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The Fatality Risks of Sport-Utility Vehicles, Vans, and Pickups*

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Abstract

This paper presents a model of vehicle choice and then empirically examines the risk posed by light trucks (sport-utility vehicles, vans, and pickups) to those that drive them and to other drivers, relative to the risk posed by cars. The paper examines both the relative risk of dying given a crash as well as the relative crash frequencies of light trucks versus cars. The identification strategy uses information on pedestrian fatalities by vehicle type to correct for the sample selection bias that may exist due to the lack of reliable data on non-fatal crashes. Using data on all two-vehicle fatal crashes from 1991 through 1998, the results suggest that, given a crash, a light truck driver is 0.29 to 0.69 times as likely to die than is a car driver. On the other hand, given a crash, a light truck driver is 1.48 to 2.63 times as likely to kill the opposing driver than is a car driver. Using data from 1991 through 1994, the crash frequency estimates suggest that light trucks are approximately 2.2 times as likely to get into a crash than are cars. The relative safety of utility vehicles and pickups (compared to cars) disappears once one factors in the greater crash frequencies of light trucks. Factoring in the greater crash frequency of light trucks also increases their relative external risk. Light trucks are 3.26 to 5.78 times as likely to kill another driver than are cars. A world in which everyone drove light trucks would result in 2.81 to 6.31 times as many fatalities than a world in which everyone drove cars.

JEL Codes: C20, D62, I18, R40

Key Words: Sample Selection Bias, Externalities, Public Health

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1 Introduction

In December 1999, President Clinton announced that the Environmental Protection Agency would soon require that light trucks (sport-utility vehicles, minivans, and pickups) meet the same nitrogen oxide emission standards as cars.[1] Nevertheless, the emission standards of other pollutants (such as carbon monoxide) will continue to remain less stringent for light trucks. Additionally, new light trucks face lower fuel economy standards than do new cars. These discrepancies in emission and fuel economy standards represent an implicit subsidy for light trucks.

Crash studies by the National Highway Traffic Safety Administration suggest that light trucks inflict greater damage in crashes than do cars (see, for example, Gabler and Hollowell, NHTSA, 1998). If light trucks pose greater external risks than do cars, and if Coasian bargaining is not feasible, then economic efficiency would be achieved through levying a tax on light trucks relative to cars. Indeed, the existence of these external risks would suggest that the current implicit subsidy on light trucks moves us further away from an efficient outcome. However, a corrective movement towards efficiency may or may not improve public health, since a priori it is ambiguous whether substituting cars for light trucks would reduce the number of traffic fatalities. In their study of fuel economy standards, Crandall and Graham (1989) find that such standards led to smaller cars and that smaller cars led to more fatalities, since a crash between two small cars is expected to lead to more fatalities than a crash between two big cars. However, these fatality estimates assume that the likelihood of getting into a crash does not vary by car type. This assumption may not hold for light trucks versus cars, in which case one can obtain estimates of aggregate fatalities only by estimating both the relative probabilities of dying given a crash with a light truck versus a car as well as the relative crash frequencies of light trucks versus cars.

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[1] The regulations call for reductions of nitrogen oxide emissions to 0.07 grams per miles by 2004 for cars and by 2007 for light trucks.

This paper presents a model of the decision to purchase a vehicle, and then discusses the conditions that lead to efficiency and the conditions that lead to a minimization of fatality risks. I use empirical estimates of fatality risks and crash frequencies in order to draw inferences from this model concerning both the efficient and the risk-minimizing regulatory response in the motor vehicle market. Specifically, the paper empirically examines the fatality risk to a driver of a sport-utility vehicle, van, or pickup relative to the fatality risk to a car driver. The paper also examines the fatality risk the driver of a sport-utility vehicle, van, or pickup driver poses to other drivers relative to the risk posed by a car driver. These empirical estimates in turn yield estimates of the expected number of traffic fatalities given different vehicle-type combinations relative to other vehicle-type combinations.

A significant complication in estimating the determinants of traffic fatalities is the unavailability of reliable data of non-fatal crashes. Relying only on data of fatal crashes could result in a sample selection bias. Levitt and Porter (2000) give a clear example of this sample selection bias in their analysis of seat belt and air bag effectiveness. If seat belts reduce the risk of dying, then crashes involving seat-belt wearers will be more likely to be excluded from the analysis, since the data set only includes crashes in which a fatality has occurred. This would lead to an underestimate of the effectiveness of seat belts. The problem is that seat belts affect the likelihood of a fatality and thus also affect whether a crash is included in the data set. In analyzing the fatality risks of vehicle types, the direction of the bias is ambiguous. For example, if cars pose less of a risk to others than do light trucks, then crashes involving cars will be over-represented in the sample. However, if the lower relative external risk of cars also means that cars pose a higher risk to their own drivers, then crashes involving cars will be under-represented in the sample relative to crashes involving light trucks.

In their analysis, Levitt and Porter (2000) address the sample selection issue by restricting the sample to include only those observations for which someone in the other vehicle dies. This leads to consistent estimates of seat belt effectiveness under the assumption that, within this subsample, crash severity is independent of seat belt use, conditional on the characteristics of the driver and the driver's vehicle. While this estimation strategy provides an innovative means of addressing sample selection in the study of seat belt and air bag effectiveness, it is less likely to lead to unbiased estimates in my analysis of the risks posed by light trucks. This is because the key independence assumption is not likely to hold. The variable of interest in this study is the type of opposing vehicle in a crash, which is quite likely to be correlated with unobservable crash characteristics.

In this paper, I offer another means of controlling for sample selection bias. I weight the regression-adjusted predicted number of fatalities (for each vehicle type combination) given a fatal crash by the number of pedestrian fatalities for each vehicle type involved in the crash. Given a set of reasonable assumptions on the relationship between the total number of crashes and the number of crashes in which a pedestrian dies, the adjustment results in unbiased estimates of the *relative* risk of fatality given a crash between different types of vehicles. I then combine these fatality estimates given a crash with estimates of relative crash frequencies by vehicle types. For the estimates of relative crash frequency, I use pedestrian fatalities by vehicle type as the dependent variable in order to proxy for the number of crashes by vehicle type. The independent variable of interest is the number of vehicle miles traveled by vehicle type. Given the same set of assumptions, the regressions yield unbiased estimates of frequency rates by vehicle type.

Using crash data from 1991 through 1998, the empirical results suggest that, given a crash, it is substantially safer for a driver to be in a light truck instead of a car. Given a crash in which the opposing vehicle is a car, a light-truck driver is 0.30 to 0.50 times as likely to die than is a car driver. Given a crash in which the opposing vehicle is a sport-utility vehicle, a light-truck driver is 0.29 to 0.46 times as likely to die than is a car driver. Given a crash in which the opposing vehicle is a van, a light-truck driver is 0.39 to 0.50 times as likely to die than is a car driver. Given a crash in which the opposing vehicle is a pickup, a light-truck driver is 0.33 to 0.69 times as likely to die than is a car driver.

On the other hand, the results also suggest that, given a crash, it is substantially more dangerous to crash into a light truck than it is to crash into a car. A car driver involved in a crash is 1.50 to 1.88 times as likely to die if the opposing vehicle is a light truck as compared to a car. A sport-utility vehicle driver involved in a crash is 1.48 to 1.96 times as likely to die if the opposing vehicle is a light truck instead of a car. A van driver involved in a crash is 1.83 to 2.06 times as likely to die if the opposing vehicle is a light truck instead of a car. A pickup driver involved in a crash is 1.52 to 2.63 times as likely to die if the opposing vehicle is a light truck instead of a car.

If one were to assume that crash frequencies do not vary over vehicle types, then these results would suggest that a shift from light trucks to cars would, while efficient, increase the aggregate level of traffic fatalities. This is because the decrease in external risk (i.e., the risk to other drivers) due to replacing a light truck with a car is less than the increase in internal risk (i.e., the risk to the driver) due to replacing a light truck with a car. But crash frequencies are not constant across vehicle types. Using state by year by road-type level data, I find that light trucks are 1.93 to 2.54 times as likely as cars to get into a crash. The results are rather robust given various combinations of controlling for state fixed effects, year by road-type indicators, and state by road-type-specific linear time trends.

Combining the estimates of the probability of dying given a crash with the estimates of crash frequencies reduces the relative safety of light trucks to drivers, with only vans remaining safer to drive than cars. The crash frequency adjustment also increases the estimated risk posed by light trucks to other drivers relative to cars. This suggests that an efficient regulatory policy should place a relative tax on light trucks with respect to cars. Finally, the crash frequency adjustment changes the implications with respect to minimizing aggregate fatalities. After adjusting for crash frequencies, the results suggest that shifting from light trucks to cars (such as would occur if light trucks were given an efficient tax instead of an implicit subsidy) would reduce the expected number of traffic fatalities. For example, a world in which everyone drives sport-utility vehicles would result in 3.84 times more traffic fatalities than a world in which everyone drives cars.

The following section gives some background on the regulatory differences between cars and light trucks. Section 3 describes the theoretical model and the implications that differential fatality risks have on societal efficiency and the expected number of traffic fatalities. Section 4 describes the data and the identification strategy I use to address the sample selection problem. Section 5 reports the empirical estimates of the relative likelihood of dying given a crash, the relative crash frequencies for cars and light trucks, and the relative expected number of fatalities given different vehicle-type compositions on the road. Section 6 concludes the paper.

2 Regulatory Background

Table 1 documents the emissions and fuel economy regulations for new cars and light trucks from 1991 through 1998. The federal government regulates the tailpipe exhaust emissions of nonmethane hydrocarbons, carbon monoxide, nitrogen oxide, and particulates.[2] These emissions each have different environmental consequences. Carbon monoxide interferes with the ability of blood to circulate oxygen within the body, nitrogen oxide contributes to the acid rain problem, particulates lead to respiratory problems, and hydrocarbons (in combination with nitrogen oxide) produce smog.[3] While in December 1999 President Clinton announced that by 2007 light trucks and cars would be held to the same nitrogen oxide emission standard, the other discrepancies in emission standards will remain. For example, the regulations require that cars not emit more than 3.4 grams per mile of carbon monoxide. Light trucks under 5,750 lbs., however, face a less stringent regulation of 4.4 grams per mile, and those over 5,750 lbs. an even

[2] For the specific regulations, see Title 40 of the Code of Federal Regulations, Subchapter C, Part 86. For a summary of the regulations, see AAMA (1996).
[3] The federal government does not directly regulate non-stationary emissions of carbon dioxide, a greenhouse gas that contributes to global warming.

less stringent regulation of 5.0 grams per mile. Similar discrepancies exist in the regulation of nonmethane hydrocarbons and particulates.

The federal government uses two means to regulate fuel economy: the corporate average fuel economy standards (CAFE) and the gas-guzzler tax. The Energy Policy and Conservation Act of 1975 (see Public Law 94-163) established CAFE standards, which are harmonic-weighted fleet averages for manufacturers of motor vehicles.[4] Currently, the fleet averages for cars must be 27.5 miles per gallon, and the fleet averages for light trucks must be 20.7 miles per gallon. In 1980, Congress established the gas-guzzler tax, which serves as the second means of regulating fuel economy.[5] The tax is levied on the consumer, and the amount of the tax varies depending on the fuel efficiency of the vehicle. Table 1 reports that a car that gets 22.0 to 22.5 miles per gallon is taxed $1,000, while a car that gets fewer than 12.5 miles per gallon is taxed $7,700.[6] There are many gradations of the tax between the endpoints listed in the table. Vehicles that get more than 22.5 miles per gallon are not taxed. Light trucks are exempt from the tax altogether. So, for example, a 2000 BMW 540i Sedan faces a $1,300 gas-guzzler tax, while a 2000 BMW X5 Sport Utility (which gets worse gas mileage than the sedan) faces no gas-guzzler tax.

It should be noted that there are other regulatory discrepancies aside from those pertaining to emissions and fuel economy. For example, light trucks with a gross vehicle weight rating (GVWR) above 6,000 lbs. (e.g., the Ford Excursion) are exempt from the luxury tax.[7] Also, cars are required to have 70 percent visibility in all their windows, while light trucks are only required to have 70 percent visibility through the windshield. Indeed, they need not have any side or rear windows at all.

[4] The CAFE standards are codified in Title 49 of the U.S. Code, section 32902.
[5] The gas-guzzler tax is codified in Title 26 of the U.S. Code, section 4064.
[6] There was a sizable increase in the gas-guzzler tax in 1991 as part of the 1990 Omnibus Budget Reconciliation Act. In 1990 the tax ranged from $500 to $3,850.
[7] In 1998, the luxury tax amounted to an 8% marginal tax rate for cars above $36,000. This tax is currently in the phase-out stage and will be completely eliminated by 2003. The luxury tax is codified in Title 26 of the U.S. Code, section 4001.

