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The Incentive Effects of No Fault Automobile Insurance

Abstract

This paper presents a theoretical and empirical analysis of the effects of no fault automobile insurance on accident rates. As a mechanism for compensating the victims of automobile accidents, no fault has several important advantages over the tort system. However, by restricting access to tort, no fault may weaken incentives for careful driving, leading to higher accident rates. We conduct an empirical analysis of automobile accident fatality rates in all U.S. states over the period 1982-1994, controlling for the potential endogeneity of no fault laws. The results support the hypothesis that no fault is significantly associated with higher fatal accident rates than tort.

The Incentive Effects of No Fault Automobile Insurance

1. Introduction

No fault automobile insurance has been adopted by several jurisdictions in the U.S., Canada, Australia, and New Zealand as a mechanism for controlling automobile insurance costs and improving the efficiency and timeliness of accident compensation.[1] No fault has two primary characteristics – compulsory first-party insurance for personal injuries and restrictions on the right to sue for automobile accidents. As a compensation system, no fault has a number of advantages over tort.[2] However, by restricting the right to sue, no fault may weaken the deterrent effect of tort law and therefore lead to an increase in automobile accidents. The purpose of the present paper is to provide a theoretical and empirical analysis of the incentive effects of no fault by analyzing the relationship between no fault and fatal accident rates. Our data base consists of all U.S. states over the period 1982-1994.

Researchers who have analyzed the pure no-fault systems adopted in Canada, Australia, and New Zealand have found a positive association with automobile accident fatality rates (McEwin 1989, Devlin 1992).[3] However, whereas pure no fault systems substantially eliminate tort liability for automobile accidents, the partial no-fault laws adopted in the U.S. retain the right to sue for death and serious injuries and thus are likely to have a weaker effect on deterrence. The prior empirical evidence on the relationship between no fault

[1]No fault has been proposed frequently as a measure for reforming the tort liability system both for automobile and medical malpractice claims (see, for example, Sloan, et al. 1997); and a national no-fault automobile insurance program has recently been considered by Congress (Brostoff 1998).

[2]In comparison with tort, a higher proportion of premiums under no fault represents loss payments as opposed to legal and administrative expenses (Grabowski, Viscusi, and Evans 1989, Carroll, et al. 1991). No fault is also superior to tort in promptness of claims payment (Rand Corporation 1985) and can reduce insurance fraud by removing relatively small bodily injury liability claims from the tort system (Weisberg and Derrig 1991). Finally, no-fault reduces the proportion of claimants who receive compensation in excess of their economic losses and increases the proportion of claimants who are fully compensated for their economic losses (Carroll, et al. 1991).

[3]Pure no-fault has been adopted in the Canadian province of Quebec, in Australia's Northern Territory, and in New Zealand. More details on the Australasian and Canadian laws are provided in McEwin (1989) and Devlin (1990, 1992), respectively.

and fatalities in the U.S. has been mixed. Landes (1982) found a positive relationship between no fault and fatal accident rates in the U.S., but other U.S. researchers have not confirmed this relationship (Kochanowski and Young 1985, Zador and Lund 1986).[4] A possible explanation for the mixed U.S. results is that prior researchers have not controlled for the potential endogeneity of no fault, an issue addressed in this paper.

The present paper provides new empirical evidence on the relationship between no fault and fatalities in the U.S. to help resolve the conflicting findings in the prior literature.[5] We innovate by using estimation methodologies that take into account the possibility that the type of automobile compensation regime (tort versus no fault) that exists in a state may be endogenous, i.e., that the compensation regimes adopted by the states may be systematically related to accident rates or other state characteristics. Two techniques are used to correct for this potential endogeneity – instrumental variables and inverse Mill's ratios. Our analysis also includes a more complete set of explanatory variables than used in prior U.S. studies. Finally, we utilize estimates of the proportion of automobile bodily injury claims ineligible for tort due to no fault thresholds to control for differences in threshold stringency across states.

The remainder of the paper is organized as follows: In section 2, we provide a theoretical investigation of the effects of no fault on care incentives. The theory yields a number of useful implications about the incentive effects of compensation systems. Section 3 describes our data base, discusses the empirical methodology we adopt, and presents the results of our empirical tests. By way of preview, the results show a significant positive relationship between no fault and fatality rates. Section 4 concludes the paper.

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[4]Fifteen U.S. states now have some form of no fault law. No fault states are defined as those that require motorists to purchase first-party medical expense coverage and place some restrictions on lawsuits (see Insurance Information Institute 1999). Twelve additional jurisdictions have enacted so-called *add-on* laws, which provide first-party medical expense coverage but place no restrictions on tort.

[5]There are three important reasons for focusing on fatality rates rather than injury rates: (1) Using fatality rates facilitates comparison with prior studies. (2) The quality of the available injury accident rate data is very poor. And (3) reported injury accident rates are affected by fraud and moral hazard so that it would be difficult to isolate the effects of no fault on driving behavior as opposed to claiming behavior (see Cummins and Tennyson 1996).

2. No Fault and Optimal Care Levels: A Theoretical Analysis

In this section, we model the effects of tort restrictions on accident rates. Prior researchers typically have argued that no fault weakens incentives, leading to lower care levels and higher accident rates. Our model extends prior work on no fault insurance by providing a more precise discussion of the effects of care levels on accident rates and negligence probabilities, analyzing the effects of expense loadings, and focusing attention on experience rating as an incentive device.

The Model

We model the negligence rule by introducing a parameter δ, where $0 \leq \delta \leq 1$. When $\delta = 0$, no liability rule is in effect. This configuration can be considered *pure no fault*. Choosing $\delta = 1$ indicates the presence of a negligence rule (*full tort*). When $0 < \delta < 1$, accident victims can bring suit for some but not all accident losses. These systems are called *partial no fault* or *limited tort*. Thus, δ can be thought of as the probability that a given claim will qualify for tort, i.e., the probability of satisfying the tort threshold. The negligence rule under full or limited tort is assumed to apply only to general damages; economic losses are assumed to be covered by first-party insurance.[6]

Accidents are assumed to be bilateral, i.e., they involve two drivers, both of whom are assumed to sustain injuries. The accident losses of each driver consist of economic losses, e.g., medical bills and lost earnings, in amount ℓ, and general damages (pain and suffering losses) in amount g. Both ℓ and g are assumed to be non-stochastic. The accident probability λ is assumed to be a function of the care expenditures of both drivers, i.e., $\lambda = \lambda(x,y)$, where x and y denote the care expenditures of drivers 1 and 2, respectively. Each driver is assumed to take the other driver's decisions as given when choosing his or her own care level, so $\lambda(x,y)$ is written as $\lambda(x)$ or, more simply, as λ. We assume that $\partial\lambda/\partial x = \lambda_x < 0$ and $\partial^2\lambda/\partial x^2 = \lambda_{xx} > 0$.

To model the effects of care expenditures on negligence, we introduce the probability functions $p_i(x,y)$,

[6]The theoretical predictions are similar if the analysis is conducted under the assumption that the victim does not have insurance for economic losses.

$i = 1, 2$, where p_1 = the probability that driver 1 is found to be negligent and driver 2 is found not to be negligent, while p_2 = the probability that driver 1 is not negligent and driver 2 is negligent. If driver 1 is negligent but driver 2 is not, then driver 1 pays driver 2's general damages, while the reverse is true if driver 2 is negligent and driver 1 is not. If neither or both are negligent, each driver bears his/her own general damages.[7] Thus, $p_1+p_2 \leq 1$. Again focusing on the decision making of driver 1, it is assumed that $\partial p_1/\partial x = p_{1x} < 0$, $\partial p_2/\partial x = p_{2x} > 0$, $\partial^2 p_1/\partial x^2 = p_{1xx} > 0$, and $\partial^2 p_2/\partial x^2 = p_{2xx} < 0$.

Modeling negligence assignment as a probabilistic process implies that there is no threshold level of care beyond which a driver cannot be found negligent. E.g., the legal system and/or drivers can make mistakes. Drivers who choose relatively high care levels (x) can still commit negligent acts or be erroneously judged negligent by the legal system. Thus, taking care does not reduce the negligence probability to zero.

Economic losses are assumed to be fully insured, and liability insurance is available to cover one's potential liability to another driver resulting from an accident. First-party general damage insurance (i.e., insurance where the driver’s own insurer pays his or her general damages) is assumed not to be available. Thus, drivers who cannot establish the negligence of the other driver bear their general damage losses directly. The insurance premium for driver 1 is: $\pi = (1+e)\ \lambda\ [\ell + \delta\ g\ p_1]$, where ℓ = economic losses, g = general damages, and e = insurer expenses as a proportion of expected losses. Thus, the premium equals expected losses, $\lambda\ (\ell + \delta g p_1)$, times a proportionate expense charge. The first component of expected loss $(\lambda\ \ell)$ represents the driver's own expected economic losses, while the second component $(\lambda\ \delta\ g\ p_1)$ equals the driver's expected liability losses, where $\lambda(x)$ has been written as λ to simplify the notation.[8]

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[7]Conducting the analysis under the assumption that drivers can obtain partial payment if both are negligent (comparative negligence) yields similar predictions.

[8]That is, the expected liability losses equal the probability that driver 1 is required to pay driver 2's general damages times the amount of the general damages (g). The probability that driver 1 is required to pay $(\lambda\ \delta\ p_1)$ equals the probability of an accident (λ) times the probability that the loss exceeds the threshold (δ) times the probability that driver 1 is found to be negligent (p_1).

