) $$\Pr ob\left(y_{it} \mid x_{it}\right) = \frac{\lambda_{it}^{y_{it}} \exp(\ \lambda_{it})}{y_{it}\,!} ,$$

where,

(4) $$\lambda_{it} = E\left(y_{it} \mid x_{it}\right) = Var\left(y_{it} \mid x_{it}\right) = \exp(x_{it}\beta + \mu_i + \tau) \cdot$$

Equations (3) and (4) specify that the conditional probability of $y_{it}$ given $x_{it}$ follows a Poisson distribution, with the conditional mean and variance of $y_{it}$ equal to $\lambda_{it}$. Equation (4) reveals a crucial assumption of the Poisson regression model that the conditional mean of $y_{it}$ is equal to its conditional variance – equidispersion. However, this assumption may not be innocuous when the data clearly show that the variance of $y_{it}$ is greater than its mean (Gourieroux et al., 1984) – overdispersion.

The Negative Binomial regression model is an alternate to the Poisson regression model, but unlike the Poisson model, the Negative Binomial model allows the variance of $y_{it}$ to be greater than its mean. Furthermore, the Negative Binomial model provides a convenient framework to formally test whether or not equidispersion is an innocuous assumption for the data being used.

The Negative Binomial regression specification of the model is given by:[2]

$$(5)\quad \Pr ob\left(y_{it} \mid x_{it}\right) = \frac{\Gamma\left(y_{it} + \alpha^{\;\,1}\right)}{y_{it}!\Gamma\left(\alpha^{\;\,1}\right)}\left(\frac{\alpha^{\;\,1}}{\alpha^{\;\,1} + \lambda_{it}}\right)^{\alpha^{\;\,1}}\left(\frac{\lambda_{it}}{\alpha^{\;\,1} + \lambda_{it}}\right)^{y_{it}}$$

where $\Gamma\left(v\right) \quad \int_0^\infty t^{v-1}e^{-t}dt$ is the gamma function and $\alpha > 0$ is a dispersion parameter (see chapter 8 in Long [1997]). Based on the expression for the conditional probability of $y_{it}$ in equation (5), the conditional mean, $E(y_{it} \mid x_{it})$, and conditional variance, $Var(y_{it} \mid x_{it})$, of $y_{it}$ are given by:

$$(6)\quad \lambda_{it} \quad E\left(y_{it} \mid x_{it}\right) \quad \exp(x_{it}\beta + \mu_i + \tau)$$

$$(7)\quad Var\left(y_{it} \mid x_{it}\right) = \lambda_{it} + \alpha\lambda_{it}^2$$

Note that the conditional mean of $y_{it}$ is the same under both the Poisson and Negative Binomial model specifications. However, since $\alpha > 0$, the conditional variance of $y_{it}$ is greater than the conditional mean under the Negative Binomial specification. Furthermore, the extent to which the conditional variance exceeds the conditional mean is positively related to the size of $\alpha$. As such, a statistical test of whether $\alpha > 0$ is a test for overdispersion, which we provide in the results section of the paper.

Table 2 contains potential determinants of motor vehicle deaths. The variables pertain to the states of California, Illinois, Louisiana, Pennsylvania, and Texas, and are measured in annual frequency for the 1970-2006 period.

The amount of driving is directly related to economic activity. Recessions lead to reduced driving and fewer accidents and fatalities. Thus, the theoretically expected sign of the unemployment rate is negative. Exposure to accidents rises with the amount of driving. Thus, an increase in vehicle miles should lead to more accidents and fatalities. As noted above, fatal accidents occur more frequently in rural areas than in urban areas, possibly due to higher speeds in rural areas. Therefore, the theoretically expected sign of RUvehmil is positive.

Many previous studies have found a positive relationship between alcohol consumption and motor vehicle fatalities. The youngest and oldest drivers have the most fatal accidents, suggesting a positive relationship between deaths and independent variables Young, Old, and Ynold. However, the empirical evidence regarding this relationship has been mixed (Loeb et al. 1994, 23-25). Thus, the theoretically expected sign is indeterminate.