This paper does not examine the effect that the current regulatory discrepancies have on vehicle sales. Instead, it focuses on the relative differences in internal and external fatality risks associated with different types of vehicles and the implication these differences have regarding efficient and risk-minimizing regulatory policy. The policy relevance is made more salient when one considers the large increase in the sales of light trucks in recent years. This trend is illustrated in Figure 1.[8] The number of light trucks sold since 1982 has risen dramatically, especially since 1991. There were 8.2 million cars sold in 1991, and this remained unchanged in 1998. Within the same period, light-truck sales increased by 76 percent, from 4.2 million to 7.4 million. Figure 2 shows the increase in light-truck sales from 1991 through 1998, subdividing the light-truck category into pickups, sport-utility vehicles and vans. Sales in each of these categories increased, with the most dramatic increase occurring in the sales of sport-utility vehicles. Within these eight years, the sales of sport-utility vehicles more than tripled, from 0.91 million to 2.82 million. Sales of pickups increased by nearly 50%, from 2.07 million to 3.04 million. Sales of vans increased more mildly, a 31% increase from 1.19 million to 1.56 million. By 1998, the top three selling light trucks (the Ford F Series, the Chevrolet Silverado, and the Ford Explorer) each outsold the top-selling car (the Toyota Camry). This dramatic rise in light-truck sales gives greater importance to an analysis of the fatality risks associated with them.

3 Efficient and Fatality-Minimizing Regulatory Policy

3.1 Willingness to Pay for Vehicle Safety and the Role of Externalities

In order to analyze the efficient distribution of vehicles, I examine the representative individual's consumption decision in purchasing a vehicle. This will lead to inferences concerning the appropriate regulatory responses in the vehicle market. Since the focus of this

[8] Sales data for light trucks and cars come from the 1991 through 1998 issues of the *Automotive News Market Data Book*.

study is on the relationship between vehicle type and fatality risk, the expected utility framework is the appropriate means of examining the individual's consumption decision.

The risk of dying in a traffic crash is subsumed into a state-dependent utility function, where utility in the different states varies depending on the health of the individual.[9] $U_1(X)$ represents utility in the fatality state, and $U_2(X)$ represents utility in the healthy state, where X is a composite good. For any given level of income, I assume that utility is higher in the healthy state ($U_2 > U_1$) and that the marginal utility of income is positive in both states ($\partial U_1 / \partial X > 0, \partial U_2 / \partial X > 0$). The model subdivides the healthy state into two parts: in one sub-state the individual is involved in a crash in which a person in the opposing vehicle dies, and in the other sub-state the individual is not involved in a fatal crash. The representative individual faces a probability of p of dying in a crash, a probability of q of being in a crash that kills someone in the opposing vehicle, and a probability of $1-p-q$ of not being in a fatal crash.[10]

Both the probability of dying and the probability of killing someone in a crash are functions of a vector of safety attributes of the individual's vehicle (s) and the ratio of cars to light trucks on the road (N). The total number of vehicles on the road is assumed to be constant, and each vehicle is either a car or a light truck, with the stock of cars equal to N_C and the stock of light trucks equal to N_T.[11] Thus, N equals N_C/N_T. For simplicity, suppose that the safety attribute we are considering is the size of the vehicle (which could include wheelbase size, length, width, height, weight, cabin space, or other size-related factors). Also assume that a vehicle is a light

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[9] See Arrow (1974) for an introduction to state-dependent utility with respect to health risks. See Viscusi and Evans (1990) for labor market evidence of state dependence.

[10] The empirical section of this paper focuses on driver fatalities in two-vehicle crashes. One can generalize the implications to include non-driver risks, crashes involving fewer or more than two vehicles, and non-fatal risks from crashes.

[11] The empirical section of this paper examines the internal and external risks associated with cars, utility vehicles, vans, and pickups. For the theoretical model I subsume the latter three types of vehicles into the light-truck category. The model can be generalized to the case of multiple vehicle types.

truck if and only if $s > s_0$.[12] Assume for now that light trucks pose lower risks of fatality to those driving them but higher risk of fatality to other drivers (i.e., $\partial p / \partial s < 0$, $\partial q / \partial s > 0$, $\partial p / \partial N < 0$, and $\partial q / \partial N > 0$). I empirically test these assumptions later in the paper.

The representative individual's income is denoted as *Y*, and there is an income loss of *L* given the individual dies and a compensatory income transfer of *V* given an individual in the other vehicle dies. The individual can purchase insurance to cover personal injury losses (*L*) due to a crash, and the individual must by law purchase liability insurance in order to cover partially the damages inflicted on others in a crash (*V*). The individual purchases an amount of personal injury coverage of *q* at a unit price of *m*, and the individual purchases an amount of liability coverage of *q'* at a unit price of *n*. As I will discuss later, insurance companies have recently started charging different premiums for personal injury coverage and liability coverage depending on whether the vehicle is a light truck or a car. Thus, the model postulates that both *m* and *n* are functions of *s*.

The individual is assumed to purchase one vehicle at price *h*, which is a function of *s* and *N*. The individual's optimization decision is as follows:

$$Max\ \ EU = p(s,N)U_1(X) + \{q(s,N)U_2(X) + [1 - p(s,N) - q(s,N)]U_2(X)\}, \quad (1)$$

subject to

$$Y = X + m(s)q + n(s)q' + h(s,N) + Z_0(L - q - V) + Z_1(V - q'), \quad (2)$$

where $Z_0 = 1$ if the driver dies, and $Z_0 = 0$ otherwise; and where $Z_1 = 1$ if the driver does not die but the person in the other vehicle does, and $Z_1 = 0$ otherwise.

The equilibrium condition for the optimal choice of vehicle size is as follows:

[12] This assumption is not entirely accurate since their exists certain cars that weigh more than some light trucks. This affects the policy implications because the large cars are treated no differently from the small cars, and the small light trucks are treated no differently from the large light trucks.

$$\frac{\partial h}{\partial s} = \frac{(U_1 - U_2)\frac{\partial p}{\partial s}}{p\frac{\partial U_1}{\partial X} + (1-p)\frac{\partial U_2}{\partial X}} - (\frac{\partial m}{\partial s}q + \frac{\partial n}{\partial s}q'). \qquad (3)$$

Equation (3) shows the representative individual's marginal willingness to pay (or marginal value) for an additional unit of vehicle size.[13] The first term shows the value placed on reducing the probability of being in the lower utility state with the associated loss of income. This suggests that the larger the price-size gradient, the more the individual is willing to pay for a larger vehicle. The second term shows the net effect of vehicle size on insurance premiums. This suggests that the larger the savings in personal injury coverage for a given increase in vehicle size, the more the individual is willing to pay for a larger vehicle. It also suggests that the larger the savings in liability coverage for a given decrease in vehicle size, the less the individual is willing to pay for a larger vehicle.

Figure 3 illustrates the optimization decision for two different individuals. The vertical axis measures the quantity of the composite good, *X*. Since the price of the composite good is standardized to one, the vertical axis also measures dollars. The size attribute, *s*, is measured on the horizontal axis. The budget constraint for each of these individuals is $Y_0 - h(s,N)$.[14] EU_1 represents the expected utility curve for individual one, and EU_2 represents the expected utility curve for individual two. As depicted, individual two is assumed to have a greater preference for vehicle safety, and this greater preference for safety leads individual two to purchase a light truck, while individual one purchases a car.

The budget constraint in Figure 3 is for a given income and for a given insurance plan. A shift in the pricing of personal injury coverage and liability coverage would lead to a different budget constraint. Up until now, insurance companies have not charged cars and light trucks differentially for personal injury and liability plans. In November 2000, State Farm Insurance,

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[13] See McConnell (1993) for a discussion of how the marginal and non-marginal values of a bundled characteristic can be estimated in a hedonic framework.

the nation's biggest motor vehicle insurer, announced plans to offer a discount on premiums for personal injury plans for drivers of many sport-utility vehicles, vans, and pickups. Whereas State Farm previously offered a 30% discount on personal injury protection for all vehicles with dual air bags, the new plan will give a 40% discount to drivers of many light trucks, while driver's of many cars will only receive a 20% discount.[15] State Farm, nonetheless, did not announce plans to charge light-truck drivers higher premiums for liability coverage. Shortly afterwards, Allstate Insurance Company and Progressive Insurance Group announced that they had begun raising the cost of liability insurance for many light trucks while lowering liability premiums for cars.[16] If the changes in the personal injury and liability premiums cancel each other out, then the budget constraint in Figure 3 would remain unchanged. Otherwise, the constraint would rotate, with the direction of rotation depending on which premium change dominated.

As discussed previously, current regulations on emissions and fuel economy provide an implicit subsidy for light-truck purchases. This implicit subsidy is equivalent to an increase in income (denoted as *W)* and results in a change of the budget constraint of equation (2) as follows:

$$Y + I_0 W = X + m(s)q + n(s)q' + h(s,N) + Z_0(L - q - V) + Z_1(V - q'), \qquad (4)$$

where $I_0 = 1$ if $s > s_0$, and $I_0 = 0$ otherwise.[17]

This new budget constraint is depicted in Figure 4, where the subsidy causes a kink at the point where the safety feature corresponds to a light truck. Given that safety is a normal good, the implicit subsidy would lead to an income effect for $s > s_0$. As illustrated in Figure 4, individual one now purchases a light truck, whereas before the implicit subsidy individual one

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14 Note that the price function need not be linear.
15 See *NY Times*, "Leading Auto Insurer to Cut Rates for Drivers of the Biggest Vehicles," by Joseph B. Treaster, November 28, 2000.
16 See *NY Times*, "2 Insurers Raising Liability Coverage on Bigger Vehicles," by Joseph B. Treaster and Keith Bradsher, December 2, 2000.
17 This increase is equivalent to a constant reduction in the price of light trucks, and could also be represented by a change in the price function.

purchased a car. Thus, the current regulatory framework leads to a greater proportion of light trucks on the road.

To the extent that the external risks of cars are lower than the external risks of light trucks, then people would be willing to pay relatively more for others to purchase cars instead of light trucks. If we return to the original optimization equation (excluding the light-truck subsidy), the equilibrium condition with respect to the composition of vehicles on the road (*N)* is as follows:

$$\frac{\partial h}{\partial N} = \frac{(U_1 - U_2)\dfrac{\partial p}{\partial N}}{p\dfrac{\partial U_1}{\partial X} + (1-p)\dfrac{\partial U_2}{\partial X}}. \qquad (5)$$

Equation (5) describes the marginal value that individuals place on changing the composition of vehicles on the road (i.e., the ratio of cars to light trucks). Given that light trucks pose a greater threat to others than cars (i.e., $\partial p / \partial N < 0$), the equation shows the value placed on reducing the probability of being in the lower utility state with the associated loss of income. Thus, the representative individual is willing to subsidize the purchase of cars relative to light trucks.

It is critical to examine closely the light-truck externality. An individual is willing to pay to reduce the relative stock of light trucks because this would reduce the individual's probability of losing *L-q-V* dollars (income loss minus personal injury compensation minus liability compensation from other driver's insurance company) and would reduce the probability of the relative disutility of being in the non-healthy state (since $U_1 < U_2$). If $q + V$ is enough to cover the income loss and the loss associated with being in a lower utility state, then equation (5) equals zero, and the individual places no value on reducing the relative stock of light trucks.

However, it is unlikely that compensation from the other driver would completely offset the losses, resulting in indifference between being in a fatal crash or not. The other driver is required by law to possess liability insurance, but the most stringent state (Alaska) only requires coverage of $50,000 per individual and $100,000 for all persons injured in the crash. This is far short of the $5 million to $10 million estimates of the value of a statistical life frequently found in the literature.[18] Even if the insurance coverage falls short of covering all losses, the other driver could be required to pay compensation out of pocket. However, this is unlikely to occur, since civil compensation is difficult to obtain in the absence of criminal misconduct. Also, liability payments and civil compensation are only possible if the driver is at fault. For most states, in a no-fault crash there is even a limit on the amount of compensation one can claim from one's own insurance company. If no one is at fault in a crash, then the driver of a large vehicle will not pay higher damages (either through insurance or through civil compensation), even though the larger vehicle may have exacerbated the damages. Therefore, while mandated liability coverage and the potential for civil compensation offers a partial alleviation of the externality, the relatively greater external fatality risks of larger vehicles is not fully internalized into the consumption decision. Even with a mechanism to fully internalize such externalities, the existing regulatory-induced implicit subsidy of light trucks increases the inefficiency, since it provides an additional incentive to purchase a light truck.[19]

If Coasian bargaining were possible, individuals would offer side-payments to encourage others to purchase a car instead of a light truck. Note that people would be willing to pay to have others purchase no vehicle at all, but the point here is that given the purchase of a vehicle, people would be willing to pay to have the purchaser buy a car instead of a light truck.[20] Therefore, the individual optimization decision described in equations (1) and (2) is different from the social optimization decision. Unlike the situation described in equation (4), these side-payments (summed over all individuals not involved in the purchasing decision) would result in an income

[18] See Viscusi (1993) for a review of the literature on the value of a statistical life.
[19] Additionally, the model does not include the relative external environmental risks associated with light trucks. To the extent that light trucks create more external environmental damages than do cars, then equation (5) would indicate a higher willingness to pay for increasing the composition of cars.
[20] That is, people are willing to pay relatively more to prevent the purchase of a light truck than to prevent the purchase of a car.

increase (denoted as *E*) for the purchase of a car instead of a light truck.[21] Therefore, the budget constraint is as follows:

$$Y + I_1 E = X + m(s)q + n(s)q' + h(s, N) + Z_0(L - q - V) + Z_1(V - q'), \qquad (6)$$

where $I_1 = 1$ if $s < s_0$, and $I_1 = 0$ otherwise.

