2005

# Fatal Crashes Caused By Light Trucks Relative To Cars: A Test Of The Offsetting Behavior Hypothesis

Adam David Zubritsky
*University of Central Florida*

# FATAL CRASHES CAUSED BY LIGHT TRUCKS RELATIVE TO CARS: A TEST OF THE OFFSETTING BEHAVIOR HYPOTHESIS

by

ADAM D. ZUBRITSKY
B.S. University of Florida, 2000

A thesis submitted in partial fulfillment of the requirements
for the Master of Arts
in the Department of Economics
in the College of Business Administration
at the University of Central Florida
Orlando, Florida

Summer Term
2005

## ABSTRACT

This thesis presents an econometric test of the offsetting behavior hypothesis concerning drivers of light trucks relative to cars. The main objective is to determine whether drivers of light trucks offset perceived safety benefits associated with larger vehicles by driving more aggressively than drivers of cars, subsequently causing more fatal crashes, holding all else constant. An empirical model using data on pedestrian fatalities across the United States over a five-year period is developed and analyzed in order to capture the desired results. Estimates provide substantial evidence in support of the offsetting behavior hypothesis. To strengthen the case for driver offsetting behavior beyond previous studies, the model is estimated again using pedalcyclist fatalities. The results also point to interesting conclusions regarding the effects of increased speed limits on the behavior of drivers.

## ACKNOWLEDGMENTS

I would like to thank Dr. Michael Caputo, thesis committee chair, for his advice and supervision in the preparation of this thesis.  Dr. Caputo has provided valuable input on the theoretical structure of the proposed model and general guidance throughout the process.

Also, I would like to thank Dr. Shelby Gerking for his helpful advice in every area of this thesis. Dr. Gerking has been a tremendously valuable source of support during this entire undertaking. Without his intuition based on extensive experience, this research would not have been possible.

I am greatly indebted to Dr. Kyung-So Im.  His valuable contributions to the econometric analysis and unwavering attention to detail cannot be overemphasized.  His quick response to my many questions was also much appreciated.

A special thanks also goes to Dr. Ted Gayer of Georgetown University for allowing the use of his data on pedestrian crash fatalities and their determinants from his prior analysis.

# TABLE OF CONTENTS

# LIST OF TABLES

# LIST OF ACRONYMS/ABBREVIATIONS

| | |
|---|---|
| BEA | Bureau of Economic Analysis |
| CAFE | Corporate Average Fuel Economy |
| DOT | Department of Transportation |
| EPA | Environmental Protection Agency |
| FARS | Fatality Analysis Reporting System |
| FGLS | Feasible Generalized Least Squares |
| FHWA | Federal Highway Administration |
| FIML | Full Information Maximum Likelihood |
| GLS | Generalized Least Squares |
| GVW | Gross Vehicle Weight |
| IV | Instrumental Variable |
| MPH | Miles per Hour |
| NASCAR | National Association for Stock Car Auto Racing |
| NHTSA | National Highway Traffic Safety Administration |
| OLS | Ordinary Least Squares |
| SUR | Seemingly Unrelated Regressions |
| SUV | Sport Utility Vehicle |
| 3SLS | Three-Stage Least Squares |
| 2SLS | Two-Stage Least Squares |
| VMT | Vehicle Miles Traveled |

# CHAPTER ONE: INTRODUCTION

In recent years, light trucks have begun to account for an increasing percentage of vehicles in the United States as more light trucks are manufactured by both domestic and foreign auto makers. Under traditional categorization by the federal government, light trucks consist of pickup trucks, vans, and sport-utility vehicles, all weighing under 10,000 pounds gross vehicle weight. The mounting concern for vehicle occupant safety has focused on the emergence of light trucks as a substitute for traditional cars, with the primary growth currently in large pickups and sport-utility vehicles. Keith Bradsher (2002) defines sport-utility vehicles (SUVs) as vehicles that are based on a truck-like steel chassis, are designed to handle off-road travel, have either standard or optional four-wheel-drive, have an enclosed cargo area, and are marketed to consumers who likely do not intend to use the off-road capabilities. Bradsher states that sales of SUVs currently account for approximately 17 percent of new vehicle sales, up from just 1.78 percent in 1982. It has also been estimated that as much as half of all new vehicles sold in the U.S. market are classified as light trucks. According to NHTSA (1997), by 1992, there were more fatalities in accidents between cars and light trucks than between cars only, with the vast majority of the fatalities being the car occupants. These concerns continue to grow as larger light trucks are built and sold in the United States each year.