No Fault and Incentives

Drivers are assumed to be identical risk averse expected utility maximizers with non-stochastic initial wealth W and utility function U(W), where $U' > 0$ and $U'' < 0$. All drivers are assumed to fully insure. There are two states of the world – the loss state, where wealth is reduced by the amount of general damages and the insurance premium, so that wealth equals $W - g - \pi$; and the no-loss state, where wealth is $W - \pi$, either because no accident occurs or because an accident occurs for which the driver is fully compensated. The wealth in the loss and no-loss states reflects the assumption that drivers are fully compensated by their own insurers for economic losses. The probability of the loss state is $\lambda_L = \lambda(1-\delta p_2)$ (i.e., the probability that an accident occurs times the probability of not collecting from the other driver), and the probability of the no-loss state is $1-\lambda_L = [1-\lambda(1-\delta p_2)]$. Thus, as the probability that the claim qualifies for tort (δ) increases, the probability of being in the loss state declines because of the higher probability of collecting general damages from the other driver. The parameter δ is the primary policy instrument used to define the compensation regime, with pure no-fault ($\delta = 0$) and pure tort ($\delta = 1$) as limiting cases.

The utility function is initially assumed to be separable in premiums and care expenditures so that the driver's expected utility is:

$$EU = [1 - \lambda(1 - \delta p_2)]\,U(W) + \lambda(1 - \delta p_2)\,U(W - g) - \pi(x) - x \qquad \textbf{(1)}$$

where π = the insurance premium = $(1+e)\,\lambda\,(\ell+p_1\delta g)$. The driver chooses x, the level of care expenditures, to maximize expected utility.

The first-order condition for optimization with respect to x is:

$$EU_x = -[\lambda_x(1 - \delta p_2) - \lambda\delta p_{2x}]\,[U(W) - U(W - g)] - \pi_x - 1 = 0 \qquad \textbf{(2)}$$

where U(W) = utility in the no-loss state,

U(W-g) = utility in the loss state, and

π_x = derivative of the premium with respect to care expenditures = $(1+e)[\lambda_x \ell + \delta g(p_1\lambda_x+\lambda p_{1x})]$.

We also define the following symbols which are used to facilitate the discussion:

λ_L = the probability of the loss state = $\lambda(1-\delta p_2)$, and

$\lambda_{Lx} = \lambda_x(1-\delta p_2)-\lambda\delta p_{2x}$ = the derivative with respect to x of the probability of being in the loss state.

Notice that $\pi_x < 0$ and $\lambda_{Lx} < 0$ so that increased care reduces both the premium and the probability of being in the loss state.

The first two terms in (2) are the marginal benefits of additional care expenditures. The first is equal to (-1 times) the derivative of the probability of being in the loss state $[\lambda_x(1-\delta p_2)-\lambda\delta p_{2x}]$ times the difference in utility between the no loss and loss states [U(W) - U(W-g)], and the second is (-1 times) the derivative of premiums with respect to x. The third term (-1) represents the marginal cost of additional care expenditures, i.e., the cost of an additional unit of care.[9]

The derivative of x with respect to an arbitrary parameter k is:

$$\frac{dx}{dk} = \frac{-EU_{xk}}{EU_{xx}} \tag{3}$$

where $EU_{xk} = \partial EU_x/\partial k$. Because $EU_{xx} = \partial^2 EU/\partial x^2$ (the second order sufficient condition) is < 0, the sign of dx/dk is the same as the sign of EU_{xk}. It is easy to show that dx/de >0 (see Appendix A). Thus, the reduction in administrative expenses under no fault exacerbates any incentive problems caused by weaker negligence rules.

The marginal effect of changes in the negligence rule on care expenditures, $dx/d\delta$, is ambiguous. To see why, consider $\partial EU_x/\partial\delta = EU_{x\delta}$:

$$EU_{x\delta} = (\lambda_x p_2 + p_{2x}\lambda)[U(W) - U(W-g)] - (1+e)g(\lambda_x p_1 + \lambda p_{1x}) \tag{4}$$

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[9] Notice that $(1+\pi_x)$ must be > 0 at the optimum in order to avoid corner solutions. This makes sense intuitively because one would continue to increase care if the marginal premium reduction exceeded the cost of care.

The second term in (4) is unambiguously positive, while the first depends on the sign of $[\lambda_x p_2 + p_{2x}\lambda]$, because $\lambda_x < 0$ and $p_{2x} > 0$. A non-negative value for this factor provides a sufficient condition for $dx/d\delta > 0$, i.e., for no fault to reduce care levels.

Intuitively, the ambiguity in $dx/d\delta$ can be easily explained in terms of the sufficient condition for $dx/d\delta > 0$, i.e., $(\lambda_x p_2 + p_{2x} \lambda) \geq 0$. The sufficient condition is (-1 times) the derivative of λ_{Lx} with respect to δ, i.e., $-\partial\lambda_{Lx}/\partial\delta = -\lambda_{Lx\delta} = \lambda_x p_2 + \lambda p_{2x}$. The ambiguity arises because stricter negligence rules have offsetting effects on incentives. A stricter rule (higher δ) increases the incentive to take more care in order to be successful in collecting from the other driver (the λp_{2x} term in $-\lambda_{Lx\delta}$) but reduces incentives by lowering the probability of being in the loss state (the $\lambda_x p_2$) term).

Additional insight can be gained by writing the sufficient condition as:

$$\frac{p_{2x}}{p_2} \geq \frac{-\lambda_x}{\lambda} \tag{5}$$

Thus, no fault unambiguously reduces care levels if the elasticity with respect to x of the probability of collecting from the other driver is larger than (-1 times) the elasticity of the accident rate. If negligence assignment is not very responsive to care expenditures, e.g., if the legal system makes significant errors in assigning fault, condition (5) is less likely to hold. The extreme case would be where p_2 is not a function of x, i.e., where negligence assignment is random so that $p_{2x} = 0$. In this case, the sufficient condition $\lambda_x p_2 + p_{2x}\lambda \geq 0$ cannot hold. The first term in equation (4) then becomes unambiguously negative, and the sign of $dx/d\delta$ is determined by the relative magnitude of the unambiguously negative first term in (4) and the unambiguously positive second term.[10] However, if negligent assignment is reasonably responsive to care expenditures, then no fault is likely to lead to reductions in care levels.

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[10]This extreme case provides a rigorous expression of the argument used by proponents of no fault that assigning fault in most auto accidents is a meaningless exercise because of the multiplicity of factors that "cause" accidents (e.g., O'Connell and Kelly 1987).

Finally, we investigate the effects of experience rating on incentives by changing the premium formula to $\pi^Z = Z\pi + (1\text{-}Z)\overline{\pi}$, where π^Z = experience rated premium, and Z = the credibility factor, $0 \leq Z \leq 1$. The experience rated premium is a weighted average of the driver's premium, π, and the average premium for all drivers in the market, $\overline{\pi}$. Experience rating is almost always less than complete due to sampling error (i.e., an individual's driving record reveals some but not all information about his/her accident and negligence probabilities), imperfections in reporting systems, etc. The degree of experience rating is captured by the credibility factor Z. In Appendix A, we show that dx/dZ is unambiguously > 0, i.e., more responsive experience rating increases care levels. Thus, policy makers concerned about the potential adverse effects of no fault on accident rates could compensate for a weaker tort deterrent by more accurate or more stringent experience rating plans.

Removing the assumption that the driver's decision problem is separable in premiums and care expenditures introduces another source of ambiguity in $dx/d\delta$, an income effect arising from the impact of higher care expenditures on the second derivative of the utility function (see Appendix A). The presence of this term requires adding another sufficient condition in order for $dx/d\delta$ to be unambiguously > 0. Intuitively, the second condition requires that risk aversion be below a specified level. This leads to the intuitively reasonable conclusion that no fault does not necessarily reduce care levels if drivers are highly risk averse. However, as risk aversion declines, a level of risk aversion is reached below which only condition (5) is required for $dx/d\delta > 0$. The limiting case is risk neutrality, where neither condition is required (although p_{1x} must be < 0). With identical drivers, dx/dZ remains unambiguously > 0 in the non-separability case.[11]

Summary: Theoretical Results

The principal difference between no fault and tort in our model is that no fault restricts the ability of

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[11]Drivers are assumed to make care decisions as if their decisions have no effect on $\overline{\pi}$. Thus, increasing the experience rating parameter Z leads to a one-time reduction in accident rates, with the new average applying to all drivers (in the identical drivers case). With two classes of drivers, good drivers ($\pi < \overline{\pi}$) and bad drivers ($\pi > \overline{\pi}$), dx/dZ is unambiguous either for good drivers or for bad drivers (see Appendix A).

motorists to sue. The effect of these tort restrictions on incentives is ambiguous. However, if negligence assignment and premium rates are relatively responsive to care levels, then no fault is likely to lead to an increase in accidents. Such a result could be mitigated by improvements in experience rating plans. We now turn to an empirical examination of the effects of no fault on fatal accident rates. In addition to the standard approach of using dummy variables to represent the presence of no fault in a state, we are able to obtain an estimate of the proportion of automobile bodily injury claims that are eligible for tort in no fault states, i.e., an estimate of δ, and then test the hypothesis that the fatal accident rate is inversely related to δ.

3. Data, Methodology, and Hypotheses

Data and Hypotheses

The sample for our study consists of pooled cross-section, time-series data on all fifty states over the period 1982-1994. The dependent variable in our analysis is the fatal accident rate by state and year, defined as fatal accidents per ten million vehicle miles (see U.S. Federal Highway Administration 1992). The first part of our analysis uses dummy variables to represent the presence in a state of a no fault law, consistent with the prior literature on automobile insurance (e.g., Grabowski, Viscusi, and Evans 1989). We then turn to an examination of the relationship between fatality rates and the stringency of no fault thresholds.