Thus, in the absence of Coasian bargaining, social efficiency is improved when a subsidy is given for car purchases. This situation is illustrated in Figure 5, where the new budget constraint is kinked in the other direction than was the case in Figure 4. This would lead to more individuals purchasing cars instead of light trucks. As illustrated in Figure 5, individual two now purchases a car, whereas previously individual two purchased a light truck.

It is important to note that the precise means of obtaining a social optimum is to subsidize each person to not purchase an additional unit of *s* (or, correspondingly, to tax each unit of *s*). In other words, certain features of a light truck may cause external risks, and efficiency would entail taxing these specific features its marginal external cost and not taxing the entire light truck per se. A Pareto tax on *s* equal to its marginal external cost would thus be the preferred policy decision, and there would be no kink in the budget constraint. Nonetheless, since there are many factors bundled into *s* (weight, height, cabin space, etc.), and it is difficult to disentangle each of these effects, a second-best policy would target light trucks versus cars (given that there are differential external risks across these types of vehicles). One of the aims of this paper is to examine these second-order external risks of light trucks. The issue is particularly salient since the current regulatory framework provides an implicit subsidy on light trucks of any size.

The model therefore implies that if light trucks provide greater safety to a driver, then individuals will be willing to pay more for a light truck. However, to the extent that light trucks are more dangerous to other drivers in crashes, then purchasing a light truck creates a negative externality, and societal efficiency only results if there is a mechanism by which side-payments

[21] This increase in income can equivalently be represented as a constant reduction in the price of cars.

can be transferred to those purchasing cars instead of light trucks. At the very least, the current policy of subsidizing light trucks moves us further away from the social optimum. While a priori one might assume that, *in the event of a crash*, the greater size of light trucks would make them safer for the driver and more dangerous to other drivers (relative to cars), this assumption might not hold if the likelihood of getting into a crash is different for light trucks relative to cars. If light trucks are more prone to crashes than are cars, then this would decrease the relative safety of light trucks to those who drive them and increase the relative danger to other drivers. Similarly, if cars are more prone to crashes than are cars, then this would reduce the relative external risk associated with light trucks and increase the relative internal risk associated with cars.

3.2 Minimizing Total Fatalities

Even if one assumes for now that light trucks pose greater external risks than do cars, the efficient policy of internalizing the relatively greater external risks of light trucks might not lead to fewer traffic fatalities. This point is demonstrated by examining Figure 6. For ease of exposition, assume that Driver 1 and Driver 2 discussed in Figures 3-5 are the only two drivers in the world. The top left cell corresponds to a world in which both people drive cars (which corresponds to Figure 3). Either the top right cell or the bottom left cell corresponds to a world in which one person drives a car and the other drives a light truck (which corresponds to Figure 4). The bottom right cell corresponds to a world in which both people drive light trucks (which corresponds to Figure 5). For each cell, the probability of Driver 1 dying in a crash is in the lower left-hand corner, and the probability of Driver 2 dying in a crash is in the upper right-hand corner. If one assumes that light trucks pose a smaller internal risk but a greater external risk than do cars, then $S<X<R$ and $S<Y<R$. However, the expected number of fatalities given a crash is ambiguous. In order to determine which vehicle-type crash combination minimizes the expected number of fatalities, one needs to know the relationship between X and Y, the relationship

between X and S+R, and the relationship between Y and S+R. The theoretical model does not yield information on these relative values.

The empirical goal of this paper is to estimate the extent of the relative internal and external risks associated with different vehicle types. This is done by first estimating the risks of dying given a crash and then combining these estimates with estimates of the relative crash frequencies of different types of vehicles. These estimates will in turn address whether the expected number of fatalities increases or decreases given a policy that provides incentives for purchasing cars.

4 Data Description and Identification Strategy

4.1 Driver Fatality Risk Given a Two-Vehicle Crash

The first goal is to estimate the probability of dying given that a crash has occurred. For simplicity, the analysis focuses on the probability of *driver* death given a two-vehicle crash. I use data from 1991 through 1998 from the *Fatal Analysis Reporting System* (FARS), which is a census of all the crashes in the United States that involved a fatality.[22] FARS contains detailed information on the characteristics of the crash, the characteristics of each vehicle involved in the crash, and the characteristics of each person involved in the crash.

The analysis considers only the crashes that involve cars, sport-utility vehicles, van-based light trucks, and pickups.[23] This excludes crashes that involve buses, trucks greater than 10,000 pounds, motorcycles, mopeds, all-terrain vehicles, all-terrain cycles, as well as other small vehicles such as snowmobiles and go-carts. That leaves 103,056 drivers involved in two-vehicle crashes from 1991 through 1998 in which at least one of the drivers died. Table 2 reports the number of such crashes by types of vehicles involved, as well as the number of driver fatalities

[22] The fatality must occur within 30 days of the crash in order to be included in the data set. FARS was started in 1975 by the Department of Transportation's National Highway Traffic Safety Administration (NHTSA).

for each vehicle, by vehicle-type pair. The top number in each cell is the number of fatalities of drivers in Type I vehicles who died in a crash with a Type II vehicle. The bottom number in parentheses is the total number of crashes involving Type I and Type II vehicles in which at least one of the drivers died.

One can obtain a sense of the relative risk of each vehicle type by comparing the symmetrical, off-diagonal cells. Since the goal of this paper is to analyze the risk differential between cars and light trucks, of particular interest is the comparison between the off-diagonal cells of the first column and their symmetrical cells on the first row. For example, there were 4,749 crashes between a car and a sport-utility vehicle in which at least one driver died. Of these crashes, 945 sport-utility vehicle drivers died, while 3,990 car drivers died. This suggests that, given such a fatal crash, the driver of the car is 4.2 times as likely to be the one who dies than is the sport-utility vehicle. Similarly, given a fatal crash between a van and a car, the driver of the car is 5.0 times as likely to be the one who dies; and given a fatal crash between a pickup and a car, the driver of the car is 3.8 times as likely to be the one who dies.

Table 3 presents data on the two-vehicle *head-on* crashes that involved a driver fatality.[24] Of the 1,173 fatal head-on crashes between a car and a sport-utility vehicle, 226 drivers in the sport-utility vehicle died, while 1,056 drivers in the car died, indicating that the car driver is 4.7 times as likely to be the one who dies. In a fatal head-on crash between a car and a van, the driver of the car is 4.7 times as likely to be the one who dies; and in a fatal head-on crash between a car and a pickup, the driver of the car is 3.1 times as likely to be the one who dies.

Comparing symmetrical off-diagonal cells is informative about the relative risks of the two-vehicles involved, but comparing non-symmetrical cells can be misleading. The naïve method would be to divide the number of fatalities by the number of fatal crashes to obtain a risk measure to compare to other cells. For example, from Table 2 one finds that, given a fatal crash

[23] For this paper, "pickups" include all light conventional trucks that have a gross vehicle weight range (GVWR) below 10,000 lbs.

between a car and a sport-utility vehicle, 84% of the drivers of cars died. Similarly, given a fatal crash between a car and a van, 87% of the drivers of the cars died. But one cannot directly compare these numbers since doing so neglects the sample selection bias that could exist due to the omission of data on nonfatal crashes. For example, assume that vans and sport-utility vehicles are equally likely to get into a crash, and also assume that sport-utility vehicles are less of a threat than are vans. In this case, a sport-utility vehicle crashing into a car would be less likely to result in a fatality, and such crashes would be excluded from the data set. In other words, the denominator (4,749) for sport-utility crashes would be under-represented relative to the denominator for vans (5,074). This would result in an upward bias of the risk that sport-utility vehicles pose to cars. However, the direction of the bias is unclear. If the less-threatening sport-utility vehicles are more dangerous to those who drive them (relative to vans), then the sport-utility denominator would be over-represented, and their would be a resulting downward bias of the risk that sport-utility vehicles pose to cars.

The sample selection problem exists because there are no reliable data on *non-fatal* crashes by vehicle type. The number of non-fatal crashes by vehicle type is the appropriate denominator to use in order to obtain unbiased estimates. As long as the type of vehicle affects the probability of death, then vehicle type will determine whether the crash is included in the data set, thus biasing the sample. Of course, even without the sample-selection problem, the information provided in Table 2 and Table 3 is limited since the estimates are not regression-adjusted. To take just one potential problem, if older people tend to sort into a certain vehicle type, then these tables would report an upwardly biased risk estimate for those types of vehicles.

4.2 Identification Strategy for Driver Fatality Risk Given a Two-Vehicle Crash

In order to control for the sample selection bias, I adjust the predicted probabilities of fatalities given a fatal crash using information on the number of pedestrian fatalities by vehicle

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[24] A head-on crash is defined as one in which the principal impact point was at 12 o'clock for both vehicles.

type. Under certain reasonable assumptions, this leads to unbiased estimates of the relative probabilities of death given crashes with different types of vehicles. The goal is to estimate the effect that opposing vehicle type has on the likelihood of a driver dying given a crash. A simple logit model using the FARS data gives an estimate of the probability a driver of a vehicle of Type i dies given a *fatal* crash with a vehicle of Type j (with i and j equal to car, sport-utility vehicle, van, or pickup).[25] To the extent that vehicle type has an effect on the severity of the crash, then it also would affect the likelihood that a crash is included in the sample. Therefore, the logit estimate would be biased. However, from this estimate, one could derive an estimate of the predicted number of deaths to drivers of vehicle Type i given a fatal crash with drivers of vehicle Type j, conditional on the other covariates. If one knew the total number of crashes involving Type i and Type j vehicles, then one could estimate the probability that a driver of a vehicle of Type i dies given a crash with a vehicle of Type j. The problem is that one does not know the number of crashes (fatal and non-fatal) by vehicle types. The FARS data set does, however, contain the cases in which a vehicle crashes into and kills a pedestrian. Under a set of reasonable assumptions, the number of crashes in which a vehicle of Type i kills a pedestrian is proportional to the total number of crashes involving Type i vehicles. Further, under certain assumptions, this proportion is the same for all vehicle types.[26]

For notational convenience, let y_{ij} equal the number of two-vehicle crashes involving Type i and Type j vehicles, and let y_i equal the total number of crashes involving Type i vehicles. Let p_{ij} equal the probability that a given two-vehicle crash involves vehicles of Type i and j, and let p_i equal the probability that a given crash involves one vehicle of Type i. Let w_i equal the number of crashes of vehicles of Type i into a pedestrian, and let w_i^f equal the number of crashes of vehicles of Type i into a pedestrian in which the pedestrian dies. Finally, let Y equal the total

[25] Throughout this paper, a *fatal* crash is one in which at least one of the drivers dies.

number of two-vehicle crashes. As mentioned before, the goal is to obtain information on y_{ij}. This information is not included in FARS, but one can instead use information on w_i^f, which is included in FARS.

Assumption 1: $p_{ij} = p_i p_j$.

This assumption is that the probability that one of the vehicles in a given two-vehicle crash is of a certain type is independent of the probability that the other vehicle is of a certain type. This seems reasonable, since there are no clear reasons why different types of vehicles would cluster in crashes disproportionately more than other types.[27]

Assumption 2: $y_i = \alpha_1 w_i$ and $y_j = \alpha_1 w_j$, for all i and j.

This assumption is that the total number of crashes of a certain type of vehicle is proportional to the total number of crashes of that type of vehicle into a pedestrian, *and this proportion is the same across vehicle types*. In other words, certain types of vehicles do not hit pedestrians disproportionately.

Assumption 3: $w_i = \alpha_2 w_i^f$ and $w_j = \alpha_2 w_j^f$, for all i and j.

This assumption is that the number of pedestrian crashes involving a certain type of vehicle is proportional to the number of crashes in which the same type of vehicle kills the pedestrian, *and this proportion is the same across vehicle types*. This means, for example, a van hitting a pedestrian is as likely to kill the pedestrian as is a car hitting a pedestrian.[28]

Implications:

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[26] See Evans (1985) for a discussion of these assumptions pertaining to passenger car sizes.