Light trucks have received more lenient regulations on fuel efficiency, safety standards, and pollution controls, which has made them attractive and profitable for auto companies to manufacture. As a result of this government subsidization, light trucks have been marketed to individuals and families with high incomes, a market segment that previously bought large and luxury cars. Auto producers have successfully marketed light trucks as being safer than cars due

to their size, weight, and availability of four-wheel drive. However, true safety benefits of light trucks, primarily SUVs, have been questioned by both the federal government and automotive safety experts because of their propensity to roll over in sudden maneuvers, difficult braking and handling of four-wheel-drive, and the dangers that large vehicles pose to other traffic. Still, it appears that buyers of light trucks are convinced that there is an added safety benefit to operating vehicles that are significantly heavier than cars and have the capability to traverse rough terrain. The focus of this thesis is to determine whether there is evidence to suggest that drivers of light trucks use the perceived safety benefits as an incentive to drive relatively more carelessly, thereby causing more accidents than drivers of cars.

Offsetting behavior studies are classic examples of the downward-sloping demand curve because they illustrate the relationship between the cost and the quantity demanded of a particular action. In this case, the cost of reckless driving is the potential to become involved in a serious traffic accident in which the driver will become injured. However, if drivers believe that they are more insulated from possible injury during accidents because they are driving light trucks instead of cars, in other words, the cost of reckless driving has fallen, then the expected behavioral result would be an increase in the "quantity demanded" of reckless driving. If this classic demand theory applies to driver behavior, we should be able to observe more accidents involving light trucks than cars, ceteris paribus.

A recent study was undertaken by Gayer (2004) to illustrate the relative fatality risks of light trucks and cars. For my analysis, I obtained the data on pedestrian fatalities across the United States from 1994 – 1998 directly from Dr. Gayer to re-analyze his model regarding offsetting behavior in light trucks. In order to obtain consistent and efficient estimates, I apply the method of seemingly unrelated regressions (SUR) to the triangular model that Gayer

developed. However, it is revealed that in this case generalized least squares (GLS) will produce estimates that are equivalent to those produced by ordinary least squares (OLS), which are based on the assumption that the triangular model is recursive. Tests are performed to determine whether the errors in the two equations are uncorrelated, and results tend to suggest the presence of correlation, rendering SUR useless for increasing efficiency.

A new theoretical model is developed that will capture the presence of offsetting behavior using that requires only slight modification of the existing data. This theoretical framework suggests that the original model must be altered to achieve the proper specification, and results indicate the presence of offsetting behavior among drivers of light trucks. The new model is then re-estimated using data on pedalcyclist fatalities by vehicle type, which strengthens the case for offsetting behavior. Pedalcyclists include all non-motorized cycle riders, not just bicycle riders. Empirical results for pedestrian fatalities indicate that speed limit increases have the largest effect on drivers of light trucks, who tend to be more reckless than drivers of cars. Because of their propensity for reckless driving, increased speed limits create an incentive for drivers of light trucks to choose open highways, where they will cause relatively less damage. Higher speed limits also reduce the speed variance, which makes light trucks relatively less dangerous to other road users than they are at lower speed limits.

Chapter 2 provides a literature review to establish a background on the research of offsetting behavior. Chapter 3 is divided into two sections. Section 3.A analyzes the model that Gayer used and its implications. Section 3.B provides an argument for a new model based on driver behavior and discusses its underlying assumptions and hypotheses. Chapter 4 interprets the empirical results, and chapter 5 provides the conclusions. Tables that show the actual results are included in the appendix section.

