



The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search

<http://ageconsearch.umn.edu>

aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

No endorsement of AgEcon Search or its fundraising activities by the author(s) of the following work or their employer(s) is intended or implied.

STATE VARIATION IN THE DETERMINANTS OF MOTOR VEHICLE FATALITIES

Michael W. Babcock
Economics Department
Kansas State University
Manhattan, Kansas 66506
email: mwb@ksu.edu
ph: 785-532-4571

Philip G. Gayle
Economics Department
Kansas State University
Manhattan, Kansas 66506
email: gaylep@ksu.edu
ph: 785-532-4581

February 2009

STATE VARIATION IN THE DETERMINANTS OF MOTOR VEHICLE FATALITIES

Abstract

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. A major conclusion is that fatalities and its determinants vary by state, and several of these determinants are subject to state policy control. As such, our coefficient estimates and econometric framework are relevant for designing policies intended to reduce motor vehicle fatalities.

JEL Classifications: R4; L92; C2

STATE VARIATION IN THE DETERMINANTS OF MOTOR VEHICLE FATALITIES

1. 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 U.S. 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 during the 1970-2006 period.

In what follows, section 2 discusses trends in motor vehicle fatalities across the five states. A review of the literature is done in section 3. The model is presented in section 4, while sources and characteristics of the data are discussed in section 5. Empirical results are discussed in section 6, and concluding remarks offered in section 7.

2. TRENDS IN STATE MOTOR VEHICLE FATALITIES

Figure 1 displays the motor vehicle deaths for the five states during the 1970-2006 period. Motor vehicle traffic fatalities in California have exhibited a “roller coaster” pattern during the 1970-2006 era. Deaths fell from 4,901 in 1970 to 4,019 in 1974, an 18% decline. This was followed by an increase to 5,542 in 1979, a 38% rise. California motor vehicle fatalities fell during 1980-1982 recession period, declining to 4,573 in 1983 (17.5% fall). In the 1983-1989 period, fatalities rose from 4,573 (1983) to 5,412 (1989), an 18% rise. Then motor vehicle traffic deaths declined steadily between 1989 and 1998, falling 35.4% from 5,412 to 3,494. Subsequently, California motor vehicle traffic deaths have risen to 4,236 (2006). For the entire 1970-2006 period, California fatalities declined 13.6%.

In contrast to California, motor vehicle traffic fatalities in Illinois declined more or less continuously from 2,346 in 1970 to 1,393 (1998), a 40.6% drop. Deaths rose slightly between 1998 and 2003, but then fell from 1,453 (2003) to 1,254 (2006), a 13.7% decrease. For the entire 1970-2006 era, Illinois motor vehicle traffic fatalities plunged 46.5%, the largest decrease in the five state sample.

The pattern of motor vehicle fatalities in Louisiana is different from California and Illinois. Deaths increased about 12% between 1970 (1,035) and 1973 (1,158). However, deaths dropped the following year to 864, a 25.4% fall. Then motor vehicle traffic fatalities rose 42.7% from 1974 (864) to 1981 (1,233). The number of deaths trended downward between 1981 and 1996 (781), falling 36.7%. However, traffic fatalities increased in the 1997-2006 period to between 900 and 1000 in most years. For the entire 1970-2006 period Louisiana motor vehicle traffic fatalities declined only 5.1%.

Pennsylvania motor vehicle fatalities were unstable between 1970 and 1990. After increasing from 2,255 (1970) to 2,444 (1973), fatalities fell nearly 30% from 1973 to 1983 (1,721). After increasing to 1,987 (1987), Pennsylvania highway-related deaths declined to 1,441 (1994), a 27.5% decline. Since the middle 1990s, motor vehicle traffic fatalities have been relatively stable at 1,500 to 1,600 in most years. For the entire 1970-2006 period, Pennsylvania highway-related deaths fell 32.4%.