[27] This assumption could be violated if certain types of vehicles present conflicting visibility conditions. For example, the greater height of utility vehicles with respect to the height of cars could lead to a disproportionate number of crashes between these two types of vehicles.

[28] This assumes that there exists a threshold vehicle size above which the probability of a pedestrian fatality given a crash remains constant (and that cars and light trucks are all above this threshold).

Given these three assumptions, let us examine what we know about the total number of two-vehicle crashes involving a vehicle of Type i and a vehicle of Type j.

1) $p_{ij} = p_i p_j$	→	By Assumption 1
2) $y_{ij} / Y = (y_i / Y)(y_j / Y)$	→	By Definition
3) $y_{ij} = y_i y_j / Y$	→	Rearranging Terms
4) $y_{ij} = (\alpha_1 w_i)(\alpha_1 w_j) / Y$	→	By Assumption 2
5) $y_{ij} = (\alpha_1 \alpha_2 w_i^f)(\alpha_1 \alpha_2 w_j^f) / Y$	→	By Assumption 3
6) $y_{ij} = k w_i^f w_j^f$	→	Where $k = \frac{(\alpha_1 \alpha_2)^2}{Y}$

Note that the constant term, *k*, is the same for all values of i and j. This is due to the second and third assumptions. The result is that once one uses the FARS data to estimate the predicted number of drivers of vehicle Type i that died in crashes with drivers of vehicle Type j, then this value can be divided by $w_i^f w_j^f$, which is a constant proportion of the number of crashes involving these types of vehicles (and which is obtainable from the FARS data). By doing this for all the vehicle-type crash combinations, one obtains an unbiased estimate of the probability of a driver in a Type i vehicle dying given a crash with a Type j vehicle.

4.3 Crash Frequencies by Vehicle Type

In order to estimate crash frequencies by vehicle type, I use the Department of Transportation's *Highway Statistics Series* data for 1994 through 1998. The data is disaggregated to the state by year by road-type level. The road-type categories are rural interstate, rural non-interstate, urban interstate, and urban non-interstate.[29] The independent variable of interest is the

[29] Urban refers to geographic areas with populations over 5,000 people, and rural refers to all other areas.

number of vehicle miles traveled (VMT) for both for cars and light trucks.[30] Unlike the FARS data discussed in the previous sub-section, the VMT data combines all information on sport-utility vehicles, vans, and pickups into one "light truck" category, so I am unable to test whether crash frequencies vary by specific types of light trucks.

For the dependent variable I use pedestrian fatalities by vehicle type on the state by year by road-type level. Given the assumptions in the previous subsection, this measure is proportional to the number of crashes by vehicle type. Without knowing the exact value of this proportionality, one can only estimate the proportional effect of VMT by vehicle type on crashes by vehicle type. However, since this proportionality is assumed constant across vehicle types, the ratio of the estimated coefficients yields an estimate of the relative crash frequency of light trucks versus cars.

The observational nature of the data makes it difficult to make strong causal claims. The ideal experiment would be to randomly assign people into light trucks and cars, and to then test whether crash frequencies vary across the vehicle types. Changes in crash frequencies could be due to how prone a vehicle is to crashing or to changes in driving behavior when one is placed in a certain type of vehicle.[31] The most obvious limit to using the observational data is the possibility of selection bias.[32] If riskier people select into certain vehicle types, then the regression coefficients would over-estimate the risk of crashing associated with the vehicle type.

In the regression estimates I first include various combinations of state fixed effects, year indicators, and state linear trend variables. I then run separate regressions using various combinations of state fixed effects, year by road-type indicators, and a state by road-type specific linear time trend variables. Each one of these controls passes an F-test in which the restricted

[30] The VMT data for each vehicle type includes most, but not all, non-interstates. For rural non-interstates, the VMT data cover rural other principal arterial and minor arterial. For urban non-interstates, the VMT data cover other freeways and expressways, other principal arterial, and minor arterial.
[31] Peltzman (1975) was the first to test whether driving behavior changes when exposed to safer conditions.
[32] The results would also be biased if the choice of vehicle type affects the number of vehicle miles traveled. For this analysis, I assume that this is not the case.

model of comparison does not include road-type specific controls. These variables allow me to control for any mean shifts in risky driving behavior on a rather disaggregated level and they also control for any trends in risky driving occurring over time within each state's four road-types. These controls should mitigate any selection bias; however, if risky drivers select into either light trucks or cars, and this selection does not either trend linearly within a state's road-types, and if the selection is also not captured in mean shifts across states or years, then the estimates will still be biased.

For each specification, I stratify the sample to estimate the gradient of pedestrian fatalities by vehicle type with respect to VMT by vehicle type for both light trucks and cars. Each specification also includes controls for each state's unemployment rate and each state by road-type speed limit.[33] I then form the ratio of these coefficient estimates in order to estimate the relative crash frequencies of light trucks versus cars.

5 Empirical Results

5.1 Driver Fatality Risk Given a Two-Vehicle Crash

Table 4 reports the estimation results of driver fatality risk for each type of driver, conditional on opposing vehicle type. As discussed in the previous section, I use pedestrian fatalities by vehicle type to adjust for the sample selection bias. Keep in mind that this method yields predicted probabilities within a proportionality factor. I stratify the sample by the type of vehicle that the driver is in, which is represented in the separate columns of Table 4. Each column represents the results of a logit model in which the dependent variable equals one if the driver died, and equals zero otherwise. The variables of interest are a series of dummies denoting the type of vehicle that the driver crashed into (i.e., car, sport-utility, van, pickup, with the car dummy withheld as the comparison group).

Though not listed in the table, the regression includes covariates for both drivers and for crash conditions. The drivers' covariates are age, age squared, sex, whether an air bag was deployed, whether the driver was wearing a seat belt, whether the driver was drunk, and whether the driver had any major or minor traffic incidents within three years before the crash. Major incidents are accidents, DWI convictions, suspensions and revocations of license. Minor incidents are speeding and other moving violations. The variables describing the crash conditions are the road condition (wet or dry), the type of road (rural interstate, rural non-interstate, urban interstate, or urban non-interstate), the speed limit, the time of day (four six-hour dummy variables), and the year.

Heteroskedastic-consistent standard errors are reported in parentheses beneath the coefficient estimate, and the mean predicted probabilities for each opposing vehicle type are reported in brackets.[34] These bracketed predicted probabilities are the estimates without adjusting for the possible sample selection bias, and thus offer a means of comparison with the adjusted estimates. The sample-selection adjusted predicted probabilities are reported in braces. For the results reported in the tables, I used total counts of pedestrian fatalities by vehicle types to adjust for the sample selection. I also used year-specific pedestrian fatality counts to weight each predicted probability. These latter results are not reported in the paper since they are nearly identical to the reported estimates. Since the sample selection adjustment yields *relative* risks across vehicle types, I standardized the predicted probabilities so that the probability of a car driver dying given a crash with another car driver is one.

Both the unadjusted and the adjusted results strongly suggest that no matter what type of vehicle one drives, crashing into a sport-utility vehicle, van, or pickup poses a greater risk than does crashing into a car. They both also suggest that no matter what type of vehicle one crashes

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[33] The speed limit data are coded as indicators for 55 mph, 65 mph, 70 mph, and 75 mph and above. I designated a road-type as a given higher speed limit if any of the roads within the road-type qualified for the higher limit.

into, one is at a significantly greater risk if one is in a car rather than a light truck. However, the sample-selection adjusted results do suggest a different ordering of risks among the different light trucks. The unadjusted estimates suggest that it is less risky to crash into a pickup than it is to crash into a sport-utility vehicle, and that it is less risky to crash into a sport-utility vehicle than it is to crash into a van. The results after correcting for sample-selection bias indicate that in a crash, vans tend to pose less risk to others than do sport-utility vehicles, and pickups tend to pose the greatest risk to others. These discrepancies suggest that the fatality crash data over-represent the risk posed by vans relative to the risk posed by sport-utility vehicles and pickups.

For ease of exposition, Panel A of Figure 7 reports the predicted relative probabilities of a driver dying given a crash with different types of vehicles. The x-axis groupings are for each possible vehicle choice of the driver, and the vertical bars show the probability of dying conditional on a crash with each type of vehicle. Each x-axis grouping is standardized so that the probability of dying given a crash with a car is equal to one. Thus, only comparisons within each grouping are possible.

The results of Panel A indicate that, given a crash, light trucks pose significantly higher risks to other drivers than do cars. For example, relative to crashing into a car, a car driver is 1.88 times as likely to die if the opposing vehicle is a sport-utility vehicle, 1.50 times as likely to die if the opposing vehicle is a van, and 1.88 times as likely to die if the opposing vehicle is a pickup. The results are similar across the driver's vehicle designation. No matter what vehicle the driver drives, pickups pose the highest external risks in a crash. And for car, sport-utility, and pickup drivers, crashing into a sport-utility is riskier than crashing into a van.

Panel B of Figure 7 reports the predicted relative probabilities of dying depending on the type of vehicle the driver is driving. The x-axis groupings are for each type of opposing vehicle, and the vertical bars show the probability of dying, given a crash, depending on the driver's

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[34] Note that the predicted probabilities given that the driver crashes into a car are reported under the coefficient estimates for the intercept term.

vehicle type. Each x-axis grouping is standardized so that the probability of a car driver dying is one. Thus, only comparisons within each grouping are possible.

The results of Panel B indicate that driving a light truck is significantly safer for a driver than is driving a car. For example, given a crash with a car, a sport-utility vehicle driver is 0.44 times as likely to die than is a car driver, a van driver is 0.30 times as likely to die than is a car driver, and a pickup driver is 0.50 times as likely to die than is a car driver. The results are similar across the different types of opposing vehicle. No matter what the opposing vehicle, driving a van poses the lowest risk to the driver in the event of a crash, driving a sport-utility vehicle is the next safest, and driving a pickup is the least safe among the light trucks.

5.2 Driver Fatality Risk Given a Two-Vehicle Head-On Crash

Approximately 30 percent of all fatal two-vehicle crashes involve head-on crashes. Table 5 reports the results of estimations using the pedestrian fatality correction in which the sample is restricted to include only crashes in which the principal impact was at 12 o'clock for each vehicle. The findings are similar to the findings using the full sample.

Figure 8 contains the relative external and internal fatality risk for head-on crashes. As with the sample of all crashes, Panel A indicates that in head-on crashes light trucks pose a substantially greater risk to other drivers than do cars. Among all light trucks, vans tend to pose the smallest risk to others, and pickups tend to pose the highest risk to others. By comparing to Panel A of Figure 7, one surprisingly finds that for a driver a car, crashing head-on into a light truck instead of a car increases the risk of dying by proportionally less than is the case for all crashes. However, the relative increase in the external risk of light trucks is greater for sport-utility vehicle, van, and pickup drivers in the case of head-on crashes. Panel B indicates that in head-on crashes, it is safer to be in a light truck rather than a car. As with the full sample results, given a head-on crash, it is safest for the driver to be in a van, and next to cars, it is least safe to be in a pickup.

5.3 Crash Frequencies by Vehicle Type

Table 6 presents the results of the regression of pedestrian fatalities caused by each vehicle type against vehicle miles traveled (VMT) of each vehicle type. The top panel is for cars and the bottom panel is for light trucks. Each observation is on the state by year by road-type level. Each of the six columns in Table 6 represents different combinations of control variables in the specification. The coefficient estimates are positive and significant at less than the one-percent level for each specification (heteroskedastic-consistent t-statistics are listed in parentheses). Given the assumptions described in sub-section 4.2, the ratios of the coefficient estimates suggest that light trucks are 2.43 to 2.54 times as likely to crash than are cars. The results are stable across specifications.

Table 7 presents results from similar specifications, except that these equations now control for state by road-type fixed effects and for a state by road-type specific linear time trend. Again the results are positive, statistically significant, and rather robust across specifications. The results suggest that light trucks are 1.93 to 2.53 times as likely to crash than are cars.

Since light trucks are more likely to crash than are cars, the relative external and internal risks of light trucks presented in Figure 7 are underestimates. In Panel A of Figure 9, I add an adjustment for crash frequency to the estimates of the probability of dying given a crash. I use an estimate of 2.2 for the relative crash frequency of light trucks versus cars. The external risks of light trucks are now much higher than was indicated in Figure 7, suggesting that a light truck is between 3.26 and 5.78 times as likely to kill another driver than is a car. In Panel B of Figure 9, I add an adjustment for crash frequency to the estimates of the probability of dying given a crash. The internal risks of light trucks are now not nearly as low relative to cars as was depicted in Figure 7, where frequency rates were assumed constant. Driving a sport-utility vehicle is now seen to be as dangerous as driving a car, and driving a pickup is slightly more dangerous than driving a car. Vans, however, still maintain a safety advantage compared to cars. For comparison, Figure 10 presents the head-on crash risks adjusted for crash frequencies.