As noted above, there are opposing theoretical views regarding the relationship of fatalities to the speed limit on rural interstate highways. Thus, the expected sign is theoretically indeterminate. Previous empirical studies have found that seat belt laws reduce the number of motor vehicle serious injuries and deaths (Loeb 1993 and 1995).

Three highway safety regulation enforcement variables are considered: Popop, Poroad, and Poexp. Enforcement of highway safety laws, such as arrests for speeding and drunk driving as well as citations for failure to fasten seat belts, help establish safer driving conditions and lead to lower fatalities. Thus, the theoretically expected sign of Popop, Poroad, and Poexp is negative.

**Table 2: State Motor Vehicle Traffic Fatality Model-Variable Definitions**

| Variable | Definition |
|---|---|
| Deaths (Dependent Variable) | State motor vehicle fatalities |
| Urate | State unemployment rate (percent) |
| Vehmil | State total vehicle miles (millions) |
| RUvehmil | State ratio of rural vehicle miles to urban vehicle miles |
| Alconsum | State apparent per capita ethanol consumption, all beverages (gallons) |
| Young | Proportion of state population (age 15 and older) in the 15-24 year age group |
| Old | Proportion of state population (age 15 and older) in the 65 years and older age group |
| Ynold | Proportion of state population (age 15 and older) in the 15-24 year age group plus the 65 years of age and older group |
| Splimit | State maximum speed limit on rural interstate highways (mph) |
| Seatbelt | State seat belt dummy variable, equals 1.0 in the year the seat belt law was effective and all subsequent years, 0 for other years |
| Popop | Police per 10,000 population |
| Poroad | Police per 100 miles of public road |
| Poexp | Real per capita state expenditure for police protection |
| Trend | Time Trend (1 to 37) |

A linear time trend represents time varying factors that could impact fatalities in the five states but are not explicitly accounted for by the model. Peltzman (1975) said that excluded variables could include the quality of roads, the private demand and supply of improved vehicle design, the demand and supply of vehicle maintenance, and the quality of trauma health care. He noted that as these factors improve over time, motor vehicle fatalities will decrease. Peltzman (1975) and Loeb and Clarke (2007) hypothesized that the time trend serves as a partial proxy for permanent income, resulting in an inverse relationship between the trend and motor vehicle fatalities.

## DATA

Data for variables in Table 2 are for the 1970-2006 period. The source for state motor vehicle fatalities, rural vehicle miles, urban vehicle miles, and total vehicle miles is the U.S. Department of Transportation, *Highway Statistics* (1970-2006 issues).

The unemployment rate of the five states for the 1970-1975 period comes from the U.S. Bureau of the Census, *Statistical Abstract of the United States*. State unemployment rate data for 1976-2006 was obtained from *Economagic.com: Economic Time Series Page* (http://www.economagic.com).

The source for per capita alcohol consumption is the National Institute on Alcohol Abuse and Alcoholism, *Per Capita Ethanol Consumption for States, Census Regions, and The United States, 1970-2006*.

State data for the age composition of the population variables (Young, Old, Ynold) are available from several U.S. Bureau of Census publications. These included *Intercensal Estimates of the Resident Population, 1970-1980, Resident Population of States by Five Year Age Groups and Sex, Population for U.S. Regions and States by Five Year Age Group and Sex: Time Series Estimates, July 1, 1990 to July 1, 1999*, and *Annual Estimates of the Population by Age and Sex for California, April 1, 2000 to July 1, 2006*. For the latter, the data for the other four states are the same as for California, except for the appropriate state name substituted. All the sources can be found at http:www.census.gov.

For the maximum speed limit on rural interstate highways (Splimit) the data source is Insurance Institute for Highway Safety, *Maximum Posted Speed Limits for Passenger Vehicles as of April 1, 2007* (http://www.iihs.org/laws/state_laws/speed_limit_laws htmd).

The data for the state seat belt dummy variable are reported in the U.S. Department of Transportation (1998), *Traffic Safety Facts: A Compilation of Motor Vehicle Crash Data From the Fatality Analysis Reporting System and the General Estimates System*.