No Fault Variables. The first no fault variable tested in the study is an indicator variable set equal to 1 if a state has a no fault law and to zero otherwise. We next consider indicator variables representing the *type* of tort threshold present in the no fault states. There are two types of thresholds – *monetary thresholds*, whereby a claim qualifies for tort if the medical expenses resulting from the accident exceed a specified dollar amount, and *verbal thresholds*, where claims qualify for tort if the injury satisfies a verbal definition of severity.[12] Because verbal no fault thresholds are conventionally considered more restrictive or at least

[12]For example, Michigan's no fault law specifies that general damages are recoverable only if the injury results in death, serious impairment of bodily function, or permanent serious disfigurement (American Insurance Association 1999).

qualitatively different from monetary thresholds, we specify two indicator variables, the first equal to 1 if a state has a monetary threshold, and equal to 0 otherwise, and the second equal to 1 if a state has a verbal threshold, and equal to 0 otherwise. If no fault significantly weakens incentives, these variables are expected to be positively related to fatal accident rates.

As a measure of δ, the proportion of bodily injury claims eligible for tort, we obtained data from a series of studies conducted by the Insurance Research Council (IRC) involving the analysis of thousands of automobile bodily injury claims (see IRC 1989, 1999). The studies, based on claims settled in 1977, 1987, 1992, and 1997, provide estimates of the proportion of personal injury protection (PIP) claimants eligible to file a tort claim under the thresholds in effect in no fault states, essentially a measure of δ from our theoretical model.[13] If tort provides an effective deterrent against hazardous driving, δ should be inversely related to fatal accident rates. To facilitate comparisons with the no fault indicator variables, which would be positively related to fatalities if no fault weakens incentives, our regression analysis uses the complement of the eligibility ratio (one minus the ratio) as a measure of the stringency of the threshold in a state, i.e., the proportion of claims that are *ineligible* for tort due to the threshold. If no fault significantly weakens incentives, the sign of this variable will be positive in our fatality rate regressions.[14]

Summary statistics on the proportion of claims ineligible for tort because of thresholds, i.e., $(1-\delta)$, are

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[13]The first-party economic loss coverage provided under no fault laws is known as *personal injury protection*.

[14]Landes (1982) also used a threshold stringency variable based on the 1977 IRC study. Whereas our variable is the percentage of PIP claimants judged *ineligible* for tort claims under a state's threshold, hers is an estimate of the proportion of tort claims *eliminated* by the threshold. The variables differ because some claims would not qualify for tort even in the absence of a no fault law. The latter group includes claims such as those resulting from single vehicle accidents and those barred from tort because of the negligence of the injured party. Landes' variable measures the stringency of thresholds after netting out claims that would be ineligible in the absence of no fault, while our variable does not net out this group of claims. Although which of the two variables is more appropriate may be arguable, we were not able to use Landes' variable in most of our analysis in any event because the IRC does not provide all of the data needed to define her variable in its 1992 and 1997 study samples. However, for the 1977 and 1987 samples, the Landes variable and our variable are highly correlated (correlation > 90 percent). Moreover, sensitivity tests reported below based on the 1987 IRC data show that the two variables produce similar results and lead to the same conclusions.

presented in Table 1. The results presented in Table 1 have the following important implications for our study: (1) A significant proportion of automobile bodily injury claims are ineligible for tort under the no fault thresholds in effect in the U.S., based on the IRC estimates. The proportion of claims ineligible in 1987 (the year with the most complete data), for example, ranged from 88 percent under Michigan's verbal threshold to 37 percent under New Jersey's monetary threshold. The average proportion of ineligible claims in the 1987, 1992, and 1997 study years has remained consistent at about 70 percent. Thus, the ineligibility proportions are sufficiently high such that no fault could indeed have a significant effect on incentives for careful driving. (2) Contrary to the conventional wisdom, verbal thresholds are not necessarily more stringent than monetary thresholds. Although Michigan's verbal threshold is associated with the largest proportion of ineligible claims, several of the state monetary thresholds lead to a higher proportion of ineligible claims than the Florida and New York verbal thresholds. And (3) the dollar value of monetary thresholds is imperfectly correlated with the proportion of ineligible claims. This reflects some differences in the types of expenses that can be used to satisfy thresholds as well as differences in the economic and social environments of the states. For example, in 1997, 78 percent of claims were ineligible due to the \$2,000 threshold in Kansas, but only 48 percent were ineligible due to a \$2,000 threshold in Massachusetts. We consider the IRC estimates to convey more information about stringency than the dollar value of monetary thresholds and accordingly rely on the IRC estimates in the empirical tests of threshold stringency presented below.

Other Explanatory Variables. In addition to no fault, other differences among states are expected to affect accident rates. Driving under the influence of alcohol has been shown to be an important factor in many fatal accidents (Bruce 1984). To test the hypothesis that alcohol is positively related to fatality rates, we use alcohol consumption in gallons per capita as an explanatory variable. Another driving behavior variable that we test is the speed variance, defined as the difference between the 85th percentile of vehicle speeds in miles per hour in a state minus the average vehicle speed in the state. Speed variance has been shown to be an important determinant of accident rates (Lave 1985). The expected sign of this variable is positive. We also test the average speed along with the variance. The expected sign of the average speed variable also is positive.

The driving environment is proxied by two variables, annual snowfall in inches and rural interstate miles driven as a proportion of total vehicle miles driven. Snowfall is expected to be inversely related to fatal accident rates because adverse weather conditions tend to reduce driving speeds and the number of miles driven. Rural interstate miles driven is used to measure rural driving intensity. Rural mileage is important because fatality rates are higher on rural highways.[15] The availability of emergency medical care services also is likely to have an impact on the proportion of injury accidents that result in fatalities. To proxy for emergency medical services we use the ratio of the number of hospitals in a state to the number of square miles of land area. A higher value of this variable should be associated with lower fatality rates.

The stringency of experience rating is expected to be inversely related to fatality rates. Experience rating is measured by a dummy variable equal to 1.0 for states that assess driver's license points for accidents in which the driver is less than 50 percent negligent and equal to zero otherwise. This is an appropriate experience rating variable because insurers use state motor vehicle records to verify self-reported accident and conviction histories of policyholders. Accident histories are less complete in states that are less rigorous in assigning driver's license points, thus increasing information asymmetries between insurers and drivers and weakening experience rating. Less stringency in assigning points also implies lower incentives for careful driving arising out of the potential loss of one's driver's license. The expected sign of this variable is negative.

Three variables are used as controls for the characteristics of the driving population. The percentage of the population ages 18 through 24 is included to control for the tendency of young, relatively inexperienced drivers to have higher accident rates. This variable is expected to be positively related to fatalities. Theoretical

[15]For example, in 1992, the fatal accident rate on rural highways was 2.58 per 100 million vehicle miles, whereas the fatality rate on urban highways was 1.21 per 100 million vehicle miles. Interstate highways are safer than other types of highways, but the fatal accident rate is higher on rural interstates (1.20 per 100 million miles) than on urban interstates (0.62 per 100 million miles). See Federal Highway Administration (1992).

and empirical research has shown that education tends to be related to behavior with a positive effect on health and safety (e.g., Farrell and Fuchs 1982). To proxy for the potential effects of education on driving safety we include the proportion of the population with a bachelor's degree. This variable is predicted to be inversely related to fatalities. Various hypotheses have been proposed regarding the relationship between income and driving behavior. On the one hand, income tends to be positively correlated with education, implying an inverse relationship between this variable and the fatality rate. However, higher income also implies higher costs of time, possibly leading to more risk-taking by relatively affluent drivers (e.g., Peltzman 1975). The latter reasoning implies a positive relationship between income and fatalities.

We use two separate approaches to capture the downward secular trend in fatality rates due to factors such as safer automobiles, better roadway design, and the aging of the driver population: a linear time trend and year dummy variables. Finally, we include dummy variables for eight of the nine U.S. regions defined by the U.S. Bureau of the Census, omitting one region to avoid singularity. Definitions and sources of variables are provided in Appendix B.

Summary statistics on these explanatory variables for no fault and tort states are presented in Table 2. The mean values for most of the variables used in our analysis differ significantly between the two groups of states. The fatal accident rate is lower in no fault states than in tort states, reflecting differences in the driving environment, demographics, and other factors; and the injury accident rate is higher in no fault states than in tort states, reflecting similar interstate differences. Rural interstate mileage accounts for 8.3 percent of miles driven in no fault states compared to 12.4 percent in tort states, and no fault states have higher annual snowfall and lower speed variance than tort states. Alcohol consumption is also lower in no fault states. No fault states also have higher per capita income and more hospitals per square mile than tort states.

Estimation Methodology

The regression equations were estimated initially using ordinary least squares (OLS), the same estimation approach used by prior researchers. OLS is potentially problematical because the presence of no fault in a state is likely to be endogenous, leading to selectivity bias. Endogeneity will be present if states tend to adopt no fault in response to high auto insurance costs or if there are other systematic differences in the types of states that adopt no fault. High costs tend to occur in states with high injury accident rates (Cummins and Tennyson 1992), but such states have relatively low fatality rates, on average (see Table 2). Thus, it is important to test for endogeneity and to make adjustments to the estimation methodology if endogeneity appears to be present.

We employ two standard methods to test for endogeneity: (1) the Hausman test for endogeneity (see Greene 1997); and (2) the inverse Mill's ratio technique (Lee 1978, Robinson 1989). Both tests led to the rejection of the hypothesis that compensation systems are exogenous.[16] Accordingly, we estimate our fatal accident rate equations using estimation techniques that control for endogeneity. The techniques differ depending upon which variable(s) are included in the equation to represent no fault. To simplify the discussion, we first discuss estimation for the case where a single indicator variable is used to represent no fault and then more briefly discuss estimation for the cases where monetary and verbal indicators and where claims ineligibility ratios are used to represent no fault.