The temporal pattern of motor vehicle traffic fatalities in Texas differs from the other states in the sample. Fatalities fell from 3,560 in 1970 to 3,046 in 1974, a decrease of 14.4%. Thereafter, deaths rose to the highest level in the Texas sample in 1981 (4,623), nearly a 52% increase from 1974. Between 1981 and 1993, Texas fatalities trended downward to 3,037 (1993), falling 34.3%. However, motor vehicle traffic fatalities increased by 14.4% between 1993

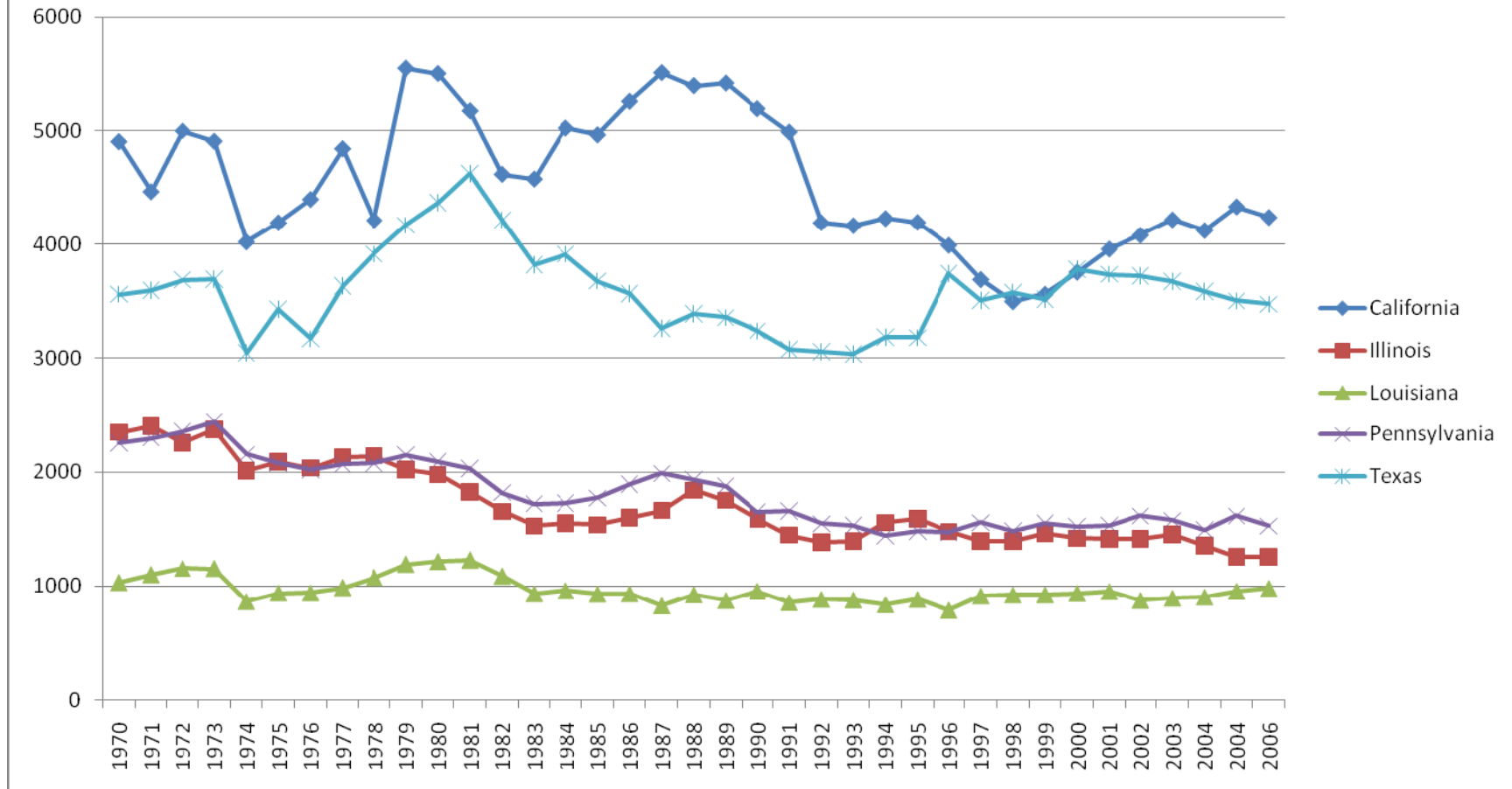
(3,037) and 2006 (3,475). Overall, Texas highway-related deaths fell only 2.4% in the 1970-2006 period; the smallest decline on any state in the sample.

3. 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); 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. During recessions driving falls 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 indeterminant. As income decreases, driving decreases resulting 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.