The police protection variables (Popop, Poroad, and Poexp) are from a wide variety of data sources. These sources included *Sourcebook of Criminal Justice Statistics, Trends in Expenditure and Employment Data for the Criminal Justice System, Justice Expenditure and Employment in the U.S., Justice Expenditure and Employment Extracts*, and *Data from the Annual General Finance and Employment Survey*. The state population data needed to calculate Popop and Poexp come from the same data sources as enumerated above for the age distribution of the population variables. The CPI required to calculate Poexp is from the *Economic Report of the President 2008*. State public road miles to calculate Poroad was obtained from *Highway Statistics*. (1970-2006 issues).

The descriptive statistics for the variables in the five state motor vehicle fatality model are in Table 3.

**Table 3: Descriptive Statistics of Variables in State Motor Vehicle Fatality Model**

| Variable | Unit of Measure | Mean | Standard Deviation | Minimum Value | Maximum Value |
|---|---|---|---|---|---|
| Deaths | Number of Deaths | 2,526.68 | 1,389.39 | 781 | 5,542 |
| Urate | Percent | 6.64 | 1.8 | 3.89 | 12.48 |
| Vehmil | Millions | 115,208.8 | 79,106.03 | 16,838 | 329,267 |
| RUvehmil | Ratio | 0.69 | 0.35 | 0.23 | 1.57 |
| Alconsum | Gallons | 2.5 | 0.35 | 1.84 | 3.4 |
| Young | Percent | 24.15 | 6.18 | 15.76 | 38.09 |
| Old | Percent | 14.63 | 2.04 | 12.26 | 19.84 |
| Ynold | Percent | 38.78 | 5.20 | 32.34 | 51.03 |
| Splimit | Miles Per Hour | 62.84 | 6.12 | 55 | 70 |
| Seatbelt | - | 0.57 | 0.50 | 0 | 1 |
| Popop | Police per 10,000 Population | 36.52 | 5.48 | 25 | 4.8 |
| Poroad | Police per 100 miles of Road | 26.33 | 11.65 | 8 | 60 |
| Poexp | Dollars | $121.30 | $37.59 | $57.91 | $215.68 |
| Trend | - | 19 | 10.71 | 1 | 37 |

**EMPIRICAL RESULTS**

First, we use ordinary least squares (OLS) to estimate the log linear specification, equation (2), of the model. These model estimates are reported in the first three data columns in Table 4. RUvehmil and Poroad were non-significant or had the wrong sign and were dropped from the model. Effects of Old and Young were combined into Ynold.

**Table 4: Empirical Results**

| | Models Estimated by Ordinary Least Squares | | | Models Estimated by Maximum Likelihood | |
|---|---|---|---|---|---|
| | Dependent Variable: Log(Deaths) | | | Dependent Variable: Death Counts | |
| Variables | Model 1 | Model 2 | Model 3 | Poisson | Negative Binomial |
| Constant | -11.03***<br>(-5.65) | -8.85***<br>(-4.91) | -9.72***<br>(-5.84) | -10.16***<br>(-5.91) | -9.75***<br>(-6.05) |
| Log(Urate) | -0.05**<br>(-2.14) | -0.06**<br>(-2.23) | -0.09***<br>(-3.43) | -0.09***<br>(-3.49) | -0.09***<br>(-3.63) |
| Log(Alconsum) | 0.95***<br>(10.41) | 0.94***<br>(10.52) | 0.88***<br>(11.65) | 0.99***<br>(12.61) | 0.89***<br>(12.17) |
| Log(Splimit) | 0.19*<br>(1.68) | 0.18<br>(1.56) | 0.19*<br>(1.7) | 0.24**<br>(2.22) | 0.19*<br>(1.79) |
| Seatbelt | -0.01<br>(-0.4) | -0.02<br>(-0.82) | -0.04<br>(-1.58) | -0.04*<br>(-1.66) | -0.04*<br>(-1.7) |
| Log(Ynold) | 2.18***<br>(7.45) | 1.88***<br>(6.95) | 1.84***<br>(7.15) | 1.74***<br>(6.65) | 1.83***<br>(7.28) |
| Log(Vehmil) | 0.80***<br>(11.83) | 0.79***<br>(12.2) | 0.92***<br>(13.87) | 0.99***<br>(15.84) | 0.93***<br>(14.67) |
| Log(Popop) | - | -0.23**<br>(-2.42) | - | - | - |
| Log(Poexp) | - | - | -0.28***<br>(-5.14) | -0.34***<br>(-6.95) | -0.28***<br>(-5.5) |
| Illinois | 0.50***<br>(3.53) | 0.44***<br>(3.43) | 0.48***<br>(4.10) | 0.52***<br>(4.24) | 0.49***<br>(4.28) |
| Louisiana | 0.65***<br>(3.41) | 0.58***<br>(3.31) | 0.70***<br>(4.32) | 0.79***<br>(4.81) | 0.72***<br>(4.6) |
| Pennsylvania | 0.61***<br>(4.48) | 0.49***<br>(3.94) | 0.49***<br>(4.35) | 0.53***<br>(4.46) | 0.50***<br>(4.54) |
| Texas | 0.85***<br>(7.45) | 0.74***<br>(7.11) | 0.64***<br>(6.29) | 0.62***<br>(5.86) | 0.64***<br>(6.44) |
| Log(Trend) | -0.17***<br>(-8.79) | -0.16***<br>(-8.36) | -0.15***<br>(-7.82) | -0.15***<br>(-8.00) | -0.15***<br>(-8.33) |
| R-squared | 0.9857 | 0.9862 | 0.9879 | | |
| Log likelihood | | | | -1714.04 | -1171.13 |
| | | | | Test for overdispersion:<br>$\alpha = 0.003$; standard error = 0.0004 | |