When no fault is represented by a single indicator variable equal to 1 in no fault states and 0 otherwise, we utilize two estimation techniques to control for endogeneity, based on instrumental variables (IV) and inverse Mill's ratios (IM). We specify the following model:

$$q_{it} = \alpha' X_{it}^{q} + \nu_{it} \tag{6}$$

$$A_{it} = \beta' X_{it}^{A} + \gamma I_{it} + I_{it}\epsilon_{nit} + (1 - I_{it})\epsilon_{fit} + \omega_{it} \tag{7}$$

[16]The F test statistic for the Hausman test is 5.578, with 2 and 636 degrees of freedom. The critical value at the 1 percent level is 4.61, leading to rejection of the hypothesis of exogeneity. The IM test of the null hypothesis of the exogeneity of the compensation systems is equivalent to testing the hypothesis that the coefficients of the inverse Mill's ratio terms in equation (7') are not jointly statistically different from zero. The F statistic for the joint significance test of the inverse Mill's ratios in equation (7)' was 21.028, with 2 and 635 degrees of freedom, leading to rejection of the hypothesis at better than the 1 percent level of significance.

where q_{it} = "sentiment" for or political support for no fault in state i and year t,

I_{it} = indicator variable equal to 1 if state i has a no fault law in year t and 0 otherwise,

$\boldsymbol{\alpha}, \boldsymbol{\beta}$ = parameter vectors,

$\mathbf{X}^{q}_{it}, \mathbf{X}^{A}_{it}$ = vectors of exogenous variables for state i, year t, applicable to equations (6) and (7), respectively,

A_{it} = fatal accident rate in state i in year t,

ν_{it} = random error term for equation (6), and

$\epsilon_{nit}, \epsilon_{fit}$ = random error terms for no fault states and tort states, respectively, in equation (7), and

ω_{it} = overall random error term for equation (7).

The specification allows for different error terms in tort and no fault states.

The variable q_i is an unobserved latent variable. The observed realization of q_i is a dichotomous variable (I_i) representing the state's auto insurance compensation system. If $q_i > 0$, I_i is equal to 1, meaning that the state has a no fault law, whereas if $q_i \leq 0$, I_i is equal to zero, indicating that the state has retained the tort system. An endogeneity problem arises if ν_i is correlated with ϵ_{nit} or ϵ_{fit}. In that case, ordinary least squares (OLS) estimates of (7) are inconsistent. This problem often arises when the units of observation (in this case states) choose or are assigned to categories (e.g., no fault or tort) in some systematic way rather than being randomly assigned. The problem could arise in state automobile accident compensation systems if, for example, states with relatively high injury accident rates and relatively low fatality rates have a tendency to choose no fault.[17] This is likely to occur because auto insurance premiums are highest in states with high injury

[17]The endogeneity that concerns us here would be a problem whether or not states adopt no fault or switch regimes during our sample period. The problem is that if states with no fault have systematically lower fatality rates than tort states for other reasons, failure to correct for the difference will bias the analysis away from finding a statistical association between no fault and fatalities. The term for this type of endogeneity in the labor economics literature is *selectivity bias*, which often arises in analyses of the effects of union membership on wages. The estimated effects of union membership on wages are likely to be biased if workers are systematically rather than randomly assigned to the union and nonunion sectors. As in our analysis, it is not necessary to observe workers who switch status during a given time period of observation in order for the problem to arise. Rather, it is only necessary that they were assigned to categories non-randomly to begin with.

accident rates and low fatal accident rates, and reducing premium costs is a primary motivation for modifying auto accident compensation systems (Cummins and Tennyson 1992).

In the instrumental variables (IV) estimation methodology, we use as an instrument for no fault the predicted probability that state i has a no fault law, $F(\hat{\alpha}'\mathbf{X}_i^q)$, based on a reduced form probit equation (equation (6)). The inverse Mill's ratio (IM) approach involves the introduction of inverse Mill's ratios as additional regressors in (7), yielding:

$$A_{it} = \beta X_{it}^A + \gamma I_{it} + I_{it}\sigma_{vn}\frac{-f(\hat{\alpha}' X_{it}^q)}{F(\hat{\alpha}' X_{it}^q)} + (1 - I_{it})\sigma_{vf}\frac{f(\hat{\alpha}' X_{it}^q)}{[1 - F(\hat{\alpha}' X_{it}^q)]} + \omega_{it} \qquad \textbf{(7')}$$

where f(.) and F(.) are standard normal density and distribution functions.[18] The addition of the inverse Mill's ratios to the set of regressors is designed to adjust for the inconsistency that arises if the error term in equation (6) is correlated with the error terms in (7).[19]

In models where no fault is represented by monetary and verbal indicators, we control for endogeneity

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[18]The probit equation is presented in Appendix C. The parameter vector $\hat{\alpha}$ for the reduced form probit equation (6) is estimated using maximum likelihood. We also tested a binary logit model, with similar results. The standard errors in the IV fatality rate regression (7') are calculated following the methodology presented in Maddala (1983). The probit equation included the regressors in X^A as well as five additional exogenous variables hypothesized to be related to the political sentiment for no fault (see Appendix C). The five variables are the cost of one day of hospitalization, the percentage of state legislators who are Democrats, a dummy variable equal to 1 if the state has a Democratic governor and 0 otherwise, population density (population per square mile), and the percentage of a state's population residing in urban areas. The two Democratic party variables are designed to proxy for political factors relating to the existence of no fault in a state. Population density and the urban population percentage provide proxies for urbanization, while hospital costs are a key factor related to personal injury insurance costs. The coefficients σ_{vn} and σ_{vt} are, respectively, covariances between the error term of the reduced form probit equation (6) and the error terms ϵ_{ni} and ϵ_{ti} from equation (7).

[19]If this type of correlation is present, the conditional means $E(\epsilon_{ni} \mid I_i = 1)$ and $E(\epsilon_{fi} \mid I_i = 0)$ are $\neq 0$, where I_i = the no fault indicator variable, equaling 1 for no fault and 0 for tort. Estimating the augmented equation (7)′ by OLS provides consistent estimates of the other parameters in these equations, as long as the assumption of multivariate normality of the error terms in (6) and (7) is satisfied. The terms $\sigma_{vn}[-f(\cdot)/F(\cdot)]$ and $\sigma_{vf}\{f(\cdot)/[1-F(\cdot)]\}$ are, in fact, the conditional means $E(\epsilon_{ni} \mid I_i = 1)$ and $E(\epsilon_{fi} \mid I_i = 0)$. One reason for also conducting the Hausman (IV) test is that this test is viewed as non-parametric and thus does not depend upon the multivariate normality of the residuals in (6) and (7) (see Addison and Portugal 1989).

using an IV estimation technique analogous to the methodology described above. However, in this case we use as the instruments for monetary and verbal no fault the predicted values from a reduced form multinomial logit model with the dependent variable consisting of three categories – tort, monetary threshold no fault, and verbal threshold no fault. Most of the explanatory variables for the reduced form multinomial logit model are the same as for the binary model used in IV estimation when no fault is represented by a single indicator variable. However, some variables had to be omitted in the multinomial logit regressions to avoid singularity (see Appendix C) due to the presence in the sample of only three verbal threshold states.

We also use IV estimation when no fault is represented by the claims ineligibility ratio. In this case, the instrument for the no fault variable is the predicted value from a reduced form Tobit regression with the proportion of ineligible claims as the dependent variable.[20] Both tort states and no fault states are included in the Tobit regression, with the dependent variable set equal to zero for the tort states, reflecting the absence of no fault restrictions on the right to sue, and equal to the proportion of ineligible claims in no fault states.

As mentioned above, time effects are accounted for in our models using, alternatively, a linear time trend variable and year dummy variables. Regional dummy variables are included in our regression models to capture differences among the U.S. Census Bureau regions not taken into account by our control variables.[21] Ordinary least squares (OLS) results are shown for comparison with the instrumental variables and inverse Mill's regressions.

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[20]The reduced form Tobit equation as well as the multinomial logit model used to generate instruments for the regressions including monetary and verbal no fault dummies are presented in Appendix C.

[21]As a robustness check, models also were estimated with random regional and time effects. The results were virtually identical and therefore not reported. We were not able to use dummy variables for each state because only one state changed compensation regime during our sample period. Consequently, in regressions with fixed effects for each state, the no fault indicator variable would be measuring only the effect of the single switch in regime rather than the overall effect of no fault. The use of the explanatory variables in our regressions along with the regional dummies provides adequate controls for state effects other than no fault. A number of other potential explanatory variables relating to state characteristics also were tested, including traffic violations, the proportion of new cars in the state (because newer cars have more safety features), the presence of comparative negligence, the presence of a seat belt law, etc. These variables proved to be statistically insignificant. Their inclusion in the regressions did not affect the findings with respect to the no fault variable.

Estimation Results

The regression models that include a single indicator variable for no fault are presented in Table 3. In the IM equations, the inverse Mill's ratio for no fault states is interacted with the no fault dummy variable, while the inverse Mill's ratio for tort states is interacted with 1 minus the no fault dummy variable.

The no fault indicator variable is positive but insignificant in the OLS models presented in Table 3. However, when the endogeneity of no fault is taken into account in the IV and IM regressions, the no fault variable is positive and statistically significant. Because our statistical tests indicate that endogeneity bias is present in the OLS regressions, the IV and IM regressions should be used to measure the effects of no fault on fatalities. Consequently, we conclude that the results support the hypothesis that no fault weakens the deterrent effect of tort and is positively associated with higher fatal accident rates.