Figure 1
Motor Vehicle Traffic Fatalities
(1970-2006)



Motor vehicle fatalities are directly related to vehicle miles traveled. Loeb et al. (1994, 25-26) cited several studies that found a significant 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 U.S. 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 higher speed and speed variance both 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 of 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.

4. 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:

$$\text{Motor vehicle fatalities} = f(\text{economic conditions, driver characteristics, traffic regulations, location of driving, traffic law enforcement, other variables}). \quad (1)$$

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

$$\log y_{it} = x_{it}\beta + \mu_i + \tau + \varepsilon_{it}, \quad (2)$$

where y_{it} is the number of deaths in state i during time period t , x_{it} is a vector of determinants of motor vehicle deaths that we subsequently describe, β is the vector of parameters associated with x_{it} , μ_i controls for state fixed effects, τ is a time trend, and ε_{it} is a random error term.

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

$$\text{Prob}(y_{it} | x_{it}) = \frac{\lambda_{it}^{y_{it}} \exp(-\lambda_{it})}{y_{it}!}, \quad (3)$$

where,

$$\lambda_{it} = E(y_{it} | x_{it}) = \text{Var}(y_{it} | x_{it}) = \exp(x_{it}\beta + \mu_i + \tau). \quad (4)$$

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 λ_{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:¹

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

where $\Gamma(v) = \int_0^\infty t^{v-1} e^{-t} dt$ 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, $E(y_{it} | x_{it})$, and conditional variance, $Var(y_{it} | x_{it})$, of y_{it} are given by:

$$\lambda_{it} = E(y_{it} | x_{it}) = \exp(x_{it}\beta + \mu_i + \tau) \quad (6)$$

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

¹ For a derivation of the Negative Binomial model, see chapter 8 in Long (1997).

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 α . 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 1 contains the variables in x_{it} . 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 Yn old. 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 1
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.

5. DATA

Data for variables in Table 1 are for the 1970-2006 period. The source for state motor vehicle fatalities, rural vehicle miles, urban vehicle miles, and total vehicle miles is U.S. Department of Transportation, *Highway Statistics* (1970-2006 issues).

The unemployment rate of the five states for the 1970-1975 period comes from 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 National Institute on Alcohol Abuse and Alcoholism, *Per Capita Ethanol Consumption for States, Census Regions, and The United States, 1978-2006*.

State data for the age composition of the population variables (Young, Old, Ynold) are available from several U.S. Bureau of Census publications. The source for 1970-1979 is U.S. Bureau of the Census, *Intercensal Estimates of the Resident Population, 1970-1980*

(<http://www.census.gov>). For the 1980-1989 period the source is U.S. Bureau of the Census, *Resident Population of States by Five-Year Age Groups and Sex* (<http://www.census.gov>). State data for the 1990-1999 era can be found in U.S. Bureau of the Census, *Population Estimates for the U.S. Regions and States by Five Year Age Group and Sex: Time Series Estimates July 1, 1990 to July 1, 1999, and April 1, 1990, Census Counts* (<http://www.census.gov>). Data for 2000-2006 are found in U.S. Bureau of the Census, *Annual Estimates of the Population by Age and Sex for California, April 1, 2000 to July 1, 2006* (<http://www.census.gov>). The data for the other four states is the same as for California except for the appropriate state name substituted.

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.htm).

The data for the state seat belt dummy variable is reported in 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. Full-time equivalent police employment and per capita expenditure for police protection are from the same data sources. For 1970, the data are reported in U.S. Department of Justice, *Sourcebook of Criminal Justice Statistics*, 1973. For 1972-1974 the data can be found in U.S. Department of Justice, *Trends in Expenditure and Employment Data for the Criminal Justice System* (1971-1977 issues). The data for 1971 and 1975-1979 is in U.S. Department of Justice, *Justice Expenditure and Employment in the U.S.*, 1971-1979. For the 1980s, the data is reported in U.S. Department of Justice, *Justice Expenditure and Employment Extracts* for various years. U.S. Department of Justice, *Justice Expenditure and Employment Extracts: Data*

from the *Annual General Finance and Employment Survey* is the source for the 1992-2006 period. Data for a few of the years is estimated by linear trend regression or interpolation. The state population data needed to calculate Popop and Poexp comes from the same data sources as enumerated above for the age distribution of the population variables. The Consumer Price Index required to calculate Poexp comes from *Economic Report of the President 2008*. State public road miles to calculate Poroad was obtained from U.S. Department of Transportation, *Highway Statistics* (1970-2006 issues).