5.4 Aggregate Fatalities Given Different Vehicle-Type Compositions

Previous studies have claimed that a crash involving two lighter vehicles tends to result in fewer expected deaths than a crash involving two heavier vehicles.[35] However, these studies implicitly assume that crash frequencies are constant for both types of vehicles. This may not be the case when comparing light trucks with cars. In order to obtain an appropriate estimate of the expected number of traffic fatalities given different compositions of vehicle types, one needs to consider whether crash frequencies vary by vehicle type.

Suppose that there are *N* vehicles in the world, that the number of cars equals *C*, and the number of light trucks equals *T*. Also assume that $C + T = N$. Let γ_{ij} equal the probability that a driver of vehicle type *i* is killed by a driver of vehicle type *j*, conditional on a crash between the two vehicles. Let β_{ij} equal the probability of vehicle type *i* crashing with vehicle type *j*. Then the probability (P_c) of a car driver being killed in a two-vehicle crash, and the probability (P_T) of a light truck driver being killed in a two-vehicle crash are given as follows:

$$P_C = \gamma_{CC}\beta_{CC}C + \gamma_{CT}\beta_{CT}T$$
$$P_T = \gamma_{TC}\beta_{TC}C + \gamma_{TT}\beta_{TT}T.$$

The expected number of traffic fatalities (*E*) is $P_C C + P_T T$. Let us examine three different cases. Case 1 is a world in which all vehicles are cars (i.e., $C=N$, $T=0$). Case 2 is a world in which all vehicles are light trucks (i.e., $C=0$, $T=N$). Case 3 is a world in which half the vehicles are cars and half are light trucks (i.e., $C=N/2$, $T=N/2$). The expected number of traffic fatalities in each state is given as follows:

[35] See, for example, Evans (1984). Crandall and Graham (1989) use Evans's estimates to suggest that the lighter vehicles resulting from CAFE standards led to more deaths.

$$E_1 = \gamma_{CC}\beta_{CC}N^2$$
$$E_2 = \gamma_{TT}\beta_{TT}N^2$$
$$E_3 = (\frac{N^2}{4})(\gamma_{CC}\beta_{CC} + \gamma_{TT}\beta_{TT} + \gamma_{CT}\beta_{CT} + \gamma_{TC}\beta_{TC}).$$

While the empirical results did not yield estimates for each of the parameters in the above equations, they do contain estimates of the ratios of the gammas and betas. Thus, one can use the empirical estimate to compute the number of fatalities in one state of the world relative to another state of the world (i.e., E_3/E_1 and E_2/E_1). The top panel of Table 8 presents the estimates of the relative expected number of fatalities given that crash frequencies do not vary across vehicle types. According to these results, a world with only sport-utility vehicles or vans (or 50 percent of each) is indeed a world with fewer traffic fatalities than is a world with only cars. However, when one includes the greater crash likelihood for light trucks relative to cars, the results change dramatically. The bottom panel of Table 8 presents the expected number of fatalities relative to a world in which everyone drives cars. The results suggest that a world in which everyone drives sport-utility vehicles would result in 3.84 times more fatalities than a world in which everyone drives cars. A world of vans would result in 2.81 times more fatalities than a world of cars. A world of pickups would result in 6.31 times more fatalities than a world of cars. The off-diagonal cells give estimates in which half the vehicles are of each respective vehicle type, and also indicate that these states lead to more fatalities than a world with only cars. Minimization of traffic fatalities results when all vehicles are cars.

5.5 Implications

The results suggest that, given a crash, it is substantially safer for a driver to be in a sport-utility vehicle, van, or pickup instead of a car. However, a light truck poses a substantially greater risk to the other driver in the crash than does a car. Light trucks are also more likely to get into a crash than are cars, thus eliminating the safety advantage that sport-utility vehicles and vans pose to their drivers and increasing the risk they pose to other drivers. An efficient regulatory policy would therefore place a relative tax on light trucks versus cars in order to account for this externality. Creating a disincentive to purchase light trucks would also lead to fewer traffic fatalities.

6 Conclusion

The currently regulatory framework for motor vehicles was developed in the 1970s and the early 1980s. The Clean Air Act Amendments of 1970 established tailpipe emission standards, the Energy Policy and Conservation Act of 1975 established fuel economy standards for the manufacturers of new vehicles, and the 1980 gas-guzzler tax created a tax on consumers who buy vehicles with poor gas mileage. At the time these regulations were established, there were only 20 million light trucks on the road, and most of them were commercial vehicles. In an attempt to protect industry, the regulations placed on light trucks were considerably more lax than those placed on cars. But in 1984, Chrysler introduced the mini-van, and since it was partly based on a pickup design, Chrysler was able to convince regulators to categorize it as a light truck. Since then, the number of light trucks driven for non-commercial purposes has increased dramatically. Today, light trucks make up nearly half of all family vehicles sold, and there are an estimated 63 million light trucks on the road (see U.S. Dept. of Transportation, 1997).

The regulatory differences create an implicit subsidy for light trucks. This subsidy is inefficient when one considers the external fatality risks associated with light trucks. From 1991 through 1998, there were 25,718 fatal crashes between a car and a light truck. Of these fatal crashes, 5,323 light-truck drivers died, while 21,629 car drivers died. A car driver is 3.29 to 4.13 times as likely to be killed by a light truck versus a car. A sport-utility vehicle driver is 3.26 to 4.31 times as likely to be killed by a light truck versus a car. A van driver is 4.04 to 4.53 times as likely to be killed by a light truck versus a car. And a pickup driver is 3.33 to 5.78 times as likely to be killed by a light truck versus a car. The existence of external risks associated with light trucks suggests that an efficient regulatory policy would be one that provides a relative disincentive for purchasing light trucks.

From an efficiency perspective, regulatory policy for vehicles should be formulated so that all risks are internalized into the consumption decision. In such a way, consumers can optimally trade off risk (both internal and external) with other characteristics of the vehicles (e.g., fuel economy and reliability). From a public health perspective, the pertinent issue is whether the greater external fatality risk posed by light trucks more than offsets the reduced internal risk posed by light trucks. The results suggest that a regulatory incentive that moves light-truck drivers into cars would likely result in fewer traffic fatalities. A world of light trucks would result in more than twice as many traffic fatalities than a world of cars. Thus, an efficient policy of providing relative disincentives for light-truck purchases would also improve public health.

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Figure 1: U.S. Car and Light Truck Sales (1982-1998)

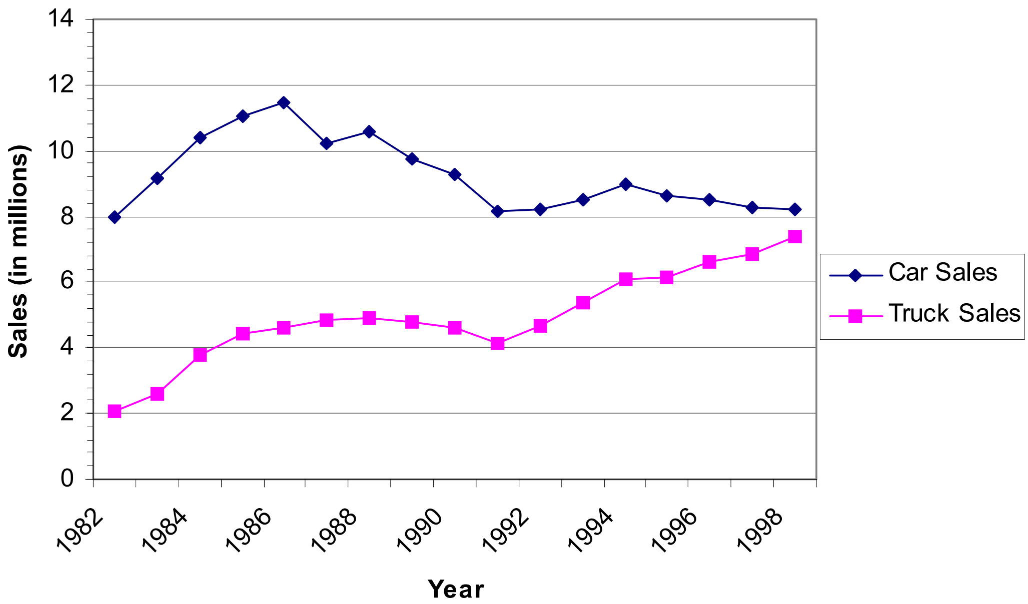


Figure 2: U.S. Light Truck Sales (1991-1998)