We computed the implied increases in fatality rates associated with no fault based on the regressions in Table 3. The implied increase was calculated as the ratio of the no fault indicator coefficients in the four models that control for the endogeneity of no fault to the mean fatality rate in tort states. The results suggest that no fault is associated with fatality rates from 5.5 to 7.8 percent higher than tort.[22] These results are consistent with the findings of Landes (1982) and Devlin (1992). Landes found estimated increases in fatalities ranging from 2 to 14 percent, depending upon threshold stringency, while Devlin estimated a 9 percent increase in fatalities in Quebec. McEwin's (1989) estimate of 16 percent higher fatalities under no fault in Australia and New Zealand is higher than ours but similar to Landes' estimates for the most stringent no fault thresholds.

The coefficients of most of the other variables are consistent with expectations. The experience rating variable (license points assessed for an accident even if the driver is less than 50 percent at fault) is negative and significant as predicted by our theory and thus reinforces the view that more rigorous experience rating

[22]As another robustness check, we also estimated the models omitting the regional dummy variables. No fault is positive and statistically significant in the versions of the models that allow for endogeneity, with larger coefficients than in Table 3. The estimates of the effect of no fault on fatality rates based on the models that exclude the regional dummies range from 10.6 to 11.4 percent.

can be used to blunt the weakening in the tort deterrent resulting from no fault.. The alcohol consumption coefficients are positive and significant, confirming earlier findings that alcohol is associated with higher fatal accident rates (Bruce 1984).

The driving environment variables, annual snowfall and rural interstate mileage are both significant and have the expected negative signs and positive, respectively, implying that fatalities are higher on rural highways and that adverse weather conditions tend to reduce the number of serious accidents. The number of hospitals per square mile is inversely related to the fatality rate, as predicted if the proximity of emergency medical services tends to reduce fatality rates. Speed variance is positive and statistically significant in three of the six equations in Table 3, consistent with prior research (e.g., Lave 1985). Also consistent with Lave (1985), average speed is not statistically significant. The results also suggest that educational attainment is related to the fatal accident rate. The proportion of the population with bachelor's degrees is inversely related to fatality rates, consistent with greater demand for safety among better-educated drivers. Neither the proportion of drivers ages 18 through 24 nor real income per capita is statistically significant in the fatality rate equations shown in Table 3. Because the time trend and year effects models yield virtually identical results, we report only the models with year effects in the following discussion.

In the next set of tests we use two indicator variables – representing monetary and verbal threshold no fault states, respectively – in place of the single no fault indicator discussed above. This set of tests is relevant because verbal no fault thresholds are conventionally considered more restrictive or at least qualitatively different from monetary thresholds, giving rise to the possibility that the single indicator variable is primarily proxying for verbal no fault. Accordingly, our first robustness test with regard to verbal thresholds was to re-estimate the models, including the probit equation used to obtain the no-fault instrument, after eliminating the verbal threshold states from the sample. In the resulting regressions (not shown) the no fault indicator variable remains statistically significant, showing that the concern about verbal threshold states is unfounded, i.e., no fault is positively related to fatality rates in monetary threshold no fault states. This is not surprising in view of the claims ineligibility ratios shown in Table 1.

The second set of monetary versus verbal no fault tests involves re-estimating the models with separate indicator variables for monetary and verbal thresholds. We estimated the models utilizing OLS, with regional and year dummy variables included, and also by instrumental variables (IV), using as the instruments the predicted values from a multinomial logit model, as discussed above. The results, shown in the first two columns of Table 4, lead to the same conclusions as the models of Table 3 – both no fault variables are statistically significant and positively related to fatality rates after controlling for endogeneity. The fact that the verbal no fault coefficient is smaller than the monetary no fault coefficient provides further evidence that verbal thresholds are not necessarily more restrictive than monetary thresholds.[23] In any event, the most important result of the verbal and monetary threshold tests reported in Table 4 is that both no fault variables are statistically significant with positive coefficients in the IV regression.

Our final set of tests is based on the IRC estimates of threshold stringency. Specifically, we replace the no fault indicator variable(s) with a variable based on the IRC estimate of the proportion of tort claims ineligible due to no fault thresholds. We specify two versions of the claims ineligibility variable – (1) a variable obtained by linearly interpolating the claims ineligibility ratios between the four IRC study years, 1977, 1987, 1992, and 1997; and (2) the proportion of ineligible claims based on the 1987 IRC data. The reason for using two variables is that the IRC provides data on only 10 no fault states in all four study years, whereas it reports on all no fault states in 1987.[24] Consequently, the first variable allows for changes in stringency over time, while the second is based on a more complete sample of no fault states. No fault states for which we do not

[23]An F-test did not reject the null hypothesis that the monetary and verbal coefficients are equal, casting doubt on the conventional wisdom that verbal thresholds are always stricter than monetary thresholds.

[24]There were fourteen no fault states in 1987. Pennsylvania is the only current no fault state excluded from the tests that utilize the 1987 ineligibility ratio. Pennsylvania had a no fault law from 1982-1984 and 1991-1994, and was included in the sample for purposes of the models reported in Table 3. However, because it did not have a no fault law in 1987, the IRC study does not provide an ineligibility estimate for Pennsylvania in that year.

have an ineligibility variable were removed from the sample for the purposes of conducting this set of tests.

The fatal accident rate models with the claims ineligibility variables were estimated using OLS and also by instrumental variables. In this case, the instrument for the claims ineligibility variable is the predicted value from a reduced form Tobit model with the dependent variable consisting of the proportion of ineligible claims for no fault states and zero for tort states, as discussed above. Separate Tobit models were used for the 1987 and the interpolated claims ineligibility variables.

The models including the claims ineligibility ratios are shown in the last four columns of Table 4. In the models based on the 1987 claims ineligibility ratios, the ineligibility variable is positive and insignificant in the OLS regression and positive and significant in the IV regression, consistent with the results presented in Table 3.[25] In the models based on the interpolated claims ineligibility ratio, the ineligibility variable is positive and significant in both the OLS and IV regressions. These results thus reinforce the inference based on Table 3 that no fault weakens the tort deterrent sufficiently to be associated with higher fatal accident rates.

Finally, we compute the increase in fatality rates due to no fault using the approximate average (0.7) claims ineligibility ratio for the three most recent IRC studies and the coefficients of the ineligibility ratios in the IV regressions in Table 4. The results indicate that fatalities are between 6.6 and 9.9 percent higher due to no fault, consistent with our results from Table 3 as well as those of Landes (1982) and Devlin (1992).

Discussion

The finding of a positive relationship between no fault and fatal accident rates in the U.S. seems reasonable in the light of the theory and empirical results developed in this paper. Recall, our theoretical

[25] As a robustness check, we also estimated the models using Landes' definition of the stringency variable based on the 1987 IRC data, i.e., the proportion of claims eliminated from the tort system by the threshold, rather than our ineligibility ratio. The results are virtually identical to those based on the 1987 ineligibility ratio, i.e., Landes' variable is positive but insignificant in the OLS model but positive and statistically significant at better than the 1 percent level in the IV model. The regressions based on Landes' variable suggest that no fault is associated with 9.4 percent higher fatalities than tort. We could not specify an interpolated variable based on Landes' definition because the IRC does not report all of the necessary data for the 1992 and 1997 study years.

analysis shows that the predicted effect of no fault on accident rates depends on the responsiveness of the tort system to care expenditures, i.e., the accuracy with which the system assigns responsibility for automobile accidents. Thus, our empirical results imply that the assignment of fault is sufficiently accurate that tort does provide a deterrent against driving behavior that is likely to lead to fatalities. The results also support the hypothesis that no fault systems sufficiently weaken the deterrent effects of tort so that fatalities are higher in no fault states.

Our results also are consistent with the prior research on pure no fault. Recall that both McEwin (1989) (for Australia and New Zealand) and Devlin (1992) (for Quebec) provide evidence of a positive relationship between no fault and fatalities. If these authors are correct that no fault laws where virtually 100 percent of claims are ineligible for the tort system are associated with higher fatal accident rates, it is not surprising that laws such as those in the U.S. where an average of 70 percent of claims are ineligible also would be associated with higher fatality rates, even though the ineligible claims are the relatively small ones.

Our results are also consistent with Landes (1982), arguably the best of the prior U.S. papers in terms of methodology, which also shows a positive association between no fault and fatality rates. Our results differ from those of Kochanowski and Young (1985) and Zador and Lund (1986), who did not find a positive relationship between no fault and fatalities. We attribute the difference between our results and these two latter studies to our use of a more sophisticated estimation methodology that controls for the endogeneity of no fault as well as our addition of some key explanatory variables which we find to be strongly related to fatalities, e.g., annual snowfall and the percentage of miles driven on rural interstates.

Our results suggest that potential increases in fatality rates should be a consideration in public policy discussions involving automobile accident compensation systems. However, the findings also suggest that the reduction in deterrence resulting from no fault can be at least partly offset by adopting more stringent automobile insurance experience rating mechanisms. Such mechanisms have the added benefit of improving the efficiency of resource allocation by discouraging the over-consumption of automobile transportation by drivers that have relatively poor accident and conviction records.

3. Conclusions

Previous researchers have hypothesized that no fault automobile insurance weakens the deterrent effects of tort liability and thus leads to higher motor vehicle fatality rates. However, empirical tests of this hypothesis based on U.S. data have led to conflicting results. Because of the potentially important role of no fault in automobile insurance reform, this paper reexamines both the theory and the empirical evidence on the incentive effects of no fault.

Our theoretical analysis implies that the effect of no fault on fatal accident rates is ambiguous. However, if negligence assignment under tort is sufficiently responsive to care levels undertaken by drivers, then no fault is likely to be associated with higher fatality rates. The theoretical analysis also reveals that more rigorous experience rating plans can be used to offset any adverse incentive effects resulting from no fault. Ironically, the reduction in administrative expense to premium ratios associated with no fault has the effect of aggravating the adverse incentive effects from restricting tort.