The descriptive statistics for the variables in the five state motor vehicle fatality model are in Table 2. The data in the table indicate that the mean of annual motor vehicle fatalities (Deaths) in the five states as a group during the 1970-2006 period is 2,527. For the economic explanatory variables in the model, the mean unemployment rate for the five states is 6.64% and the mean number of annual vehicle miles (Vehmil) is about 115,209 million.

For the driver characteristics, the mean per capita alcohol consumption for the five states as a group is 2.5 gallons. The mean proportion of the age 15 and over population aged 15-24 (Young) is 24.15% and for the age 65 and older group (Old) it is 14.63%. Thus, these two population groups account for well over a third (38.78%) of the five state population age 15 and over in the years studied.

The maximum speed limit on rural interstate highways (Splimit) and seat belt laws (Seatbelt) represent government highway regulation in the analysis. The average speed limit of the five states as a group during the 1970-2006 period was about 63 miles per hour, and the seat belt laws of the sample states were in effect a little over half of this interval. The amount of travel on urban highways exceeded that of rural highways for the five states as a group in the

analysis period. The mean ratio of rural to urban vehicle miles (RUvehmil) was 0.69. Louisiana was the only state of the five that had a ratio above 1.0.

Table 2
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

Highway safety regulation enforcement is represented in the study by police per 10,000 population (Popop), police per 100 miles of road (Poroad), and real per capita expenditure for police protection (Poexp). Data in Table 2 indicates that the mean of Popop is about 37, for Poroad the mean is about 26, and for Poexp it is \$121.30. The appendix contains additional descriptive statistics tables for the five states.

6. 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 3. 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.

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 3. The t-statistics reported for all regression estimates are computed using robust standard errors to account for possible heteroskedasticity. 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, $\text{Log}(\text{Urate})$, has a negative and statistically significant effect on deaths. Second, per capita alcohol consumption, $\text{Log}(\text{Alconsum})$, has a positive and statistically significant effect on deaths. Third, increasing the maximum speed limit, $\text{Log}(\text{Splimit})$, 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, $\text{Log}(\text{Ynold})$, is positively related to deaths. Sixth, the total amount of vehicle miles, $\text{Log}(\text{Vehmil})$, 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.

Table 3
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*** (-5.65)	-8.85*** (-4.91)	-9.72*** (-5.84)	-10.16*** (-5.91)	-9.75*** (-6.05)
Log(Urate)	-0.05** (-2.14)	-0.06** (-2.23)	-0.09*** (-3.43)	-0.09*** (-3.49)	-0.09*** (-3.63)
Log(Alconsum)	0.95*** (10.41)	0.94*** (10.52)	0.88*** (11.65)	0.99*** (12.61)	0.89*** (12.17)
Log(Splimit)	0.19* (1.68)	0.18 (1.56)	0.19* (1.7)	0.24** (2.22)	0.19* (1.79)
Seatbelt	-0.01 (-0.4)	-0.02 (-0.82)	-0.04 (-1.58)	-0.04* (-1.66)	-0.04* (-1.7)
Log(Ynold)	2.18*** (7.45)	1.88*** (6.95)	1.84*** (7.15)	1.74*** (6.65)	1.83*** (7.28)
Log(Vehmil)	0.80*** (11.83)	0.79*** (12.2)	0.92*** (13.87)	0.99*** (15.84)	0.93*** (14.67)
Log(Popop)	-	-0.23** (-2.42)	-	-	-
Log(Poexp)	-	-	-0.28*** (-5.14)	-0.34*** (-6.95)	-0.28*** (-5.5)
Illinois	0.50*** (3.53)	0.44*** (3.43)	0.48*** (4.10)	0.52*** (4.24)	0.49*** (4.28)
Louisiana	0.65*** (3.41)	0.58*** (3.31)	0.70*** (4.32)	0.79*** (4.81)	0.72*** (4.6)
Pennsylvania	0.61*** (4.48)	0.49*** (3.94)	0.49*** (4.35)	0.53*** (4.46)	0.50*** (4.54)
Texas	0.85*** (7.45)	0.74*** (7.11)	0.64*** (6.29)	0.62*** (5.86)	0.64*** (6.44)
Log(Trend)	-0.17*** (-8.79)	-0.16*** (-8.36)	-0.15*** (-7.82)	-0.15*** (-8.00)	-0.15*** (-8.33)
R-squared	0.9857	0.9862	0.9879		
Log likelihood				-1714.04	-1171.13
				Test for overdispersion: $\alpha = 0.003$; 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 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 Appendix). Model 2 includes number of police per 10,000 population, $\text{Log}(\text{Popop})$, while Model 3 includes real per capita expenditure for police protection, $\text{Log}(\text{Poexp})$. 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 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 and 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 zero. 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 to 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 suggest 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. 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.²

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.