# CHAPTER TWO: LITERATURE REVIEW

The movement towards designing and building safer automobiles began with Ralph Nader's 1965 book, *Unsafe at Any Speed*, which exposed various safety shortcomings with cars produced by the American automotive industry. Primarily, the book concentrated on General Motors and Ford, pinpointing models such as the Chevrolet Corvair, which was built with an independent rear swing-axle suspension that made it especially prone to rollovers and tire air-outs under normal operation. Other safety hazards identified include vehicles with sharp protrusions such as tail fins that can easily impale and kill pedestrians, even when a pedestrian strikes a parked vehicle. Steering columns that thrust dangerously into the passenger compartment during an accident, blinding headlights, and a lack of seat belts were also cited as common safety hazards that are unacceptable. As a result of this initial push towards safer automobiles, many lives have been saved as vehicles of all types have been designed with standard safety equipment such as energy-absorbing steering columns, seat belts, crumple-zones, rounded corners, anti-lock brakes, and more recently air bags. Responsible design of automotive safety equipment must strive to eliminate injuries from what Nader termed the "second accident," which takes place when the driver or occupants contact parts of the vehicle's interior during a collision. Vehicles must not cause accidents or injuries because of negligent design and engineering. However, safety engineering walks a fine line with promoting reckless driving. Nader quoted industry experts who explained that the design of vehicles cannot permit total crashworthiness. The avoidance of collisions must be the assumed responsibility of the driver, and while safety features are effective in preventing death and serious injury from crashes when they occur, building crash-proof vehicles would not only be mechanically impossible, but it

would also defeat the purpose of driver education and responsible vehicle operation. This is the essence of offsetting behavior, namely that a tradeoff exists between safety features intended to prevent crash injuries and people's natural willingness to engage in risky behavior while behind the wheel.

Lave and Weber (1970) examined the costs and benefits of automotive safety features, including padded instrument panels, seat belts, energy absorbing steering columns, and dual braking systems. They did not believe that the government should mandate these safety features in cars due to possible market failure associated with government intervention. Additionally, they argued that having seat belts standard in all cars does not guarantee that the driver or occupants will use them, or use them properly, rendering them ineffective. Another social cost associated with mandated safety equipment, according to Lave and Weber, is that drivers will drive faster if their vehicles have more safety devices. A driver will take greater risk to compensate for the additional safety in order to arrive at their destination sooner. The last point, although not further investigated in this study, laid the groundwork for future investigation into the presence of offsetting behavior.

Peltzman (1975) was the first to examine driver offsetting behavior comprehensively. Earlier quantitative analysis was impossible because the beginning of safety regulations, including seat belts, came into effect in 1968, shortly after the publication of *Unsafe at Any Speed*. An in-depth analysis into the effectiveness of the safety features had to be built on substantial data obtained over the first several years after the new regulations were put in place. Peltzman's main conclusion was that the first decade of automobile safety regulation did not result in fewer accident fatalities. His results showed an increase in pedestrian fatalities that offsets the reduction in occupant fatalities. He offered a few explanations for this finding which

indicate the presence of offsetting behavior. It is possible that the safety regulations have been effective in reducing the fatality rate, but drivers have taken more risks which outweigh the benefits of additional safety features. The rise in drunk driving and the increased proportion of young drivers seems to confirm this. Peltzman also discussed the possibility that market factors are responsible for a steady decline in the overall accident rate independent of safety regulation, but that as a result of increased aggressive driving, the accidents that do occur are more severe. Peltzman supports the first conjecture with time-series data and the second with cross-sectional data. Although the results are far from definitive, this is the first study that offers statistical evidence in support of offsetting behavior, and accordingly, the effect is sometimes termed the Peltzman effect (or the Peltzman hypothesis). More analyses have followed in the ensuing years, with a variety of results which do not completely confirm or refute the hypothesis.

A study involving the offsetting behavior hypothesis concerning seat belts was conducted by Evans and Graham (1991). They compared states that have primary seat belt enforcement laws with states that only have secondary seat belt laws. Primary enforcement laws give officers the right to stop motorists who are not using their seat belts and cite them for that offense alone. Secondary enforcement laws only allow citations for nonuse of seat belts in the event that another chargeable offense has also occurred. Evans and Graham only found weak evidence to support offsetting behavior, or what they termed risk compensation, in secondary enforcement states. In primary enforcement states, the life-saving benefits far outweigh the offsetting behavior costs. A later study by Cohen and Einav (2001) did not find any evidence of offsetting behavior. They determined that there is no correlation between wearing seat belts and driving more aggressively because drivers who are reckless are the least likely to use seat belts and are most likely to become involved in an accident. Using a time-series analysis involving data on