t-statistics in parentheses below the coefficients. The t-statistics are computed using robust standard errors. * indicates statistically significant at the 10% level. ** indicates statistically significant at the 5% level. *** indicates statistically significant at the 1% level. The sample size is 185.

Since the variable, Deaths, only takes on nonnegative integer values, it is appropriate to estimate count data models, such as Poisson and Negative Binomial. Regression estimates for these count data models are reported in the last two columns of Table 4. The t-statistics reported for all regression estimates are computed using robust standard errors to account for possible heteroskedasticity.[3] All regression models include state fixed effects and a time trend.

Given the double log specifications in Models 1 through 3, the coefficient estimates are elasticities. First, the estimates for Model 1 reveal that the unemployment rate, Log(Urate), has a negative and statistically significant effect on deaths. Second, per capita alcohol consumption, Log(Alconsum), has a positive and statistically significant effect on deaths. Third, increasing the maximum speed limit, Log(Splimit), has a positive and statistically significant effect on deaths. Fourth, the coefficient on Seatbelt has the expected negative sign but is not statistically significant in Model 1. Fifth, the proportion of the population that falls into the young or old categories, Log(Ynold), is positively related to deaths. Sixth, the total amount of vehicle miles, Log(Vehmil), is positively related to deaths. With the exception of the statistical insignificance of the marginal effect of the Seatbelt variable, all the marginal effects described above are consistent with theoretical expectations.

Since the measures of safety regulation enforcement are highly correlated (correlation of 0.61), we do not simultaneously include them in the models (see correlation matrix in the Appendix). Model 2 includes number of police per 10,000 population, Log(Popop), while Model 3 includes real per capita expenditure for police protection, Log(Poexp). Both these variables have the expected negative signs and are statistically significant, but Model 3 has a slightly higher R-squared value. Thus, Model 3 is the preferred model due to better fit and one additional significant variable.

The variables with the highest elasticities in Model 3 are Ynold (1.84), Vehmil (0.92), and Alconsum (0.88). These elasticity estimates suggest: (1) a 1% increase in the proportion of state population in young and old age groups is associated with a 1.84% increase in the number of road deaths; (2) a 1% increase in total vehicle miles is associated with a 0.92% increase in road deaths; and (3) a 1% increase in alcohol consumption is associated with a 0.88% increase in road deaths. Based on average annual road deaths in California, Texas, Pennsylvania, Illinois, and Louisiana (see state level descriptive statistics tables in the Appendix), a 1.84% increase in road deaths correspond to 84, 66, 33, 31, and 18 more road deaths in these states respectively.

The elasticity estimate for the unemployment variable suggests that a 1% increase in the unemployment rate is associated with a 0.09% decline in road deaths. In the case of the speed limit elasticity, a 1% increase in the speed limit is associated with a 0.19% increase in road deaths; or put differently, a 10% increase in the speed limit (e.g., 70 miles per hour to 77 miles per hour) is associated with a 1.9% increase in road deaths, which corresponds to 87 more road deaths based on California's annual average road deaths.