² 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 3 and A7, Log(Splimit) and Seatbelt are not statistically significant when Log(Popop) is used in Table A7.

7. 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, 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 [Log(Urate)], alcohol consumption [Log(Alconsum)], vehicle miles [Log(Vehmil)], proportion of the state population in the young and old age groups [Log(Ynold)], and [Log(Poexp)], were statistically significant at the .01 level in both models. Police per 10,000 population [Log(Poexp)] was significant at .05 level. The maximum speed limit on rural interstate highways [Log(Splimit)] 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 its 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.

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.

References

- Adams, B. "Deregulation's Negative Effect on Safety." L.N. Moses and I. Savage eds. *Transportation Safety in an Age of Deregulation*. New York: Oxford University Press (1989): 21-27.
- Alexander, D.L. "Motor Carrier Deregulation and Highway Safety: An Empirical Analysis." *Southern Economic Journal* 59(1), (1992): 28-38.
- Babcock, M.W., T. J. Zlatoper, and A.M. Welki. "Determinants of Motor Vehicle Fatalities: A Kansas Case Study." *Journal of the Transportation Research Forum* 47(1), (2008): 89-106.
- Cameron, A. C. and P. K. Trivedi. "Econometric Models Based on Count Data: Comparisons and Applications of Some Estimators and Tests." *Journal of Applied Econometrics*, 1, (1986): 29-53.
- Daicoff, D.W. "Deregulation and Motor Carrier Safety." *Logistics and Transportation Review* 24, (1988): 175-183.
- Economagic.com. *Economic Time Series Page* (<http://www.economagic.com>).
- Evans, L.E. *Traffic Safety and the Driver*. Van Nostrand Reinhold, New York, NY, 1991.
- Evans, W. and J.P. Graham. "Traffic Safety and the Business Cycle." *Alcohol, Drugs, and Driving* 4(1), (1988): 31-38.
- Fowles, R. and P.D. Loeb. "Effects of Policy-Related Variables on Traffic Fatalities: An Extreme Bounds Analysis Using Time Series Data." *Southern Economic Journal* 62(2), (1995): 359-366.
- Fowles, R. and P.D. Loeb. "Speeding, Coordination, and the 55 mph Limit: Comment." *American Economic Review* 79(4), (1989): 916-921.
- Gourieroux, C., A. Monfort, and A. Trognon. "Pseudo Maximum Likelihood Methods: Applications to Poisson Models." *Econometrica*, 52, (1984): 701-720.
- Insurance Institute for Highway Safety. *Maximum Posted Speed Limits for Passenger Vehicles, as of April 2007*. http://www.iihs.org/laws/state_laws/speed_limit_laws.html (accessed May 2008).
- Keeler, T.E. "Highway Safety, Economic Behavior, and the Driving Environment." *The American Economic Review* 84(3), (1994): 684-693.
- Kraas, A. "The Impact of the U.S. Motor Carrier Act of 1980 on Road Safety in California: An Econometric Policy Evaluation." *Logistics and Transportation Review* 29(2), (1993): 179-192.

Lave, C.A. "Speeding, Coordination, and the 55 mph Limit." *American Economic Review* 75(5), (1985): 1159-1164.

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

Loeb, P.D. and W.A. Clarke. "The Determinants of Truck Accidents." *Transportation Research Part E* 43(4), (2007): 442-452.

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

Loeb, P.D. "The Effectiveness of Seat Belt Legislation in Reducing Injury Rates in Texas." *American Economic Review* 85(2), (1995): 81-84.

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

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

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

Long, J. Scott. "Regression Models for Categorical and Limited Dependent Variables." *SAGE Publications, Inc.*, (1997): 217-250.