fatalities, Chirinko and Harper (1993) found that safety regulations and increases in the national speed limit have opposite effects. They argued that the mandatory use of seat belts and the availability of air bags will lead to reduced traffic fatalities, but due to potential offsetting behavior, the net effect of this is questionable. In addition, having a national speed limit set at 55 MPH would prevent some of the high-speed driving associated with offsetting behavior. Traynor (1993) looked directly at the demand relationship between a driver's environment and his behavior, and found evidence to support the Peltzman hypothesis. He concluded that if a driver is less likely to sustain an injury in a crash, he will necessarily respond by driving less cautiously. Keeler (1994) confirmed these results in a study that looked more closely at the cost of accidents, for which he included data on hospital costs as well as demographic and traffic characteristics. Keeler's results provide some support for the offsetting behavior hypothesis since the data failed to produce evidence that the implementation of safety regulations significantly reduced fatalities. Interestingly, he found that individuals with higher education levels tend to have greater safety awareness. This contradicts the common logic that greater education levels lead to greater income levels, which in turn lead to more aggressive driving due to one's value of time. Higher-income drivers also tend to drive newer vehicles equipped with more safety features. Instead, Keeler believes that there is a positive correlation between higher education and concern for health and safety, so highly-educated drivers are the least likely to engage in risky behavior to compensate for increased safety.

An analysis by Peterson, Hoffer, and Millner (1995) focused on air bags. Unlike a seat belt, which has no effect if a driver chooses not to use it, an air bag, particularly on the driver's side, will deploy in a crash regardless of action taken by the driver. Air bags significantly reduce second accident injuries when a driver comes in contact with the windshield, steering wheel,

dashboard, or gear shift, as a result of a serious crash. The study found that cars equipped with air bags tend to be driven more recklessly than cars without air bags, even when accounting for drivers sorting into air bag equipped vehicles if they feel that they are more likely to become involved in an accident. This indicates that air bags indirectly increase fatality risks to other drivers, occupants, and non-motorists.

Very strong support for the offsetting behavior hypothesis was found by Sobel and Nesbit (2003) who used a data set on NASCAR crashes. Examining NASCAR data eliminates any possible bias arising from different types of drivers across the country sorting into vehicles according to safety features. They found that as vehicles used by NASCAR drivers have become safer, drivers have taken greater risks and have driven more recklessly, leading to an increase in serious crashes.

It is important to note that from a behavioral standpoint, the evidence supporting the offsetting behavior hypothesis is not confined only to vehicle safety studies. Dickie and Gerking (1997) discovered that individuals with darker skin who may have less genetic risk of skin cancer often spend more time in direct sunlight and use fewer skin protection products. Viscusi (1984) determined that the use of child-proof bottles and packaging on medications has not reduced the number of child ingestions of these products. All studies of the Peltzman effect have one common goal: to emphasize the need to consider human behavioral implications which can have costs that outweigh the intended benefits of a policy.

Safety regulations have not been the only factor shaping the types of vehicles that are produced and driven on our nation's roads. Beginning in 1978, auto makers were required to meet fuel economy standards for all new cars that were produced. These standards are known as the Corporate Average Fuel Economy (CAFE) standards. Conceived in response to the fuel

crisis of the early 1970s, the standards were originally set to grow from an initial average of 18 miles per gallon in 1978 to 27.5 miles per gallon by 1985 for each corporation's fleet of cars produced for sale in the U.S. market. The projected average was actually relaxed to 26 miles per gallon through the 1988 model year and then increased to 27.5. This level continues to stand for cars, but the dramatic increase in fuel economy standards from the initial level of 18 miles per gallon to 27.5 miles per gallon one decade later prompted major design and technological changes to new cars.

Automotive engineers have been unable to increase the fuel efficiency of combustion engines enough to accommodate the rapidly rising CAFE standards. This made a reduction in the size of cars inevitable. Failure to meet the CAFE standards, which are set by Congress and enforced by the Department of Transportation (DOT), carries hefty penalties for auto producers as well as a potential siege of legal consequences and negative publicity. Efforts by government officials and environmental groups to raise CAFE standards beyond their current levels have not been successful. The necessity of CAFE was questioned in the 1980s and 1990s as fuel prices remained relatively low with a generally prosperous domestic economy, but completely abolishing the standards has also met with serious opposition. CAFE prohibits auto producers from simply importing more economical cars to meet the standards, which is a trade restrictive policy. This has led to political implications in states with a prominent domestic auto industry presence. Such states tend to have powerful influence during presidential elections.