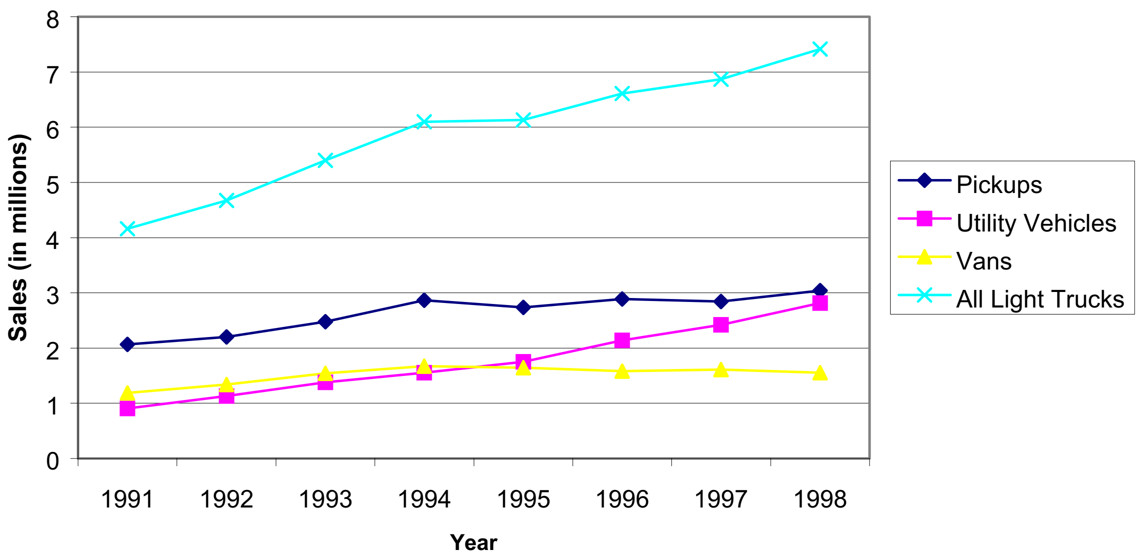


Figure 3: Individual Optimization of Vehicle Size

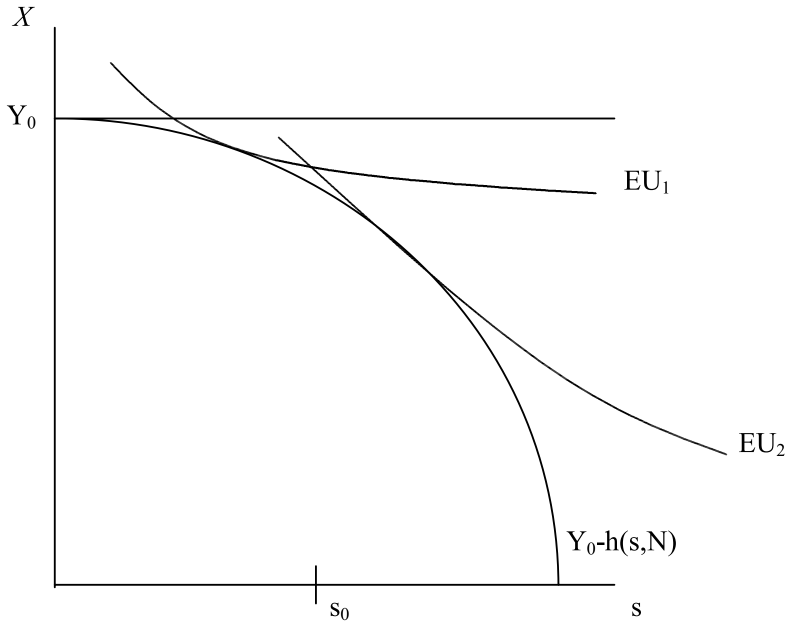


Figure 4: Individual Optimization of Vehicle Size Given a Light-Truck Subsidy

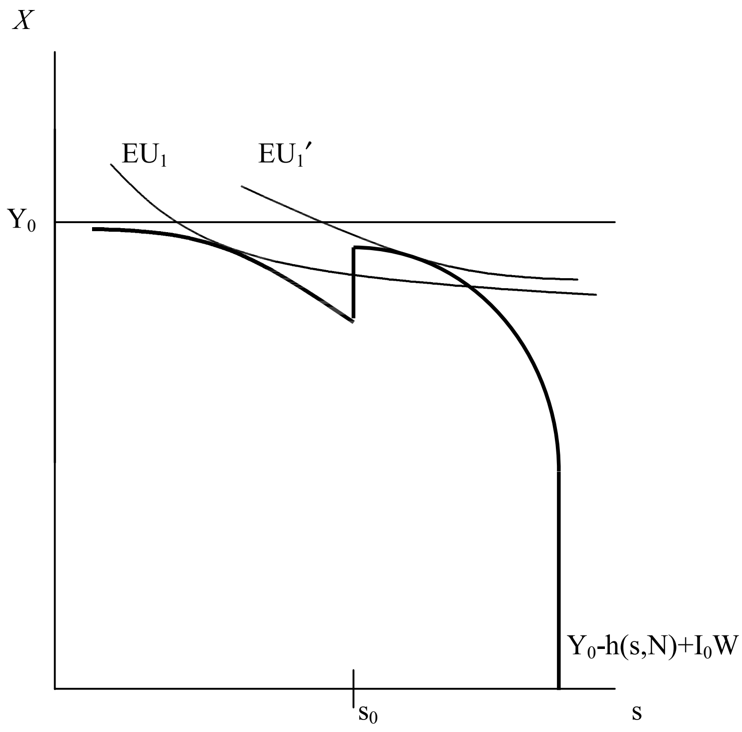


Figure 5: Individual Optimization of Vehicle Size Given a Car Subsidy

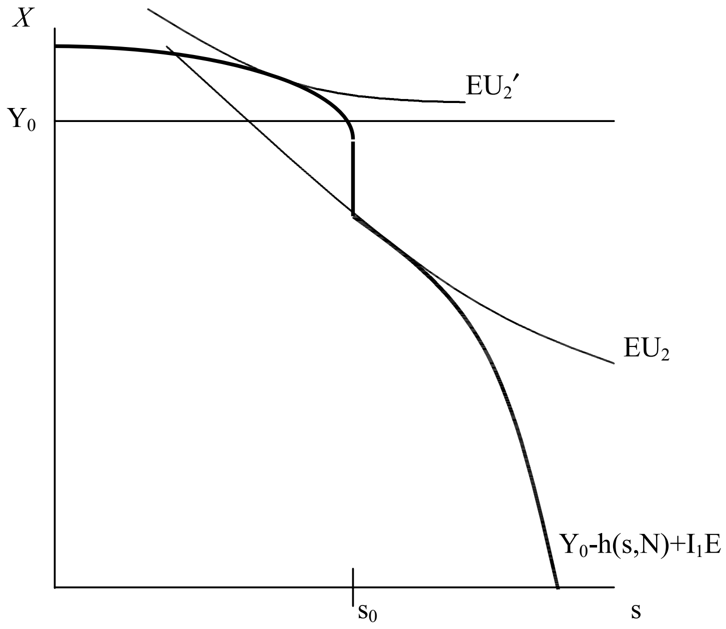


Figure 6: A Matrix of Driver Fatality Risks by Vehicle Types

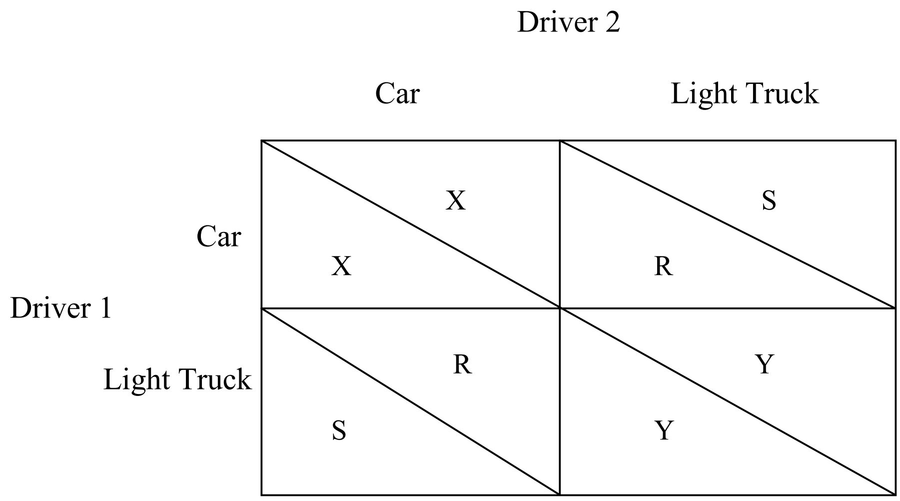


Figure 7: Relative External and Internal Driver Risk in a Two-Vehicle Crash

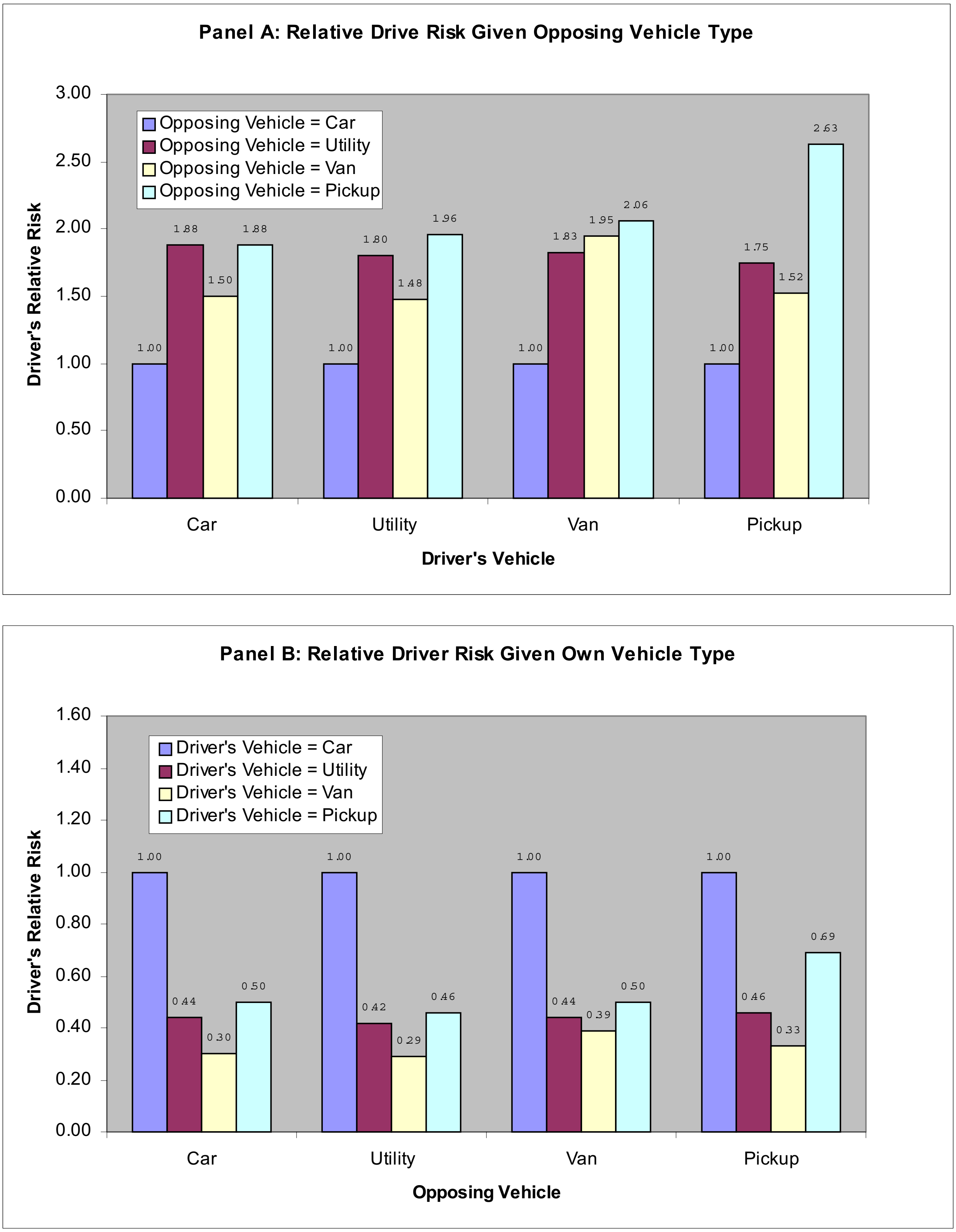


Figure 8: Relative External and Internal Driver Risk in a Two-Vehicle Head-On Crash

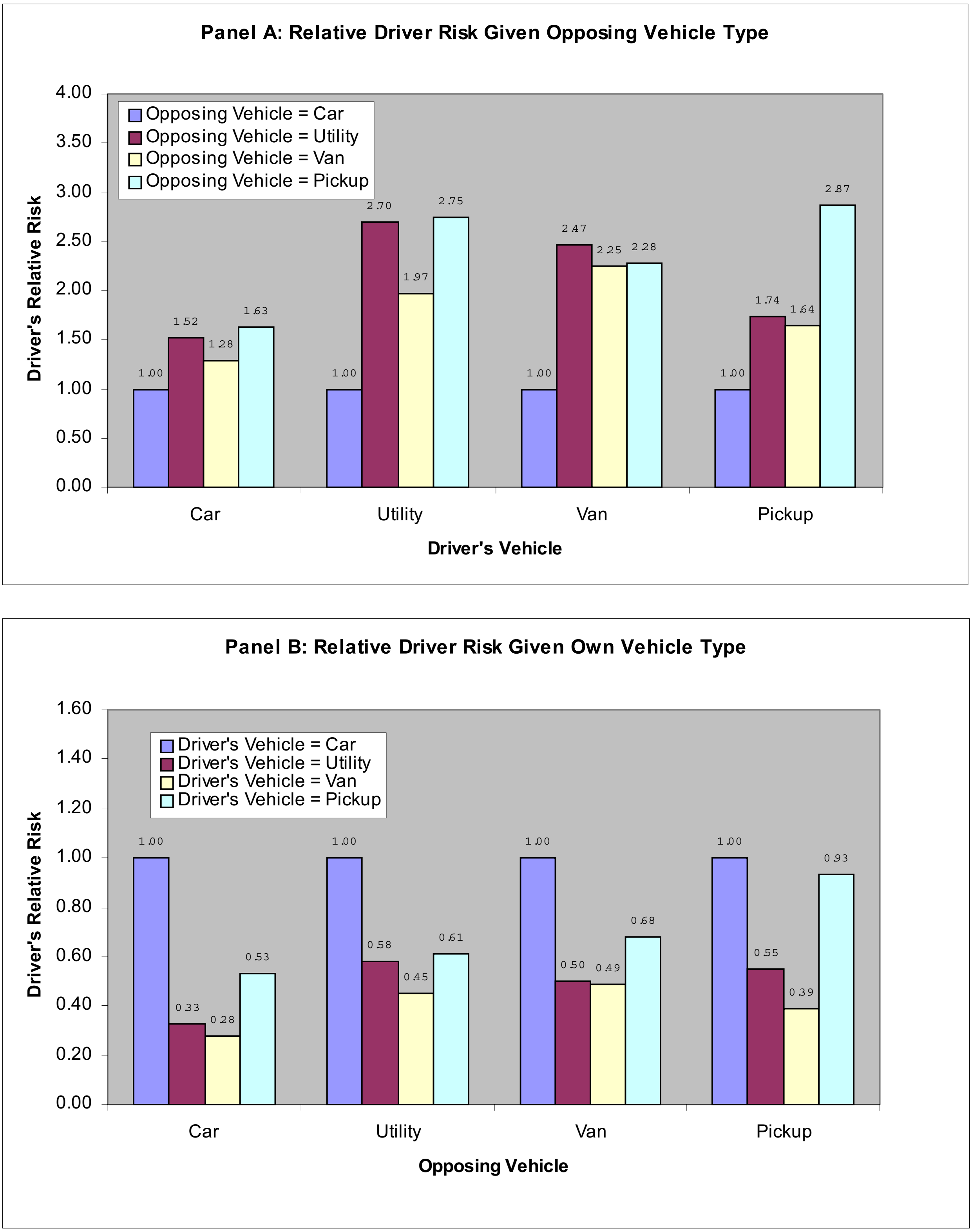
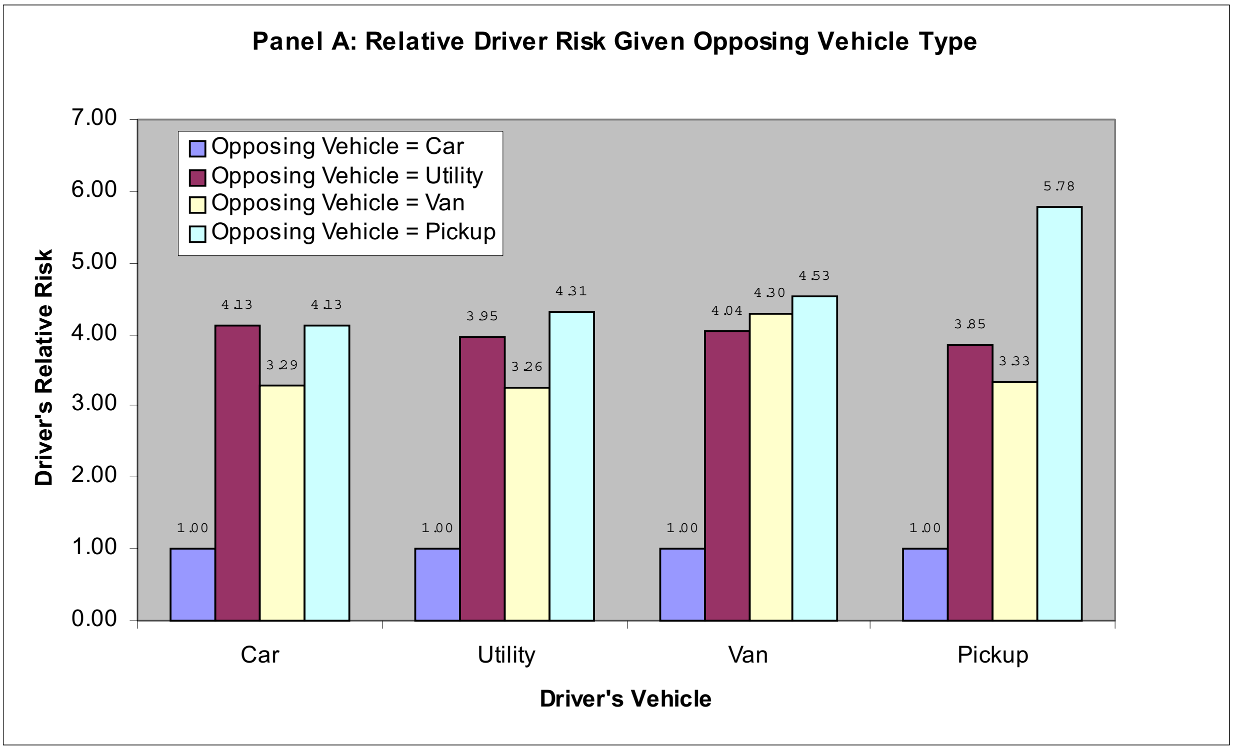