Merrell, D., M. Poitras, and D. Sutter. "The Effectiveness of Vehicle Safety Inspections: An Analysis Using Panel Data." *Southern Economic Journal* 65(3), (1999): 571-583.

Moore, T.G. "The Myth of Deregulation's Negative Effect on Safety." L.N. Moses and I. Savage eds. *Transportation Safety in an Age of Deregulation*. New York: Oxford University Press (1989): 8-20.

National Institute on Alcohol Abuse and Alcoholism. *Per Capita Ethanol Consumption for States, Census Regions, and the United States, 1970-2006*. National Institute of Health, 2008. <http://www.niaaa.nih.gov/Resources/DatabaseResources/QuickFacts/AlcoholSales/Consum03.htm> (accessed May 2008).

Partyka, S.C. "Simple Models of Fatality Trends Using Unemployment and Population Data." *Accident Analysis and Prevention* 16(3), (1984): 211-222.

Peltzman, S. "The Effects of Automobile Safety Regulation." *Journal of Political Economy* 83(4), (1975): 677-725.

President's Council of Economic Advisors. *Economic Report of the President*. Washington, D.C., 2008, p. 275.

Robertson, L.S. "Automobile Safety Regulation: Rebuttal and New Data." *American Journal of Public Health* 74(12), (1984): 1390-1394.

U.S. Bureau of the Census, Population Division. *Annual Estimates of Population by Age and Sex for California, April 1, 2000 to July 1, 2006* (SC-EST2006-02-20, 2007). <http://www.census.gov> (accessed May 2008).

U.S. Bureau of the Census. *Annual Estimates of the Population by Age and Sex for Illinois, April 1, 2000 to July 1, 2006* (<http://www.census.gov>).

U.S. Bureau of the Census. *Annual Estimates of the Population by Age and Sex for Louisiana, April 1, 2000 to July 1, 2006* (<http://www.census.gov>).

U.S. Bureau of the Census. *Annual Estimates of the Population by Age and Sex for Pennsylvania, April 1, 2000 to July 1, 2006* (<http://www.census.gov>).

U.S. Bureau of the Census. *Annual Estimates of the Population by Age and Sex for Texas, April 1, 2000 to July 1, 2006* (<http://www.census.gov>).

U.S. Bureau of the Census, Population Division. *Population Estimates for the U.S., Regions, and States by Five-Year Age Groups and Sex: Time Series Estimates, July 1, 1990 to July 1, 1999 and April 1, 1990 Census Counts*, 2007. <http://www.census.gov> (accessed May 2008).

U.S. Bureau of the Census, Population Estimates Branch. *Resident Population of States by Five-Year Age Group and Sex (also in Current Population Reports, Series P25-1106)*, 2007. <http://www.census.gov> (accessed May 2008).

U.S. Bureau of the Census, Population Distribution Branch. *Intercensal Estimates of the Resident Population 1970 to 1980* (also in *Current Population Reports*, Series P25, No. 998), 2007. <http://www.census.gov> (accessed May 2008).

U.S. Department of Commerce, Economics and Statistics Administration, U.S. Census Bureau. *Statistical Abstract of the United States*, various issues.

U.S. Department of Justice, National Criminal Justice Information and Statistics Service. *Sourcebook of Criminal Justice Statistics*, 1973, (1974): 30-36.

U.S. Department of Justice, National Criminal Justice Information and Statistics Center. *Trends in Expenditure and Employment Data for the Criminal Justice System*, 1973, 1974, 1975, 1976, and 1977 issues, pages 68 and 72.

U.S. Department of Justice, Bureau of Justice Statistics. *Justice Expenditure and Employment in the U.S.*, 1971-1979, (1980): 64, 70, and 71.

U.S. Department of Justice, Bureau of Justice Statistics. *Justice Expenditure and Employment Extracts: 1982 and 1983*, (1984): 3, 16, 27, 52, 68, and 79.

U.S. Department of Justice, Bureau of Justice Statistics. *Justice Expenditure and Employment Extracts: 1984, 1985, and 1986*, (1987): 25, 38, 49, 50, 77, 101, 129, 142, and 153.

U.S. Department of Justice, Bureau of Justice Statistics. *Justice Expenditure and Employment in the U.S. 1988*, (1989): 14 and 28.