The obvious effect of the CAFE standards has been for auto makers to produce vehicles that weigh far less than their predecessors, which created numerous safety concerns. Crandall and Graham (1989) determined that CAFE standards have reduced the average weight of new cars by 500 pounds during the year of their study, which they estimate has resulted in an

increased fatality risk of approximately 14 - 27 percent. By the offsetting behavior hypothesis, drivers should compensate for the loss in safety of smaller cars by driving more carefully, thereby avoiding accidents. Blomquist (1988) discussed evidence that drivers of small cars tend to use seat belts more frequently to adjust for the increased risk associated with operating smaller vehicles, which clearly supports Peltzman's hypothesis on human behavior. However, during this period, loopholes in both safety standards and CAFE standards encouraged the emergence of light trucks as alternatives to small cars or safer large cars.

In 1975, Congress gave the Department of Transportation wide authority to set the CAFE standards for light trucks. The level was initially set in 1982 at 17.5 miles per gallon, and was gradually increased to 20.5 miles per gallon in 1987. In 1992, the level inched up to 20.7 miles per gallon, where it has remained ever since. The definition of light trucks has been rather nebulous, but it is understood to cover vans, pickup trucks, and sport-utility vehicles that are under 8,500 pounds gross vehicle weight (GVW). The initial weight requirement was that light trucks intended for personal use must weigh below 8,500 pounds GVW to come under the fuel economy standards set by the DOT and the emissions standards set by the EPA, but many light trucks produced today for personal use are actually between 8,500 and 10,000 pounds GVW. They become exempt from many regulations at this level, but are still marketed for "personal use." What is defined as a light truck and what is defined as a car in terms of fuel economy and EPA regulations is largely determined by the auto manufacturers themselves. With more relaxed standards applying to light trucks than to cars, it is not surprising that manufacturers make great efforts to design and market vehicles that can easily qualify as light trucks. At the present time, consumer demand for light trucks and vehicles that combine characteristics of both cars and light trucks, known as crossover vehicles, remains strong.

From motorists' perspective, it is clear that light trucks tend to be heavier than cars and are taller, giving trucks high centers of gravity which make them more susceptible to rollovers. Light trucks are also frequently equipped with four-wheel-drive and have high ground clearances which allow them to traverse off-road terrain. Four-wheel-drive makes the handling of light trucks much different from that of cars, while higher ground clearances have been especially dangerous for car occupants. High-mounted bumpers on light trucks have frequently passed over hoods and door sills of cars in accidents, severely injuring or killing the occupants. Tall vehicles obstruct car drivers' view of the road ahead, limiting the reaction times needed to avoid collisions. By holding light trucks to more lenient standards for safety and fuel consumption than cars, the federal government has been subsidizing their manufacture.

Godek (1997) claimed that CAFE standards have caused the switch to light trucks as consumers responded to the decrease in safety with downsized cars. Godek found that the shift to light trucks has reduced the fatality risk associated with small cars, but has not eliminated it. This result could be due to the fact that light trucks are less safe than drivers tend to believe, and they are reacting to perceived safety benefits by driving more aggressively, a classic demonstration of Peltzman's offsetting behavior hypothesis. On the other hand, Yun (2002) claimed that CAFE has not directly resulted in loss of life because drivers are actually driving more carefully overall than they were prior to the implementation of the standards. Yun looked at light trucks as simply heavier cars in the analysis, and concurs with the theory that light trucks make their occupants better off, while occupants of cars are worse off, in accidents.

Gayer used a panel data analysis over the five-year period from 1994 to 1998 to examine the relative crash frequencies of cars and light trucks. He used pedestrian fatalities caused by each vehicle type as the dependent variables, and he controlled for vehicle miles traveled in each

vehicle type as well as other observed characteristics. He concluded that the crash frequency for light trucks is higher than that for cars, holding all else constant, but that light trucks offer a higher degree of accident protection for their drivers and occupants. Considering the higher relative crash frequency, the added fatality risk to other drivers posed by light trucks makes them very unsafe in traffic, and there would be an efficiency gain realized by eliminating government subsidies for light trucks. Moreover, according to Gayer, if all vehicles on our nation's roads were light trucks, the fatality rate would be higher than if all vehicles were cars. These statements lead one to expect that there are more factors than just the size of light trucks relative to cars responsible for the difference in crash frequencies between the two vehicle classes. Gayer suggested that that if drivers of light trucks feel safer, they are more inclined to drive recklessly. There is evidence from Gayer's work that aggressive driver behavior based on a perception of occupant safety combined with design characteristics of SUVs, pickups, and vans that naturally puts them at greater accident risk, will inevitably lead to more fatal crashes. The following chapter will analyze the model originally presented by Gayer to explain the relative crash frequency between the two vehicle types. A new model will then be proposed that is designed to determine driver offsetting behavior between the two vehicle types. The specification of the proposed model and its basic assumptions will then be discussed in detail.