Figure 9: Relative External and Internal Driver Risk (Frequency Adjusted)



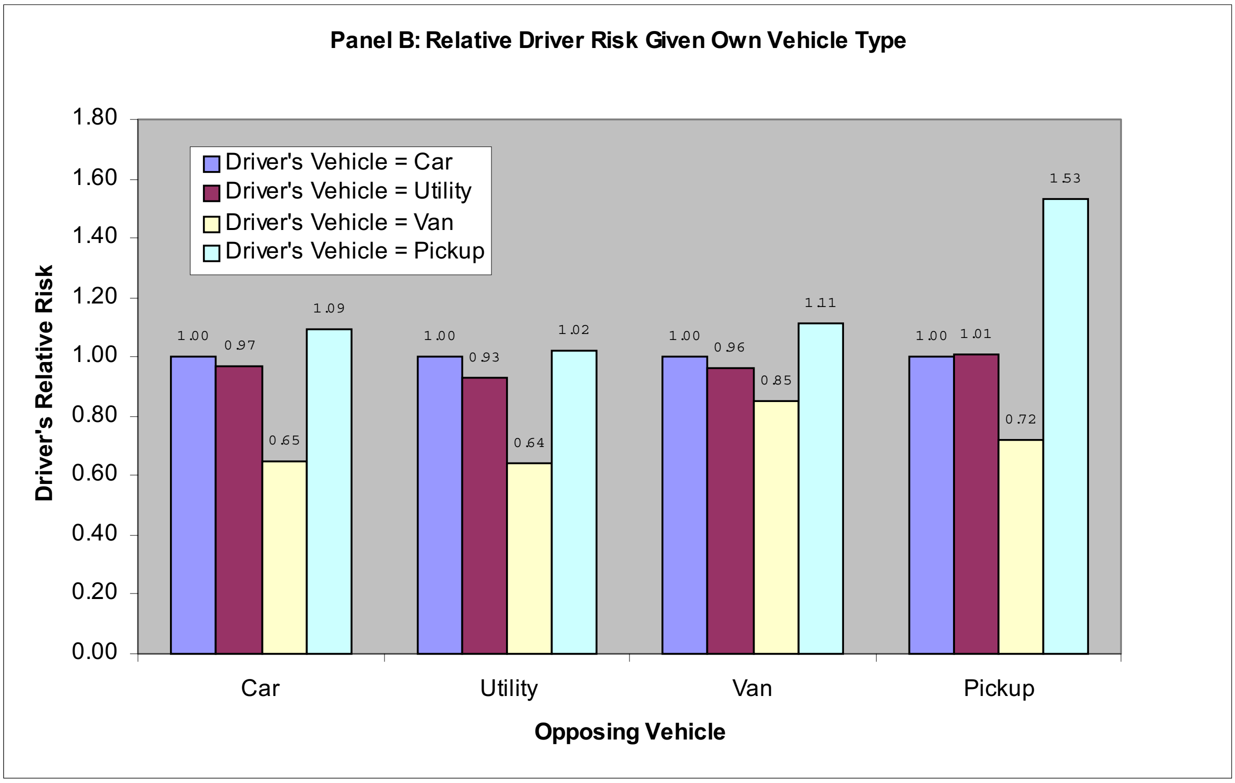
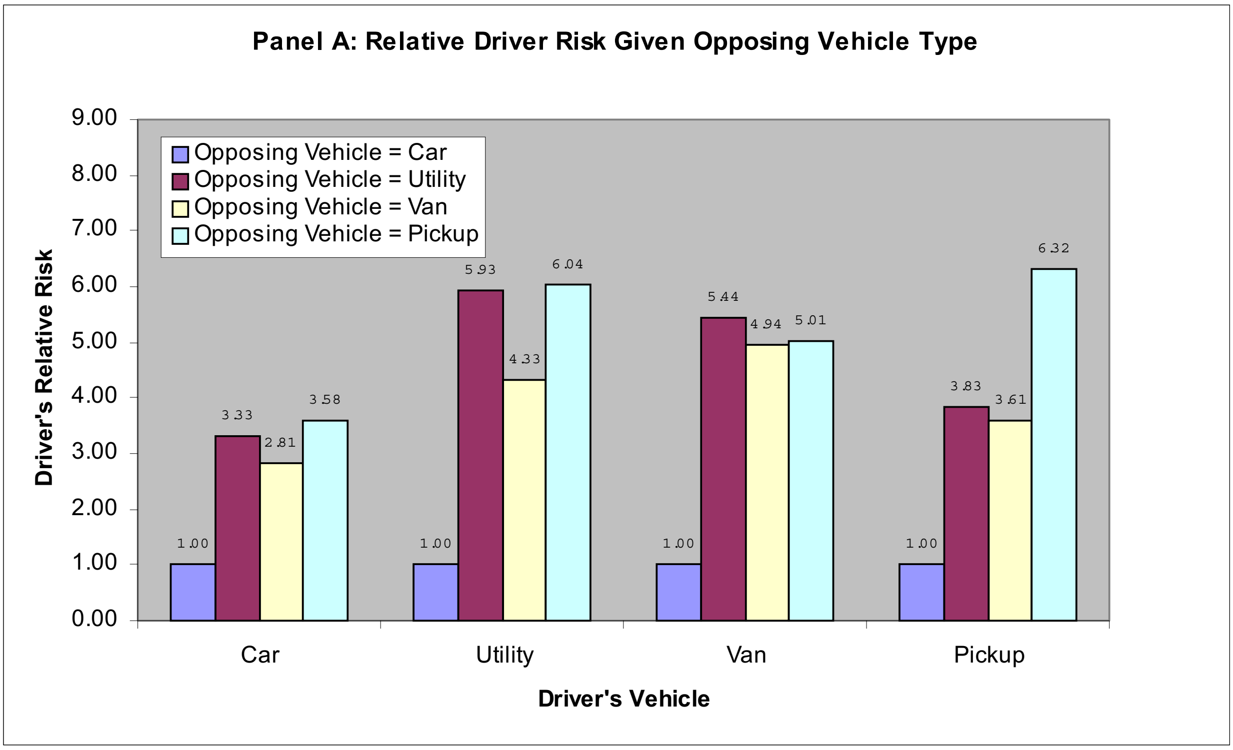


Figure 10: Relative External and Internal Driver Risk (Head-On Crashes, Frequency Adjusted)



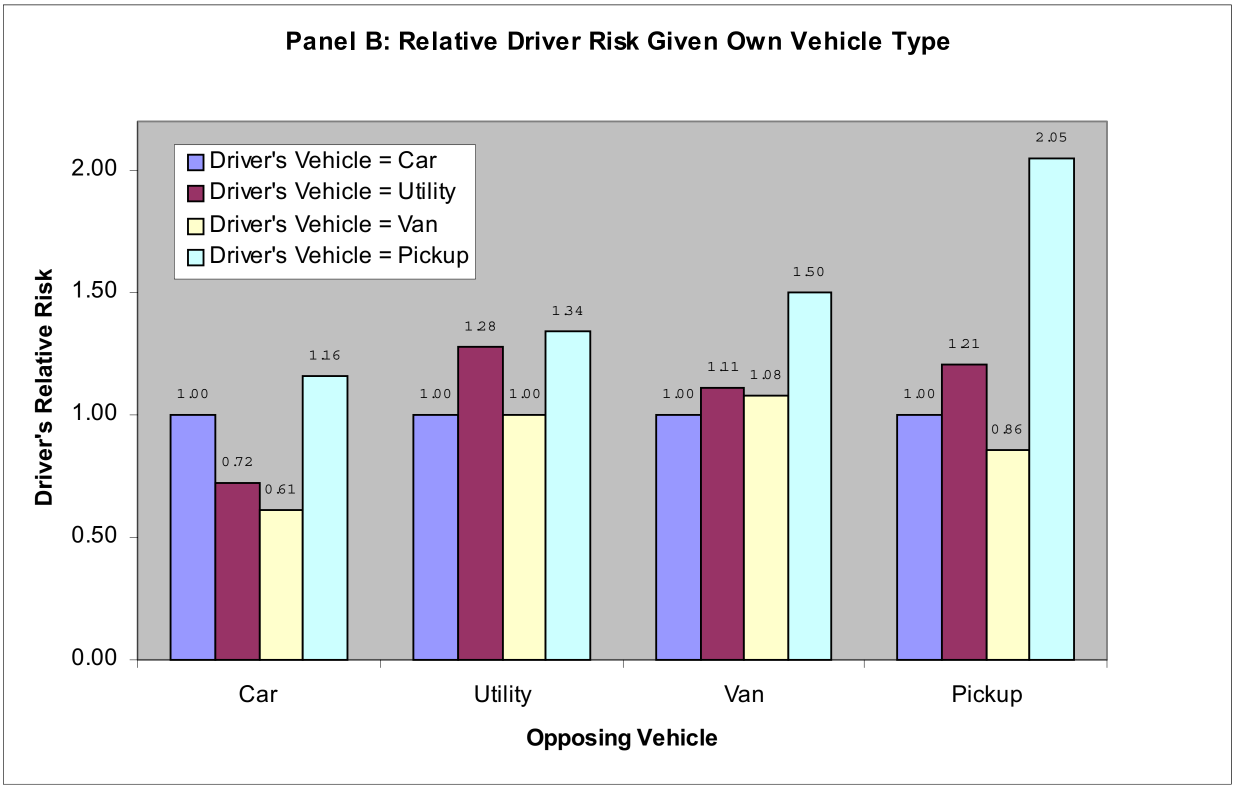


Table 1: Federal Emission and Fuel Economy Regulations for Cars and Trucks

Vehicle Type	Year	NMHC	CO	NOx	Particulates	CAFE Standard	Gas Guzzler Tax (0-12.5 mpg)	Gas Guzzler Tax (22.0-22.5 mpg)
Passenger Cars	1991-1993	0.41	3.4	1.0	0.20	27.5	$7,700	$1,000
	1994-1998	0.25	3.4	0.4	0.08	27.5	$7,700	$1,000
Light-Duty Trucks	1991	0.80	10.0	1.7	0.13	20.2	$0	$0
(under 5,750 lbs.)	1992	0.80	10.0	1.7	0.13	20.2	$0	$0
	1993	0.80	10.0	1.7	0.13	20.4	$0	$0
	1994	0.80	10.0	1.7	0.13	20.5	$0	$0
	1995	0.80	10.0	1.7	0.13	20.6	$0	$0
	1996	0.46	6.4	0.98	0.10	20.7	$0	$0
	1997	0.32	4.4	0.7	0.10	20.7	$0	$0
	1998	0.32	4.4	0.7	0.10	20.7	$0	$0
Light-Duty Trucks	1991	0.80	10.0	1.7	0.13	20.2	$0	$0
(over 5,750 lbs.)	1992	0.80	10.0	1.7	0.13	20.2	$0	$0
	1993	0.80	10.0	1.7	0.13	20.4	$0	$0
	1994	0.80	10.0	1.7	0.13	20.5	$0	$0
	1995	0.80	10.0	1.7	0.13	20.6	$0	$0
	1996	0.56	7.3	1.53	0.12	20.7	$0	$0
	1997	0.39	5.0	1.1	0.12	20.7	$0	$0
	1998	0.39	5.0	1.1	0.12	20.7	$0	$0

Notes: NMHC stands for Nonmethane hydrocarbons, CO stands for carbon monoxide, and NOx stands for nitrogen oxide. The emission standards are measured in grams per mile, the corporate average fuel economy (CAFE) standards are measured as a harmonic-weighted fleet averages in miles per gallon.
Sources: For the gas guzzler tax, see 26 U.S.C.S. 4064. For the emission regulations, see 40 C.F.R. 80. For CAFE standards, see 49 U.S.C.S. 32902.