U.S. Department of Justice, Bureau of Justice Statistics. *Justice Expenditure and Employment Extracts: Data from the Annual General Finance and Employment Surveys, 1992-2006 issues* (<http://www.ojp.usdoj.gov/bjs>).

U.S. Department of Transportation, National Highway Traffic Safety Administration. *Traffic Safety Facts 2001: A Compilation of Motor Vehicle Crash Data from the Fatality Analysis Reporting System and the General Estimates System*, 2002.

U.S. Department of Transportation, National Highway Traffic Safety Administration. *Traffic Safety Facts: A Compilation of Motor Vehicle Crash Data from the Fatality Analysis Reporting System and the General Estimates System*, 1998 Edition, Table 126, p. 186.

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics 1970*, 1971. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics 1971*, 1972. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics 1972*, 1973. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics 1973*, 1974. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics 1974*, 1975. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics 1975*, 1976. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics 1976*, 1977. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics 1977, 1978*. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics 1978, 1979*. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics 1979, 1980*. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics Summary to 1985, 1986*. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics 1986, 1987*. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics 1987, 1988*. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics 1988, 1989*. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics 1989, 1990*. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics Summary to 1995, 1996*. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics 1996, 1997*. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics 1997, 1998*. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics 1998, 1999*. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics 1999, 2000*. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics 2000, 2001*. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics 2001, 2002*. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics 2002*, 2003. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics 2003*, 2004. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics 2004*, 2005. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics 2005*, 2006. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. Department of Transportation, Federal Highway Administration. *Highway Statistics 2006*, 2007. <http://www.fhwa.dot.gov/policy/ohpi/index.htm> (accessed May 2008).

U.S. General Accounting Office. *Highway Safety: Safety Belt Use Laws Save Lives and Reduce Costs to Society*. GAO/RCED-92-106, Washington, D.C., 1992.

Viscusi, W.K. "The Effect of Transportation Deregulation on Worker Safety." L.N. Moses and I. Savage eds. *Transportation Safety in an Age of Deregulation*. New York: Oxford University Press (1989): 70-89.

Welki, A.M. and T.J. Zlatoper. "The Impact of Highway Safety Regulation Enforcement Activities on Motor Vehicle Fatalities." *Transportation Research Part E* 43(2), (2007): 208-217.

Zlatoper, T.J. "Determinants of Motor Vehicle Deaths in the United States: A Cross Sectional Analysis." *Accident Analysis and Prevention* 23(5), (1991): 431-436.

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	13.88	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

	logfatal	logurate	logalconsum	logsplimit	Seatbelt	logynold	logTvehmile	logpoexp	logpopop
logfatal	1								
logurate	-0.0809	1							
logalconsum	0.3272	0.3249	1						
logsplimit	-0.0238	-0.4818	-0.4953	1					
Seatbelt	-0.1445	-0.1978	-0.5597	0.5822	1				
logynold	0.5479	0.2406	0.5285	-0.2175	-0.4001	1			
logTvehmile	0.8184	-0.1353	-0.059	0.2063	0.3514	0.2839	1		
logpoexp	0.0556	-0.0572	-0.0818	0.3444	0.575	0.1207	0.463	1	
logpopop	-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*** (-5.04)	-8.79*** (-5.08)
Log(Urate)	-0.061** (-2.32)	-0.058** (-2.41)
Log(Alconsum)	1.08*** (12.40)	0.955*** (11.05)
Log(Splimit)	0.19* (1.81)	0.172 (1.62)
Seatbelt	-0.015 (-0.70)	-0.022 (-0.86)
Log(Ynold)	1.73*** (6.69)	1.86*** (7.15)
Log(Vehmile)	0.839*** (13.81)	0.794*** (12.86)
Log(Popop)	-0.33*** (-3.72)	-0.239*** (-2.65)
Illinois	0.471*** (3.74)	0.44*** (3.57)
Louisiana	0.663*** (3.90)	0.59*** (3.49)
Pennsylvania	0.517*** (4.33)	0.49*** (4.12)
Texas	0.717*** (7.13)	0.73*** (7.35)
Log(Trend)	-0.16*** (-8.59)	-0.16*** (8.82)
R-squared		
Log likelihood	-1861.71	-1183.70
	Test for overdispersion: $\alpha = 0.004$; 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.