# CHAPTER THREE: MODEL ANALYSIS

**Section 3.A: Basic Model**

In his analysis, Gayer developed and estimated the following triangular model:

$$y_{jst} = VMT_{jst}\delta_j + x'_{jst}\beta_j + \varepsilon_{jst}, \quad (1)$$

$$VMT_{jst} = x'_{jst}\pi_j + \eta_{jst}. \quad (2)$$

In equation (1), the dependent variable is the number of pedestrian fatalities $y_{jst}$ caused by a vehicle of type *j* in state *s* and year *t*. The vehicle type *j* can either represent cars or light trucks. The dependent variable in (2) is the vehicle miles traveled (VMT) per vehicle type. The variation in both crashes and vehicle miles traveled are believed to depend on the same set of observed characteristics, denoted by the $x'_{jst}$ vector, where *j* again denotes the vehicle type, *s* denotes the state, and *t* denotes the year. The set of observed characteristics in $x'_{jst}$ include the unemployment rate for each state, controls for urban and rural road types, controls for speed limits of 65 MPH, 70 MPH, and 75 MPH and over, and percentages of the population of each state who are men age 65 and over, women age 65 and over, men between the ages of 15-29, and women between the ages of 15-29. In equation (1), the crashes are also determined by the vehicle miles traveled in each vehicle type. The only difference between equations (1) and (2) is that equation (1) includes VMT as an independent variable, and that it is the dependent variable in (2). In some of the estimations, combinations of state and time fixed effects, as well as less restrictive controls, are applied to both equations.

Gayer initially produces the results from these estimations under the method of ordinary least squares (OLS), but there is a possible endogeneity problem that must be addressed. Drivers

choosing different types of vehicles due to unexamined effects could potentially lead to biased results. While drivers may operate light trucks more aggressively and cause more accidents according to Peltzman's offsetting behavior hypothesis, they may also choose to drive light trucks as opposed to cars where they observe adverse weather conditions or a high number of fatal crashes. In order to produce unbiased results in the face of this concern, Gayer introduced the instrumental variable (IV) of daily snow depth. He argued that snow depth is related to the number of VMT in each vehicle type. Presumably, light trucks are viewed as well-suited to climates with heavy snowfall because of their added weight and four-wheel-drive capabilities. Both the OLS results and those using the snow depth IV support the argument that light trucks are involved in more fatal crashes than cars, which can be traced back to the behavior of drivers.

Under the structure of this model, if no identifying restrictions are imposed, then equation (2) is identified under OLS, but equation (1) is not identified as noted by Greene (2003). Let $\Sigma$ be the $2 \times 2$ covariance matrix for the errors in equations (1) and (2), so that

$$\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix}.$$

If it is somehow known that $\sigma_{12} = 0$, which is unlikely given the endogeneity problem discussed above, then equation (1) is identified allowing the system to be efficiently and consistently estimated by OLS. If it is not known that $\sigma_{12} = 0$, then identification of equation (1) can be achieved by imposing restrictions on the coefficients of $x$. There is no obvious method of doing this, and prior intuition about the variables included in the $x'_{jst}$ vector does not offer any suggestions. The problem of inconsistency can be solved by using instrumental variables and the method of two-stage least squares (2SLS), but these estimates are still inefficient if correlation exists between the error terms in the two equations.