The excluded state dummy from the regressions is California, so California is the benchmark for comparison when interpreting the coefficients on the included state dummies. The coefficient estimates on Illinois, Louisiana, Pennsylvania, and Texas dummies are positive and statistically significant, which suggest that deaths in these states are higher than California if all five states had equivalent values for the control variables used. In fact, based on the relative sizes of the dummy coefficients on the state dummy variables in Model 3, our preferred specification among the log linear models, if all five states had equivalent values for the control variables, then Louisiana is predicted to have the highest death count followed by Texas, Pennsylvania, Illinois, and California respectively. Of course, in reality, the five states do not have equivalent values for the control variables, therefore, the actual ordering of states based on death counts, as previously seen in Figure 1, is different than the ordering just described.

The coefficient on the time trend is negative and statistically different from 0. This result suggests that, after accounting for the effects of our control variables, road deaths declined on average over the sample period.

When the Poisson and Negative Binomial model specifications are used, it is notable that the Seatbelt variable becomes statistically significant, suggesting that implementation of seatbelt laws may reduce deaths in accidents. The other qualitative results obtained using the double log specifications of our model remain robust when we use the Poisson and Negative Binomial model specifications. However, the coefficient estimates for the Negative Binomial regression model seem to better match the coefficient estimates in Model 3 compared with the coefficient estimates for the

Poisson regression model. The Poisson regression model has the well-known restriction that the conditional mean of the count variable is equal to its conditional variance – equidispersion. Casual empiricism suggests that this equidispersion restriction is violated in our data since the sample mean of deaths is 2526.68, while the sample variance is 1930404.57 – overdispersion.[4] The Negative Binomial regression relaxes the equidispersion assumption of the Poisson model and instead allows for overdispersion, which is consistent with our data and may explain why the Negative Binomial estimates better match Model 3. A formal statistical test for overdispersion ($\alpha > 0$) also rejects the Poisson regression model in favor of the Negative Binomial regression model.[5]

In summary, the regression results suggest that state government policy can influence the number of road deaths. For example, the number of road deaths can be reduced by policies that reduce alcohol consumption and the speed limit, or increase per capita expenditure on police protection and number of police per 10,000 population. In the case of California, the mean per capita alcohol consumption is 2.78 gallons per year while the mean number of annual road deaths is 4567.92 over the sample period. The alcohol coefficient in Model 3 suggests that a 1% fall in alcohol consumption will be associated with a 0.88% fall in road deaths, which corresponds to approximately 40 fewer road deaths in the case of California. Alternatively, a 1% increase in per capita spending on police protection, which is an increase of approximately $1.58 per capita in the case of California, is associated with a 0.28% reduction in road deaths, which corresponds to approximately 13 fewer road deaths in California. These are just some examples of the "hard numbers" our econometric estimates can provide to inform potential policy strategies to reduce road deaths.

## CONCLUSION

This paper specifies a model of motor vehicle fatalities for the states of California, Illinois, Louisiana, Pennsylvania, and Texas that collectively accounted for 27% of the U.S. highway-related deaths in 2006. The model makes fatalities a function of economic conditions, driver characteristics, government highway regulations, location of driving, and highway traffic safety law enforcement. The model is estimated in log linear specification and Poisson and Negative Binomial regression in annual frequency for the 1970-2006 period.

The Poisson regression does not account for overdispersion, so the preferred log linear model estimates (Model 3) are compared to the Negative Binomial results. All the independent variables in the final models have the theoretically expected sign. The unemployment rate, alcohol consumption, vehicle miles, proportion of the state population in the young and old age groups, and real per capita expenditure for police protection were statistically significant at the .01 level in both models. Police per 10,000 population was significant at the .05 level. The maximum speed limit on rural interstate highways was significant at the .10 level in both models (significant at .05 level in the Poisson regression) while the Seatbelt dummy variable was non-significant in Model 3, but significant at the .10 level in the Negative Binomial regression.