Prior empirical research on Australia/New Zealand and Canada (McEwin 1989, Devlin 1992) found positive relationships between fatal accident rates and the existence of no fault plans. Prior empirical results based on U.S. experience have been mixed. Landes (1982) found evidence of a positive relationship between no fault and fatality rates, but Kochanowski and Young (1985) and Zador and Lund (1986) did not find such a relationship. However, none of the prior U.S. studies controlled for the potential endogeneity of no fault.

In our empirical analysis, we adopt a more sophisticated estimation approach than previous no fault researchers. The most important innovation is to allow for the possible endogeneity of no fault, and our empirical tests indicate that no fault should be treated as an endogenous variable. Our results are consistent with the hypothesis that no fault weakens the tort deterrent sufficiently to be associated with higher fatality rates. Based on the models that control for the endogeneity of no fault, our models suggest that fatality rates are between 5.5 and 9.9 percent higher under no fault than they would be under tort.

The results are important because they suggest that policy makers should take into account possible increases in fatal accident rates when considering the adoption of no fault laws. Thus, there is a tradeoff between the advantages of no fault as an accident compensation system and its adverse effects on incentives. However, concerns about higher accident rates could be mitigated by strengthening experience rating systems. Better experience rating plans would have the added benefit of discouraging the over-consumption of automobile transportation by drivers with relatively poor driving records.

APPENDIX A

A.1. COMPARATIVE STATICS PREMIUM AND CARE EXPENDITURES SEPARABLE

The driver is assumed to maximize the following function with respect to the level of care, x:

$$EU = [1 - \lambda(1 - \delta p_2)]\, U(W) + \lambda(1 - \delta p_2)\, U(W - g) - \pi(x) - x \quad \textbf{(A.1)}$$

where π = the insurance premium = $(1+e)\lambda(\ell + p_1\delta g)$. We assume that $U' > 0$, $U'' < 0$, $\lambda_x = d\lambda/dx < 0$, $\lambda_{xx} > 0$. It is easy to show that $\pi_x = d\pi/dx < 0$ and $\pi_{xx} > 0$. We also assume the following with respect to negligence probabilities $p_1(x)$ and $p_2(x)$: $p_{1x} = dp_1/dx < 0$, $p_{1xx} > 0$, $p_{2x} > 0$, $p_{2xx} < 0$, and $p_{1x} = -p_{2x}$.

The first-order condition for optimization with respect to x is:

$$EU_x = [-\lambda_x(1 - \delta p_2) + \lambda\delta p_{2x}]\,(U_N - U_L) - \pi_x - 1 = 0 \quad \textbf{(A.2)}$$

where U_N = utility in the no-loss state = U(W),
U_L = utility in the loss state = U(W-g),
π_x = reduction in premium due to additional care = $(1+e)[\lambda_x \ell + \delta g(p_1\lambda_x+\lambda p_{1x})]$,
λ_L = the probability of the loss state = $\lambda(1-\delta p_2)$, and
$\lambda_{Lx} = \lambda_x(1-\delta p_2)-\lambda\delta p_{2x}$.

Notice that $\lambda_{Lx} < 0$ so that increased care reduces the probability of being in the loss state.

The second order sufficient condition for maximization is the following:

$$EU_{xx} = \lambda_{Lxx}(U_L - U_N) - \pi_{xx} \quad \textbf{(A.3)}$$

To check whether the condition is satisfied, we need to define:

$$\lambda_{Lxx} = \lambda_{xx}(1 - \delta p_2) - 2\lambda_x\delta p_{2x} - \delta\lambda p_{2xx} \quad \textbf{(A.4)}$$

All terms in (A.4) are positive. Also note that:

$$\pi_{xx} = (1 + e)[\lambda_{xx}(\ell + \delta g p_1) + 2\lambda_x p_{1x}\delta g + \lambda p_{1xx}\delta g] \quad \textbf{(A.5)}$$

Since all terms in π_{xx} are positive, all terms in λ_{Lxx} are positive, and U_L - U_N is negative, the second order condition is satisfied.

Totally differentiating (A.2) with respect to x and an arbitrary parameter k, we find that:

$$\frac{dx}{dk} = \frac{-EU_{xk}}{EU_{xx}} \quad \textbf{(A.6)}$$

Thus, the sign of dx/dk is the same as the sign of EU_{xk}. For $EU_{x\delta}$ we have:

$$EU_{x\delta} = (U_L - U_N)(-\lambda_x p_2 - p_{2x}\lambda) - (1+e)(\lambda_x g p_1 + \lambda g p_{1x}) \qquad \textbf{(A.7)}$$

The second term in (A.7) is positive so (A.7) is positive if the first term is positive. This occurs if $-\lambda_x p_2 - p_{2x}\lambda < 0$, leading to condition (8) in the text. Similarly, we find:

$$EU_{xe} = -[\lambda_x(\ell + p_1 \delta g) + \lambda p_{1x} \delta g] > 0 \qquad \textbf{(A.8)}$$

Finally, we model the effect of experience rating by introducing the premium formula: $\pi^Z = Z\pi + (1\text{-}Z)\,\overline{\pi}$, where $\overline{\pi}$ = the average premium. Substituting π^Z for π in (A.1) and differentiating, the revised first-order condition is:

$$EU_x = \lambda_{Lx}(U_L - U_N) - Z\pi_x - 1 \qquad \textbf{(A.9)}$$

Because $EU_{xZ} = -\pi_x > 0$, we have $dx/dZ > 0$.

A.2. COMPARATIVE STATICS: DECISION PROBLEM NOT SEPARABLE IN PREMIUMS AND CARE EXPENDITURES

Negligence Rule (δ)

This section derives the sufficient conditions for $\partial x/\partial\delta > 0$, for the case where the decision problem is not separable in premiums and care expenditures. Expected utility in this case is defined as:

$$EU = [1 - \lambda(1 - \delta p_2)]\, U(W - x - \pi) + \lambda(1 - \delta p_2)\, U(W - x - \pi - g) \tag{A.10}$$

where π = the insurance premium = $(1+e)\lambda(\ell + p_1\delta g)$,
e = the expense loading as a proportion of expected insured losses,
λ = the accident rate,
δ = negligence rule parameter, $0 \leq \delta \leq 1$, $\delta = 0$ for no liability rule and $\delta = 1$ for a pure negligence rule (full tort),
g = general damages in the event of an accident,
ℓ = economic losses,
p_1 = the probability that driver A is found to be negligent and driver B not negligent, and
p_2 = the probability that driver B is found to be negligent and driver A not negligent.

Recall that $\partial p_1/\partial x = p_{1x} < 0$, $p_{2x} > 0$, and $\lambda_x < 0$.

The decision maker chooses x, the optimal level of care, to maximize expected utility. The first-order condition for optimization with respect to x is:

$$EU_x = -[\lambda_x(1 - \delta p_2) - \lambda\,\delta p_{2x}]\,(U_N - U_L) - (1 + \pi_x)\,[(1 - \lambda_L)\, U_N' + \lambda_L\, U_L'] = 0 \tag{A.11}$$

where EU_x = the first partial derivative of expected utility with respect to x,
U_N = utility in the no-loss state = $U(W\text{-}x\text{-}\pi)$,
U_L = utility in the loss state = $U(W\text{-}x\text{-}\pi\text{-}g)$,
π_x = reduction in premium due to additional care = $(1+e)[\lambda_x \ell + \delta g(p_1\lambda_x + \lambda p_{1x})]$,
λ_L = the probability of the loss state = $\lambda(1\text{-}\delta p_2)$

The subscript x indicates differentiation with respect to care expenditures (x).

Denote the second partial derivative of utility with respect to x as EU_{xx}. The second order condition for a maximum is assumed to be satisfied so that $EU_{xx} < 0$. Let ξ stand for an arbitrary parameter. Then by total differentiation of (A.11),

$$\frac{dx}{d\xi} = -\frac{EU_{x\xi}}{EU_{xx}} \tag{A.12}$$

so that the sign of $dx/d\xi$ is the same as the sign of $EU_{x\xi}$, the cross partial derivative of expected utility with respect to x and ξ.

We wish to find the sign of $dx/d\delta$, and in particular to establish sufficient conditions for $dx/d\delta > 0$, or, equivalently for $EU_{x\delta} > 0$, where $EU_{x\delta}$ is given by

$$EU_{x\delta} = (-\lambda_x p_2 - \lambda p_{2x})(U_L - U_N) + \lambda_{Lx}(U_L' - U_N')(-\pi_\delta)$$
$$- \pi_{x\delta}[(1-\lambda_L)U_N' + \lambda_L U_L'] - (1+\pi_x)\lambda_{L\delta}(U_L' - U_N') \qquad \textbf{(A.13)}$$
$$+ (1+\pi_x)\pi_\delta[\lambda_L U_L'' + (1-\lambda_L)U_N'']$$

where $\lambda_{Lx} = \lambda_x(1\text{-}p_2\delta) - \lambda p_{2x}\delta < 0$,
$\lambda_{Lx\delta} = -\lambda_x p_2 - p_{2x}\lambda$,
$\pi_\delta = (1+e)p_1\lambda g > 0$,
$\lambda_{L\delta} = -p_2\lambda < 0$,
$\pi_{x\delta} = (1+e)g(p_{1x}\lambda + \lambda_x p_1) < 0$, and

U_L'', U_N'' are second derivatives of the utility function in the loss and no loss states, respectively, with respect to wealth.