In order to proceed, we must employ a method that produces consistent and efficient estimates when the error covariance is not diagonal. Lahiri and Schmidt (1978) reached the conclusion that when estimating triangular systems like equations (1) and (2), the method of seemingly unrelated regressions (SUR) will generally provide such estimates. Zellner (1962) proves that in many situations, SUR provides coefficient estimates that are asymptotically more efficient than OLS estimates, but under some conditions, the two methods are equivalent. If the equations are actually unrelated, then the error covariance matrix is diagonal, and there will be no efficiency gain in applying GLS over OLS. If all of the equations to be estimated by SUR contain an identical set of regressors, there will again be no gain from using GLS. If the regressors in the $n^{\text{th}}$ equation in a system of $n$ equations are a subset of those in the other $n$-1 equations in the system, Revankar (1974) shows that GLS is equivalent to OLS applied to the $n^{\text{th}}$ equation. For the other $n$-1 equations in the system, Revankar illustrates that GLS provides more efficient estimates than OLS.

When estimating the above triangular model where equation (2) contains a subset of the regressors in equation (1), one might assume that there would be an efficiency gain in the coefficient estimates $\hat{\beta}_j$ and $\hat{\delta}_j$ by applying GLS instead of OLS (while $\hat{\pi}_j$ would be the same regardless) due to Revankar's results, but this assumption is incorrect.

A simplified form of the triangular model in (1) and (2) is

$$y_1 = x_1\beta_1 + \varepsilon_1, \tag{3}$$

$$y_2 = x_2\beta_2 + \varepsilon_2, \tag{4}$$

where $x_2$ is a sub-matrix of $x_1$ such that

$x_1 = [y_2, x_2]$, and

$$\beta_1 = [\delta, \beta_3].$$

Alternatively, (3) and (4) can also be written as

$$y_1 = y_2\delta + x_2\beta_3 + \varepsilon_1, \tag{5}$$

$$y_2 = x_2\beta_2 + \varepsilon_2. \tag{6}$$

Equation (4) determines $y_2$, while $y_2$ is included in the set of explanatory variables of $y_1$. In this simplified case, just as in equations (1) and (2), the only difference between the regressors in the two equations is $y_2$. Let $\hat{\beta}_1$ and $\hat{\beta}_2$ denote FGLS estimators of $\beta_1$ and $\beta_2$, respectively, and $b_1$ and $b_2$ denote the OLS estimators. Using the SUR model, we can re-write (3) and (4) as:

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} x_1 & 0 \\ 0 & x_2 \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix},$$

or simply as $y = x\beta + \varepsilon$. The error covariance matrix of the disturbances is:

$$\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{21} & \sigma_{22} \end{bmatrix},$$

$$\mathrm{E}\left[\varepsilon_1\varepsilon_2' \middle| x_1, x_2\right] = \Omega = \Sigma \otimes \mathrm{I} = \begin{bmatrix} \sigma_{11}\mathrm{I} & \sigma_{12}\mathrm{I} \\ \sigma_{21}\mathrm{I} & \sigma_{22}\mathrm{I} \end{bmatrix},$$

$$\Omega^{-1} = \Sigma^{-1} \otimes \mathrm{I}.$$

Letting $\hat{\sigma}_{ij} = s_{ij} = \frac{1}{n}\hat{e}_i'\hat{e}_j$, $i, j = 1, 2$,

$$\hat{\Omega} = S \otimes \mathrm{I} = \begin{bmatrix} s_{11}\mathrm{I} & s_{12}\mathrm{I} \\ s_{21}\mathrm{I} & s_{22}\mathrm{I} \end{bmatrix}, \text{ and}$$

$$\hat{\Omega}^{-1} = S^{-1} \otimes \mathrm{I}.$$

Letting $s^{ij}$ denote the $ij^{\text{th}}$ element of $S^{-1}$, we find the FGLS estimator to be

$$\hat{\beta} = \left[x'\hat{\Omega}^{-1}x\right]^{-1} x'\hat{\Omega}^{-1}y \text{, or}$$

$$\begin{bmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \end{bmatrix} = \left\{ \begin{bmatrix} x_1' & 0 \\ 0 & x_2' \end{bmatrix} \begin{bmatrix} s_{11}\mathrm{I} & s_{12}\mathrm{I} \\ s_{21}\mathrm{I} & s_{22}\mathrm{I} \end{bmatrix}^{-1} \begin{bmatrix} x_1 & 0 \\ 0 & x_2 \end{bmatrix} \right\}^{-1} \begin{bmatrix} x_1' & 0 \\ 0 & x_2' \end{bmatrix} \begin{bmatrix} s_{11}\mathrm{I} & s_{12}\mathrm{I} \\ s_{21}\mathrm{I} & s_{22}\mathrm{I} \end{bmatrix}^{-1} \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}$$

$$= \begin{bmatrix} s^{11}x_1'x_1 & s^{12}x_1'x_2 \\ s^{21}x_2'x_1 & s^{22}x_2'x_2 \end{bmatrix}^{-1} \begin{bmatrix} s^{11}x_1'y_1 + s^{12}x_1'y_2 \\ s^{21}x_2'y_1 + s^{22}x_2'y_2 \end{bmatrix}, \tag{7}$$