Fatalities in the five states are most sensitive to Log(Ynold), Log(Vehmil), and Log(Alconsum) with Negative Binomial elasticities of 1.84, 0.93, and 0.89 respectively. Log(Urate), Log(Splimit), Seatbelt had relatively lower elasticities of -0.09, 0.19, and -0.04 respectively.

A major conclusion is that highway fatalities and their determinants vary by state. All of the state dummy variables in Model 3 and the Negative Binomial regression are statistically significant at the .01 level. After controlling for the impact of several variables, each state dummy variable has a unique influence on highway-related deaths. Future research is needed to explore alternate sources of the unexplained state variations in highway-related deaths that are measured by our state dummy variables.[6]

Another important conclusion is that several of the variables in the model are subject to state policy, including alcohol taxes, speed limits, seatbelt laws, and police enforcement. Statistical results of models similar to the one in this paper would allow state policy makers to quantify the impacts on motor vehicle fatalities of policy changes in these variables.

## APPENDIX

**Table A1: Descriptive Statistics of Variables in State Motor Vehicle Fatality Model – California**

| Variable | Unit of Measure | Mean | Standard Deviation | Minimum Value | Maximum Value |
|---|---|---|---|---|---|
| Deaths | Number of Deaths | 4567.92 | 596.34 | 3494 | 5542 |
| Urate | Percent | 7.14 | 1.51 | 4.9 | 10.03 |
| Vehmil | Millions | 226009.80 | 72282.87 | 116992 | 329267 |
| RUvehmil | Ratio | 0.32 | 0.09 | 0.23 | 0.55 |
| Alconsum | Gallons | 2.78 | 0.49 | 2.17 | 3.4 |
| Young | Percent | 34.66 | 2.30 | 32.2 | 38.09 |
| Old | Percent | 13.46 | 0.59 | 12.41 | 14.56 |
| Ynold | Percent | 48.12 | 1.80 | 46.02 | 51.03 |
| Splimit | Miles Per Hour | 63.51 | 6.65 | 55 | 70 |
| Seatbelt | – | 0.57 | 0.50 | 0 | 1 |
| Popop | Police per 10,000 Population | 35.81 | 1.48 | 33.3 | 37.8 |
| Poroad | Police per 100 miles of road | 53.91 | 4.69 | 46.2 | 60 |
| Poexp | Dollars | 158.03 | 33.67 | 113.56 | 215.68 |
| Trend | – | 19 | 10.82 | 1 | 37 |

**Table A2: Descriptive Statistics of Variables in State Motor Vehicle Fatality Model – Illinois**

| Variable | Unit of Measure | Mean | Standard Deviation | Minimum Value | Maximum Value |
|---|---|---|---|---|---|
| Deaths | Number of Deaths | 1703 | 334.78 | 1254 | 2400 |
| Urate | Percent | 6.46 | 1.85 | 4 | 11.68 |
| Vehmil | Millions | 81177.16 | 17811.25 | 55313 | 109135 |
| RUvehmil | Ratio | 0.46 | 0.05 | 0.36 | 0.56 |
| Alconsum | Gallons | 2.60 | 0.28 | 2.21 | 3 |
| Young | Percent | 20.72 | 2.94 | 17.47 | 24.98 |
| Old | Percent | 15.07 | 0.88 | 13.69 | 16.19 |
| Ynold | Percent | 35.79 | 2.19 | 33.15 | 38.9 |
| Splimit | Miles Per Hour | 62.03 | 5.46 | 55 | 70 |
| Seatbelt | – | 0.59 | 0.50 | 0 | 1 |
| Popop | Police per 10,000 Population | 42.92 | 3.27 | 36.2 | 47.8 |
| Poroad | Police per 100 miles of road | 28.72 | 3.31 | 22.2 | 34.7 |
| Poexp | Dollars | 141.16 | 32.47 | 96.55 | 213.82 |
| Trend | – | 19 | 10.82 | 1 | 37 |