Diminishing marginal utility implies that $(U_L'\text{-}U_N') > 0$. Also, $U_L < U_N$ by the increasing utility of wealth. These results plus the partial derivatives shown above imply that all terms in (A.13) are unambiguously positive except the first and the last.

If the sign of $(-\lambda_x p_2\text{-}\lambda p_{2x})$ is negative, then the first term in (A.13) is positive, implying the following condition:

$$-\frac{p_{2x}}{p_2} < \frac{\lambda_x}{\lambda} \qquad \textbf{(A.14)}$$

The sign of the last term in (A.13) is unambiguously negative. However, this term may be offset by the positive terms in (A.13), giving $dx/d\delta > 0$. Along with (A.14), a sufficient condition for $dx/d\delta > 0$ is for the first four terms of (A.13) to offset the last term. Some interesting observations can be made if we impose a stronger condition, i.e., that the expected marginal utility term (the third term), which is positive, exceeds the last term. After some manipulations, this condition implies,

$$-\frac{EU''}{EU'} = -\frac{U_N''(1-\lambda_L) + U_L''\lambda_L}{U_N'(1-\lambda_L) + U_L'\lambda_L} < -\frac{1}{1+\pi_x}\left(\frac{\lambda_x}{\lambda} + \frac{p_{1x}}{p_1}\right) \qquad \textbf{(A.15)}$$

Condition (A.15) can be loosely interpreted as a condition on risk aversion. We know that $dx/d\delta$ is unambiguously > 0 under risk neutrality. Thus, if $dx/d\delta$ is ambiguous under risk aversion there must be some level of risk aversion below which the sign of $dx/d\delta$ becomes unambiguous. The implication of (A.15) is that drivers with relatively high risk aversion do not necessarily reduce care expenditures in response to reductions in δ (weakening of tort incentives). In other words, drivers with risk aversion below the level implied by the right hand side of (A.15) are likely to adjust care expenditures downward in response to limitations on tort. This makes sense intuitively.

Experience Rating

Experience rating can be introduced by changing the premium formula to:

$$\pi^Z = Z\pi + (1 - Z)\bar{\pi} \tag{A.16}$$

where π^Z = experience rated premium,

$\bar{\pi}$ = average premium for an appropriate class of drivers, and

Z = credibility factor, $0 \le Z \le 1$.

The experience rated premium is a weighted average of the driver's premium, π, and the average premium across all drivers in his/her risk class, $\bar{\pi}$. Experience rating is almost always less than complete due to sampling error (i.e., a driver's accident history reveals some but not all information about his/her accident and negligence probabilities), imperfections in reporting systems, etc. The degree of experience rating is captured by the credibility factor Z.

Differentiating (A.11) with respect to Z yields:

$$\begin{aligned} EU_{xZ} = {} & \lambda_{Lx}(U_N^{/} - U_L^{/})(\pi - \bar{\pi}) + (1 + Z\pi_x)(\pi - \bar{\pi})[\lambda_L U_L^{//} + (1 - \lambda_L) U_N^{//}] \\ & - \pi_x [\lambda_L U_L^{/} + (1 - \lambda_L) U_N^{/}] \end{aligned} \tag{A.17}$$

This expression is unambiguously positive for average drivers, i.e., drivers for whom $\pi = \bar{\pi}$. It is unambiguously positive for good drivers ($\pi < \bar{\pi}$) if the sum of the terms multiplying (π-$\bar{\pi}$) in (A.17) is negative and unambiguously positive for bad drivers if the sum of these terms is positive. Thus, it is unambiguous for average and good drivers or for average and bad drivers.

APPENDIX B
DEFINITIONS AND SOURCES OF VARIABLES

Alcohol Consumption	Gallons of alcoholic beverages consumed per capita (Distilled Spirits Council of the U.S. [1])
Fatal Accident Rate	Total fatal accidents per 10 million vehicle miles (FHWA[9])
No Fault Dummy	Dummy variable equal to one if no-fault law exists, and 0 otherwise (Rand[6] and III[2])
Verbal Threshold Indicator	Dummy variable equal to one if verbal threshold exists, and zero otherwise Rand[6] and III[2])
Monetary Threshold Indicator	Dummy variable equal to one if monetary threshold exists, and zero otherwise Rand[6] and III[2])
Proportion of Claims Ineligible for Tort	Proportion of claims that do not satisfy the no fault threshold (IRC[3])
Annual Snowfall in Inches	Annual snowfall in inches (NOAA[5])
% of Population in Urban Area	Proportion residing in urban areas (DOC [8])
Miles Driven: Rural Interstates %	Rural interstate vehicle miles as a proportion of total miles driven (FHWA[9])
Points Assigned if Driver is Less Than 50 Percent Negligent	Dummy variable equal to one if points are assigned for drivers who are 50% or less negligent (ISO[4])
Real Income Per Capita	Constant dollar income per capita, 1982 dollars (DOC[8])
Speed Variance	85th percentile of statewide vehicle speed in miles per hour minus statewide average speed (FHWA[9])
Average Speed	Statewide average speed in miles per hour (FHWA[9])
Per Day Cost of Hospital Care	Average cost of one day of care (DOC[8])
Population Density	Total population per square mile of land area (DOC[8])
Democratic Governor	Dummy variable = 1 if state has Democratic governor, 0 otherwise (DOC[8])
% of Population Age 18-24	Percentage of population aged 18-24 (BLS[7])
Hospital Per Square Mile of Land Area	Number of hospitals divided by land area (DOC[8])

% Democratic State Legislators	Percentage of state legislators who are Democrats (DOC[8])
% of Pop. With Bachelors Degree	Percentage of population age 25 and over with a bachelor's degree (BLS[7])

The following abbreviations are used in the data source descriptions:

BLS	U.S. Bureau of Labor Statistics
DOC	U.S. Department of Commerce
FHWA	U.S. Federal Highway Administration
III	Insurance Information Institute
IRC	Insurance Research Council
ISO	Insurance Services Office
NOAA	National Oceanic and Atmospheric Administration

Sources:

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5. National Oceanic and Atmospheric Administration. *Local Climatological Data*. Asheville, NC, various years.
6. Rand Corporation 1985. *Auto Accident Compensation.* Santa Monica, CA.
7. U.S. Bureau of Labor Statistics. March CPS Supplement, Washington, D.C., various years.
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TABLE 1
PERCENT OF PIP CLAIMS INELIGIBLE FOR TORT CLAIM UNDER STATE NO FAULT THRESHOLDS

State	1977	1987	1992	1997	Threshold[1]
Colorado	84%	74%	66%	70%	$500
Connecticut		59%			$400
Florida	69%	68%	63%	66%	Verbal
Georgia		51%			$500
Hawaii	97%	81%	64%	79%	$6,000
Kansas	87%	71%	83%	78%	$2,000
Kentucky	90%	75%	67%	58%	$1,000
Massachusetts	74%	47%	37%	48%	$2,000
Michigan	94%	88%	81%	85%	Verbal
Minnesota	90%	78%	66%	71%	$4,000
New Jersey		37%			$1,700[2]
New York	73%	71%	69%	78%	Verbal
North Dakota		87%			$2,500
Utah	81%	81%	77%	76%	$3,000
Average	**84%**	**69%**	**67%**	**71%**	

Sources: IRC (1989, 1999) for estimates of claims ineligible for tort. American Insurance Association (1989), *Summary of State Laws and Regulations Relating To Automobile Insurance* (Washington, DC), for thresholds.

Note: PIP = personal injury protection (first-party economic loss coverage).

[1]In 1989, approximately the midpoint of our sample period.

[2]Insured has a choice of a lower threshold ($200) for a higher premium.

TABLE 2
STATISTICAL PROFILE OF STATES BY COMPENSATION SYSTEM
SAMPLE MEANS: 1982-1994

Variable	No-Fault		Tort
Fatal Accident Rate (per 10 million vehicle miles)	18.58	***	21.91
Injury Accident Rate (per 10 million vehicle miles)	1053.00	*	858.57
Alcohol Consumption (gallons per capita)	25.82	***	27.99
Annual Snowfall (inches)	36.76	***	26.18
Miles Driven: Rural Interstates (%)	8.34%	***	12.39%
Real Income Per Capita	$6,889	***	$6,228
% of Population with Bachelor's Degree	13.22%	***	11.61%
Points Assigned if < 50% At Fault	86.24%	***	68.98%
Average Speed	56.54		56.31
Speed Variance (85th percentile - average speed)	6.89	*	7.07
% of Population Age 18-24	11.18%		11.20%
Hospitals per Square Mile of Land Area	59.69	***	30.82
Number of Observations	189		461

Note: Asterisks denote significance levels for tests of differences between the tort state and no fault state means.
***significant at the 1% level, **significant at the 5% level, *significant at the 10% level