Table 2: The Number of Fatalities of Drivers in Type I Vehicles in Crashes with Type II Vehicles (1991-1998)

		Type II				
		Car	Utility	Van	Pickup	
	Car	21728	3990	4414	13225	43357
		(40152)	(4749)	(5074)	(15895)	(65870)
Type I	Utility	945	164	190	598	1897
		(4749)	(296)	(326)	(1091)	(6462)
	Van	882	158	234	586	1860
		(5074)	(326)	(432)	(1213)	(7045)
	Pickup	3496	598	721	2979	7794
		(15895)	(1091)	(1213)	(5480)	(23679)
		27051	4910	5559	17388	54908
		(65870)	(6462)	(7045)	(23679)	(103056)

Notes: The top number in each cell reports the number of fatalities of drivers in Type I vehicles in crashes with Type II vehicles. The bottom number in parentheses reports the total number of two-vehicle fatal crashes that occurred between vehicles of Type I and Type II. The data are from the Federal Analysis Reporting System (FARS) from 1991 through 1998.

Table 3: The Number of Fatalities of Drivers in Type I Vehicles in Head-On Crashes with Type II Vehicles (1991-1998)

		Type II				
		Car	Utility	Van	Pickup	
	Car	7103	1056	1236	3754	13149
		(12088)	(1173)	(1380)	(4443)	(19084)
Type I	Utility	226	59	62	201	548
		(1173)	(98)	(111)	(346)	(1728)
	Van	262	65	82	199	608
		(1380)	(111)	(142)	(415)	(2048)
	Pickup	1208	209	272	1136	2825
		(4443)	(346)	(415)	(1951)	(7155)
		8799	1389	1652	5290	17130
		(19084)	(1728)	(2048)	(7155)	(30015)

Notes: The top number in each cell reports the number of fatalities of drivers in Type I vehicles in *head-on* crashes with Type II vehicles. The bottom number in parentheses reports the total number of two-vehicle, head-on, fatal crashes that occurred between vehicles of Type I and Type II. The data are from the Federal Analysis Reporting System (FARS) from 1991 through 1998.

Table 4: Estimated Logit Models for Driver Fatality Risk, by Vehicle Type
(With Sample Selection Adjustment, Two-Vehicle Crashes, 1991-1998)

Independent Variables	*Driver in Car*	*Driver in Utility Vehicle*	*Driver in Van*	*Driver in Pickup*
Intercept	-0.0432	-0.9023	-2.0467	-1.2447
	(0.1227)	(0.3941)	(0.4314)	(0.2106)
	[0.5418]	[0.1981]	[0.1731]	[0.2201]
	{1.0000}	{0.4417}	{0.2972}	{0.4964}
Opposing Vehicle	1.2780	1.4896	1.3019	1.2982
is a Utility Vehicle	(0.0461)	(0.1667)	(0.1428)	(0.0785)
	[0.8419]	[0.5588]	[0.4839]	[0.5490]
	{1.8771}	{0.7932}	{0.5452}	{0.8680}
Opposing Vehicle	1.6490	1.7330	1.6811	1.5841
is a Van	(0.0491)	(0.1490)	(0.1297)	(0.0767)
	[0.8717]	[0.5806]	[0.5394]	[0.5938]
	{1.4966}	{0.6541}	{0.5804}	{0.7522}
Opposing Vehicle	1.4191	1.6290	1.5653	1.4442
is a Pickup	(0.0286)	(0.0930)	(0.0928)	(0.0429)
	[0.8323]	[0.5471]	[0.4833]	[0.5431]
	{1.8770}	{0.8650}	{0.6123}	{1.3034}
Pseudo-R^2	0.3097	0.3198	0.3126	0.3020
Number of Observations	62,395	6,167	6,661	22,703
Number of Missing Obs.	3,475	295	384	976

Notes: The sample consists of all two-vehicle crashes from 1991 through 1998 in which at least one driver died. Each column pulls from this sample those observations involving drivers of the type of vehicle listed in the column heading. The dependent variable of the logit model equals one if the driver of the vehicle died. The driver covariates are for both drivers. They include age, age squared, sex, air bag deployment, seat belt use, drunk driver, and previous major and minor traffic incidents. The crash covariates are the road condition, type of road, speed limit, time of day, and year. Heteroskedastic consistent standard errors are reported in parentheses. The predicted probabilities given a crash with each opposing vehicle are reported in brackets. These probabilities are adjusted for sample selection bias and standardized, and the values are reported in braces.

Table 5: Estimated Logit Models for Driver Fatality Risk, by Vehicle Type
(With Sample Selection Adjustment, Two-Vehicle *Head-On* Crashes, 1991-1998)

Independent Variables	*Driver in Car*	*Driver in Utility Vehicle*	*Driver in Van*	*Driver in Pickup*
Intercept	0.2879	-0.6667	-1.6821	-1.2113
	(0.2266)	(0.7497)	(0.7822)	(0.3631)
	[0.5889]	[0.1942]	[0.1950]	[0.2746]
	{1.0000}	{0.3268}	{0.2783}	{0.5290}
Opposing Vehicle	1.7162	1.9074	1.8550	1.2960
is a Utility Vehicle	(0.1072)	(0.2981)	(0.2156)	(0.1321)
	[0.9002]	[0.6136]	[0.5865]	[0.6006]
	{1.5150}	{0.8812}	{0.6876}	{0.9203}
Opposing Vehicle	1.7470	1.6263	1.8262	1.7020
is a Van	(0.0971)	(0.2274)	(0.2238)	(0.1257)
	[0.8939]	[0.5481]	[0.5781]	[0.6551]
	{1.2756}	{0.6425}	{0.6248}	{0.8677}
Opposing Vehicle	1.3655	1.8305	1.4344	1.3993
is a Pickup	(0.0517)	(0.1574)	(0.1546)	(0.0681)
	[0.8447]	[0.5856]	[0.4789]	[0.5820]
	{1.6273}	{0.8973}	{0.6343}	{1.5196}
Pseudo-R^2	0.2245	0.2557	0.2615	0.2168
Number of Observations	18,171	1,637	1,917	6,890
Number of Missing Obs.	913	91	131	265

Notes: The sample consists of all two-vehicle head-on crashes from 1991 through 1998 in which at least one driver died. Each column pulls from this sample those observations involving drivers of the type of vehicle listed in the column heading. The dependent variable of the logit model equals one if the driver of the vehicle died. The driver covariates are for both drivers. They include age, age squared, sex, air bag deployment, seat belt use, drunk driver, and previous major and minor traffic incidents. The crash covariates are the road condition, type of road, speed limit, time of day, and year. Heteroskedastic consistent standard errors are reported in parentheses. The predicted probabilities given a crash with each opposing vehicle are reported in the brackets. These probabilities are adjusted for sample selection bias and standardized, and the values are reported in braces.

Table 6: Estimated OLS Models for Pedestrian Fatalities, by Vehicle Type

	(1)	(2)	(3)	(4)	(5)	(6)
Cars						
Vehicle Miles Traveled (millions)	0.00220	0.00285	0.00221	0.00285	0.00261	0.00287
	(10.46)	(13.69)	(10.49)	(13.66)	(11.57)	(14.08)
R-squared	0.7804	0.8559	0.7811	0.8562	0.8318	0.8609
Light Trucks						
Vehicle Miles Traveled (millions)	0.00552	0.00720	0.00551	0.00722	0.00633	0.00728
	(6.80)	(7.30)	(6.83)	(7.30)	(6.77)	(7.19)
R-squared	0.6470	0.7674	0.6474	0.7683	0.7300	0.7714
State Fixed Effects	No	Yes	No	Yes	No	Yes
Year Indicators	No	No	Yes	Yes	Yes	Yes
State-Specific Linear Time Trend	No	No	No	No	Yes	Yes
Light Truck Crash Frequency Relative to Car Crash Frequency	2.51	2.53	2.49	2.53	2.43	2.54

Notes: For the top panel the independent variable of interest is the vehicle miles traveled by cars, and the dependent variable is the number of pedestrian fatalities caused by cars. For the bottom panel the independent variable of interest is the vehicle miles traveled by light trucks, and the dependent variable is the number of pedestrian fatalities caused by light trucks. Each model contains roadtype indicator variables, and each model controls for the state unemployment rate and the legal speed limit. Heteroskedastic consistent t-statistics are reported in parentheses.
Notes: The data set in on a state by year by roadtype level. There are fifty-one states (including DC), and the years of available data for VMT distribution by vehicle type are from 1994 through 1998. The four roadtypes are rural interstate, rural non-interstate, urban interstate, and urban non-interstate. This yields 1,020 observations; however, 234 observations either have no available data or did not have any vehicle travel within the roadtype (e.g., DC rural interstate). Thus, each regression contains 786 observations.

Table 7: Estimated OLS Models for Pedestrian Fatalities, by Vehicle Type
(Less Restrictive Controls)

	(1)	(2)	(3)	(4)	(5)	(6)
Cars						
Vehicle Miles Traveled (millions)	0.00251	0.00322	0.00221	0.00285	0.00251	0.00321
	(6.17)	(8.98)	(10.48)	(13.74)	(6.15)	(8.90)
R-squared	0.9111	0.9434	0.7822	0.8572	0.9117	0.9438
Light Trucks						
Vehicle Miles Traveled (millions)	0.00512	0.00621	0.00551	0.00721	0.00518	0.00627
	(3.47)	(3.61)	(6.83)	(7.30)	(3.47)	(3.61)
R-squared	0.8969	0.9278	0.6485	0.7692	0.8983	0.9284
State Fixed Effects	No	Yes	No	Yes	No	Yes
Year by Roadtype Indicators	No	No	Yes	Yes	Yes	Yes
State by Roadtype-Specific Linear Time Trend	Yes	Yes	No	No	Yes	Yes
Light Truck Crash Frequency Relative to Car Crash Frequency	2.04	1.93	2.49	2.53	2.06	1.95

Note: For the top panel the independent variable of interest is the vehicle miles traveled by cars, and the dependent variable is the number of pedestrian fatalities caused by cars. For the bottom panel the independent variable of interest is the vehicle miles traveled by light trucks, and the dependent variable is the number of pedestrian fatalities caused by light trucks. Each model contains roadtype indicator variables, and each model controls for the state unemployment rate and the legal speed limit. Heteroskedastic consistent t-statistics are reported in parentheses.

Note: The data set in on a state by year by roadtype level. There are fifty-one states (including DC), and the years of available data for VMT distribution by vehicle type are from 1994 through 1998. The four roadtypes are rural interstate, rural non-interstate, urban interstate, and urban non-interstate. This yields 1,020 observations; however, 234 observations either had no available data or did not have any vehicle travel within the roadtype (e.g., DC rural interstate). Thus, each regression contains 786 observations.

Table 8: The Expected Relative Number of Fatalities

Panel A: Constant Crash Frequencies
(Cell [i,j] represents vehicle composition of 50% i and 50% j vehicles)

	Car	Utility	Van	Pickup
Car	1.00	1.03	0.84	1.17
Utility		0.79	0.64	0.96
Van			0.58	0.81
Pickup				1.30

Panel B: Variable Crash Frequencies
(Cell [i,j] represents vehicle composition of 50% i and 50% j vehicles)

	Car	Utility	Van	Pickup
Car	1.00	2.49	1.94	3.13
Utility		3.84	3.11	4.63
Van			2.81	3.93
Pickup				6.31