**Table A3: Descriptive Statistics of Variables in State Motor Vehicle Fatality Model – Louisiana**

| Variable | Unit of Measure | Mean | Standard Deviation | Minimum Value | Maximum Value |
|---|---|---|---|---|---|
| Deaths | Number of Deaths | 965.65 | 114.22 | 781 | 1233 |
| Urate | Percent | 7.32 | 2.12 | 3.96 | 12.48 |
| Vehmil | Millions | 32129.89 | 9076.13 | 16838 | 45417 |
| RUvehmil | Ratio | 1.26 | 0.21 | 0.76 | 1.57 |
| Alconsum | Gallons | 2.50 | 0.13 | 2.27 | 2.78 |
| Young | Percent | 23.35 | 3.41 | 19.11 | 28.07 |
| Old | Percent | 3.88 | 1.05 | 12.26 | 15.44 |
| Ynold | Percent | 37.23 | 2.40 | 34.55 | 40.86 |
| Splimit | Miles Per Hour | 63.24 | 6.48 | 55 | 70 |
| Seatbelt | – | 0.57 | 0.50 | 0 | 1 |
| Popop | Police per 10,000 Population | 40.04 | 4.32 | 32.7 | 47 |
| Poroad | Police per 100 miles of road | 21.97 | 3.12 | 15.5 | 27.3 |
| Poexp | Dollars | 111.68 | 24.76 | 64.36 | 151.3 |
| Trend | – | 19 | 10.82 | 1 | 37 |

**Table A4: Descriptive Statistics of Variables in State Motor Vehicle Fatality Model – Pennsylvania**

| Variable | Unit of Measure | Mean | Standard Deviation | Minimum Value | Maximum Value |
|---|---|---|---|---|---|
| Deaths | Number of Deaths | 1810.46 | 293.55 | 1441 | 2444 |
| Urate | Percent | 6.35 | 1.84 | 4 | 11.63 |
| Vehmil | Millions | 83865.24 | 15482.75 | 56677 | 108278 |
| RUvehmil | Ratio | 0.81 | 0.11 | 0.56 | 0.96 |
| Alconsum | Gallons | 2.16 | 0.18 | 1.84 | 2.39 |
| Young | Percent | 19.45 | 3.02 | 15.76 | 23.54 |
| Old | Percent | 17.81 | 1.82 | 14.7 | 19.84 |
| Ynold | Percent | 37.26 | 1.35 | 35.52 | 39.14 |
| Splimit | Miles Per Hour | 62.03 | 5.46 | 55 | 70 |
| Seatbelt | – | 0.51 | 0.51 | 0 | 1 |
| Popop | Police per 10,000 Population | 30.41 | 1.36 | 27.5 | 32.7 |
| Poroad | Police per 100 miles of road | 24.59 | 1.38 | 21.6 | 26.6 |
| Poexp | Dollars | 99.45 | 26.55 | 68.14 | 158.35 |
| Trend | – | 19 | 10.82 | 1 | 37 |

**Table A5: Descriptive Statistics of Variables in State Motor Vehicle Fatality Model – Texas**

| Variable | Unit of Measure | Mean | Standard Deviation | Minimum Value | Maximum Value |
|---|---|---|---|---|---|
| Deaths | Number of Deaths | 3586.38 | 366.02 | 3037 | 4623 |
| Urate | Percent | 5.91 | 1.24 | 3.89 | 8.94 |
| Vehmil | Millions | 152862 | 52450.94 | 68031 | 238256 |
| RUvehmil | Ratio | 0.60 | 0.11 | 0.45 | 0.86 |
| Alconsum | Gallons | 2.45 | 0.23 | 2.19 | 2.93 |
| Young | Percent | 22.58 | 2.97 | 19.42 | 26.87 |
| Old | Percent | 12.94 | 0.35 | 12.33 | 13.52 |
| Ynold | Percent | 35.51 | 2.79 | 32.34 | 39.72 |
| Splimit | Miles Per Hour | 63.38 | 6.57 | 55 | 70 |
| Seatbelt | – | 0.59 | 0.50 | 0 | 1 |
| Popop | Police per 10,000 Population | 33.41 | 4.03 | 25 | 40.1 |
| Poroad | Police per 100 miles of road | 15.13 | 3.94 | 8 | 20.5 |
| Poexp | Dollars | 96.20 | 26.30 | 57.91 | 147.28 |
| Trend | – | 19 | 10.82 | 1 | 37 |