TABLE 3
REGRESSION RESULTS USING SINGLE NO FAULT INDICATOR VARIABLE
DEPENDENT VARIABLE = FATAL ACCIDENT RATE

	OLS Time Trend	OLS Year Effects	IV Time Trend	IV Year Effects	IM Time Trend	IM Year Effects
Intercept	23.414 ***	16.927 ***	22.247 ***	15.707 ***	26.578 ***	20.304 ***
No Fault Indicator	0.194	0.365	1.371 *	1.718 **	1.210 *	1.373 **
Alcohol Consumption[1]	0.124 ***	0.122 ***	0.154 ***	0.159 ***	0.137 ***	0.137 ***
Annual Snowfall (Inches)	-0.014 ***	-0.020 ***	-0.017 ***	-0.023 ***	-0.018 ***	-0.023 ***
Miles Driven: Rural Interstates (%)	25.994 ***	27.847 ***	30.029 ***	32.482 ***	25.897 ***	27.440 ***
Real Income Per Capita	-0.058	0.098	-0.103	0.031	-0.203	-0.114
% of Population with Bachelor's Degree	-0.447 ***	-0.534 ***	-0.491 ***	-0.585 ***	-0.423 ***	-0.491 ***
Points Assigned if < 50% At Fault	-2.563 ***	-2.538 ***	-2.716 ***	-2.711 ***	-2.399 ***	-2.356 ***
Average Speed	0.033	0.060	0.039	0.069	0.012	0.032
Speed Variance[2]	0.180	0.185 *	0.157	0.160	0.202 *	0.209 **
% of Population Age 18-24	4.265	-7.192	5.166	-6.303	-2.048	-12.469
Hospitals Per Square Mile	-0.017 ***	-0.018 ***	-0.018 ***	-0.018 ***	-0.017 ***	-0.018 ***
Inverse Mill's Ratio: No Fault					2.373 ***	2.456 ***
Inverse Mill's Ratio: Tort					-2.631 ***	-2.840 ***
Time Trend (1982 = 1)	-0.508 ***		-0.480 ***		-0.532 ***	
Adjusted R-Squared	71.2%	73.2%	71.3%	73.4%	73.7%	76.1%

NOTE: Regressions are based on fifty states for the period 1982-1994. All models include dummy variables (not shown) for eight of the nine U.S. Census Bureau regions, with one region omitted to avoid singularity. Time Trend models include a linear time trend (1982=1), and the Year Effects models include dummy variables for years (1982 omitted). The inverse Mill's variable for no fault is interacted with the no fault dummy variable, and the inverse Mill's variable for tort is interacted with 1 minus the no fault dummy variable. Variables are defined in Appendix B.

OLS = ordinary least squares, IV = instrumental variables, and IM = inverse Mill's.

Significance levels are given to the right of the coefficients. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

[1]Alcohol consumption is in gallons per capita.

[2]Speed variance = 85th percentile-average speed.

TABLE 4
REGRESSION RESULTS USING DOLLAR AND VERBAL INDICATORS AND CLAIMS INELIGIBILITY RATIOS
DEPENDENT VARIABLE = FATAL ACCIDENT RATE

	OLS[4]	IV[4]	OLS 1987 Ratio[5]	IV 1987 Ratio[5]	OLS Interpolated[6]	IV Interpolated[6]
Intercept	20.230 ***	18.688 ***	20.371 ***	20.954 ***	18.240 ***	17.384 ***
Monetary Threshold Indicator	0.148	2.164 ***	-	-	-	-
Verbal Threshold Indicator	0.952	1.241 **	-	-	-	-
Proportion of Claims Ineligible for Tort[1]	-	-	0.451	3.087 ***	1.028 **	2.056 ***
Alcohol Consumption	0.119 ***	0.164 ***	0.125 ***	0.165 ***	0.189 ***	0.202 ***
Annual Snowfall (Inches)	-0.021 ***	-0.023 ***	-0.020 ***	-0.028 ***	-0.017 ***	-0.020 ***
Miles Driven: Rural Interstates (%)	28.354 ***	32.186 ***	27.900 ***	35.906 ***	30.658 ***	33.892 ***
Real Income Per Capita	0.092	0.021	0.059	0.042	-0.528 **	-0.536 **
% of Pop. with Bachelor's Degree	-0.518 ***	-0.621 ***	-0.539 ***	-0.611 ***	-0.508 ***	-0.523 ***
Points Assigned if < 50% At Fault	-2.360 ***	-2.829 ***	-2.522 ***	-2.793 ***	-2.419 ***	-2.490 ***
Average Speed	0.040	0.076	0.040	0.050	0.059	0.068
Speed Variance[2]	0.186 *	0.159	0.199 *	0.119	0.212 *	0.199 *
% of Population Age 18-24	-1.005	-6.228	-8.351	-14.936	11.734	11.467
Hospitals Per Square Mile	-0.017 ***	-0.019 ***	-0.018 ***	-0.017 ***	-0.014 ***	-0.014 ***
Adjusted R-Squared	73.3%	73.7%	73.4%	71.8%	73.5%	73.2%
F-Statistic[3]		1.249 (0.263)				

NOTE: All models include dummy variables (not shown) for the nine U.S. Census Bureau regions, with one region omitted to avoid singularity. Dummy variables for years also are included (1982 omitted). Variables are defined in Appendix B. OLS = ordinary least squares, IV = instrumental variables.
Significance levels are given to the right of the coefficients. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

[1]Equal to the IRC (1989, 1999) estimate of the proportion of personal injury protection (PIP) claims ineligible for tort due to thresholds in no fault states and equal to zero in tort states.

[2]Speed variance = 85th percentile-average speed.

[3]The F-statistic reports the test of H_0: $\beta_{Dollar} = \beta_{Verbal.}$ The p-value is reported in parantheses.

[4]Based on fifty states for the period 1982-1994. The IV model uses as instrumental variables for monetary and verbal no fault the predicted values from a multinomial logit model with a three-category dependent variable, with categories for tort states, monetary threshold no fault states and verbal threshold no fault states.

[5]Based on forty-nine states for the period 1982-1994. Pennsylvania is excluded. The proportion of PIP claims ineligible for tort is the IRC (1989) estimate for 1987 claims. The IV model uses as the instrumental variable for the proportion of claims ineligible the predicted value from a reduced form Tobit regression with dependent variable equal to the 1987 proportion of PIP claims ineligible for tort for no fault states and zero for tort states.

[6]Based on forty-five states for the period 1982-1994. The models include all tort states and the ten no fault states included in all four IRC studies (see Table 1). The proportion of PIP claims ineligible for tort is based on linear interpolation of the IRC (1999) estimates for the four IRC study years, 1977, 1987, 1992, and 1997. The IV model uses as an instrumental variable for the interpolated proportion of ineligible claims the predicted value from a reduced form Tobit regression with dependent variable equal to the interpolated proportion of PIP claims ineligible for tort for no fault states and zero for tort states.

APPENDIX C

REDUCED FORM PROBIT, MULTINOMIAL LOGIT, AND CLAIMS INELIGIBILITY RATIO TOBIT ESTIMATION RESULTS

Estimation Method	Probit[2]		Multinomial Logit[3]				Tobit			
Dependent Variable	No Fault Indicator		Monetary Threshold		Verbal Threshold		1987 Ineligibility Ratio[4]		Interpolated Ineligibility Ratio[5]	
Intercept	11.255	***	12.884	*	22.805		1.806		7.653	***
Alcohol Consumption[1]	-0.151	***	-0.423	***	-0.058		-0.022	**	-0.018	**
Annual Snowfall (Inches)	0.013	***	0.010		0.091	***	0.009	***	0.012	***
Miles Driven: Rural Interstates (%)	-16.191	***	-29.771	***	-153.810	***	-5.698	***	-11.760	***
Real Income Per Capita	-0.011		0.195		-0.478		-0.121	*	-0.049	
% of Population with Bachelor's Degree	0.146	***	0.594	***	-1.224	***	0.073	***	-0.005	
Points Assigned if < 50% At Fault	0.218						0.126		-0.262	***
Average Speed	-0.077		-0.184	**	2.019	***	-0.023		-0.130	***
Speed Variance	0.096		0.238	*	1.095	**	0.010		-0.039	
% of Population Age 18-24	-27.438	**	33.122		-746.130	***	-2.925		-9.348	**
Hospitals Per Square Mile	0.028	***	0.070	***	-0.156	**	0.009	***	0.026	***
Time Trend (1982 = 1)			0.187	**	-1.981	***				
Per Day Cost of Hospital Care	-0.639	***	-0.777	***	-0.285		-0.065		0.089	*
% Democratic State Legislators	-0.038	***	-0.047	***	-0.114	**	-0.016	***	-0.017	***
Democratic Governor	1.189	***					0.982	***	2.400	***
Population Density	-6.596	***	-12.847	***	16.817		-1.319	**	-5.041	***
% Population in Urban Areas	0.044	***					0.013	***	0.016	***
Log Likelihood Function	-221.695		-234.669				-267.242		-76.121	
Psuedo R-Squared[6]	43.42%									

Note: Variables are defined in Appendix B. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

[1]Alcohol consumption is in gallons per capita.

[2] The dependent variable equals 1 for no fault states and 0 for tort states. The regression is based on fifty states for the period 1982-1994. The model includes dummy variables (not shown) for eight of the nine U.S. Census Bureau regions and for years (1982 omitted).

[3]The dependent variable is a three category variable equal to 0 for tort states, 1 for no fault states with monetary thresholds, and 2 for no fault states with verbal thresholds. The regression is based on fifty states for the period 1982-1994. A linear trend (1982=1) variable is used instead of year dummy variables to avoid over-fitting the model for the verbal threshold states. Also omitted are the U.S. Census Bureau region dummy variables, the experience rating variable, population density, and the percent of population in urban areas variables as the inclusion of these variables provided a perfect fit in the verbal threshold states.

[4]The dependent variable is the proportion of personal injury protection (PIP) claims estimated to be ineligible for tort claims due to the threshold in no fault states and 0 for tort states. The ineligibility ratio in this regression is the IRC (1989, 1999) estimate for **1987.** The model includes forty-nine states, with Pennsylvania excluded because its tort claims ineligibility ratio is not available.

[5]The dependent variable is the proportion of personal injury protection (PIP) claims estimated to be ineligible for tort claims due to the threshold in no fault states and 0 for tort states. The ineligibility ratio in this regression is linearly interpolated based on the IRC (1989, 1999) estimates for **1977, 1987, 1992, and 1997.** The model includes all tort states and the 10 no fault states with data on the ineligibility ratio for all IRC survey years.

[6]See Greene (1997), p. 891 for the definition of probit Psuedo R-Squared.