**Table A6: Correlation Matrix**

| | Log(Deaths) | Log(Urate) | Log(Alconsum) | Log(Splimit) | Seatbelt | Log(Ynold) | Log(Vehmil) | Log(Poexp) | Log(Popop) |
|---|---|---|---|---|---|---|---|---|---|
| Log(Deaths) | 1 | | | | | | | | |
| Log(Urate) | -0.0809 | 1 | | | | | | | |
| Log(Alconsum) | 0.3272 | 0.3249 | 1 | | | | | | |
| Log(Splimit) | -0.0238 | -0.4818 | -0.4953 | 1 | | | | | |
| Seatbelt | -0.1445 | -0.1978 | -0.5597 | 0.5822 | 1 | | | | |
| Log(Ynold) | 0.5479 | 0.2406 | 0.5285 | -0.2175 | -0.4001 | 1 | | | |
| Log(Vehmil) | 0.8184 | -0.1353 | -0.059 | 0.2063 | 0.3514 | 0.2839 | 1 | | |
| Log(Poexp) | 0.0556 | -0.0572 | -0.0818 | 0.3444 | 0.575 | 0.1207 | 0.463 | 1 | |
| Log(Popop) | -0.3931 | 0.0834 | 0.1296 | 0.1296 | 0.3587 | -0.2339 | -0.1417 | 0.6144 | 1 |

**Table A7: Additional Empirical Results**

| | Models Estimated by Maximum Likelihood | |
|---|---|---|
| | Dependent Variable: Death Counts | |
| Variables | Poisson | Negative Binomial |
| Constant | -8.74***<br>(-5.04) | -8.79***<br>(-5.08) |
| Log(Urate) | -0.061**<br>(-2.32) | -0.058**<br>(-2.41) |
| Log(Alconsum) | 1.08***<br>(12.40) | 0.955***<br>(11.05) |
| Log(Splimit) | 0.19*<br>(1.81) | 0.172<br>(1.62) |
| Seatbelt | -0.015<br>(-0.70) | -0.022<br>(-0.86) |
| Log(Ynold) | 1.73***<br>(6.69) | 1.86***<br>(7.15) |
| Log(Vehmile) | 0.839***<br>(13.81) | 0.794***<br>(12.86) |
| Log(Popop) | -0.33***<br>(-3.72) | -0.239***<br>(-2.65) |
| Illinois | 0.471***<br>(3.74) | 0.44***<br>(3.57) |
| Louisiana | 0.663***<br>(3.90) | 0.59***<br>(3.49) |
| Pennsylvania | 0.517***<br>(4.33) | 0.49***<br>(4.12) |
| Texas | 0.717***<br>(7.13) | 0.73***<br>(7.35) |
| Log(Trend) | -0.16***<br>(-8.59) | -0.16***<br>(8.82) |
| R-squared | | |
| Log likelihood | -1861.71 | -1183.70 |
| | Test for overdispersion: α=0.004 ; standard error =0.0005 | |

t-statistics in parentheses below the coefficients. The t-statistics are computed using robust standard errors. * indicates statistically significant at the 10% level. ** indicates statistically significant at the 5% level. *** indicates statistically significant at the 1% level. The sample size is 185.

**Endnotes**

1. See also Wooldrige (2003), Vogus and Welbourne (2003), Gittelman and Kogut (2003), Henderson and Cockburn (1994), Jensen (1987), Shane (2001), Shane (2002), and Cantor, Corsi, and Grimm (2008).

2. For a derivation of the Negative Binomial model, see chapter 8 in Long (1997).

3. STATA statistical software package is used to estimate the regressions, which uses the Huber/White/Sandwich method to compute robust standard errors.

4. State level descriptive statistics found in the appendices also suggest that the equidispersion assumption is violated for each state. We thank an anonymous referee for pointing this out.

5. Table A7 in the appendix reports Poisson and Negative Binomial regression results when Log(Popop) is used as a regressor instead of Log(Poexp). While signs of independent variables are unchanged across Tables 4 and A7, Log(Splimit) and Seatbelt are not statistically significant when Log(Popop) is used in Table A7.

6. An anonymous referee suggested that alternate sources of the state variation in road fatalities may include: (1) health care availability; and (2) differences in alcohol laws, e.g., drinking ages, DUI levels for arrests, etc.

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