Revankar (1974) and Srivastava and Giles (1987) indicate that from (7) above and letting $\mathrm{M}_i = \left[I - x_i\left(x_i'x_i\right)^{-1}x_i'\right]$ will yield the following FGLS estimators:

$$\hat{\beta}_1 = \left(x_1'x_1\right)^{-1}x_1'y_1 - \frac{s_{12}}{s_{22}}\left(x_1'x_1\right)^{-1}x_1'\mathrm{M}_2 y_2, \tag{8}$$

$$\hat{\beta}_2 = \left(x_2'x_2\right)^{-1}x_2'y_2 - \frac{s_{12}}{s_{11}}\left(x_2'x_2\right)^{-1}x_2'\mathrm{M}_1 y_1. \tag{9}$$

Kakwani (1967) proved that $\hat{\beta}_1$ and $\hat{\beta}_2$ are unbiased.

First, consider equation (9). Since $x_2'\mathrm{M}_1 = 0$, the second right-hand side term disappears, and Revankar noted that $\hat{\beta}_2$ is equivalent to the OLS estimator, $b_2 = \left(x_2'x_2\right)^{-1}x_2'y_2$. In (8), since $\mathrm{M}_2 y_2$ simply denotes the residuals from a regression of $y_2$ on $x_2$, it can be written as $y_2 = x_2 b_2 + \hat{e}_2$. It follows that $\hat{e}_2 = \mathrm{M}_2 y_2$ and similarly that $\hat{e}_1 = \mathrm{M}_1 y_1$. It is then straightforward that,

$$\hat{e}_1'\hat{e}_2 = y_1'\mathrm{M}_1\mathrm{M}_2 y_2 = y_1'\left[\mathrm{I} - x_1\left(x_1'x_1\right)^{-1}x_1' - x_2\left(x_2'x_2\right)^{-1}x_2' + x_1\left(x_1'x_1\right)^{-1}x_1'x_2\left(x_2'x_2\right)^{-1}x_2'\right]y_2.$$

Note that $x_1\left(x_1'x_1\right)^{-1}x_1'x_2 = x_2$, so

$$y_1'\mathrm{M}_1\mathrm{M}_2 y_2 = y_1'\left[\mathrm{I} - x_1\left(x_1'x_1\right)^{-1}x_1'\right]y_2$$

$$= y_1'\mathrm{M}_1 y_2.$$

Since $x_1$ contains $y_2$, it follows that $y_1'M_1y_2 = 0$, hence $s_{12} = 0$. Again, the second right-hand side term disappears. This indicates that the GLS estimator is equivalent to the OLS estimator, $b_1 = (x_1'x_1)^{-1} x_1'y_1$, and the covariance of the residuals is zero. In such a case, GLS will be equivalent to OLS applied to each equation independently. Using the seemingly unrelated regressions approach does not improve efficiency because it does not take into account a nonzero error covariance. Therefore, we are left with the same results as estimating each equation independently under OLS.

Tests must be performed to determine if there is evidence that the error terms in equations (1) and (2) are actually correlated. To conduct this test, the three-stage least squares (3SLS) method is employed using snow depth as the instrument for VMT in equation (1). Gayer provided data on average daily snow depth and maximum daily snow depth for each state in each year in the data set. The snow depth variables are argued to be orthogonal to the error term in the first equation, yet highly correlated with VMT. For the IV estimations, Gayer used the number of pedestrian fatalities caused by each vehicle type during summer months as the dependent variable to ensure that there would not be any correlation between the snow depth figures and the error term. The test is performed as follows:

$$H_0 : \rho = 0$$

$$H_a : \rho \neq 0$$

Here, $\rho$ refers to the correlation between $\varepsilon$ and $\eta$, and $\hat{\rho}$ represents the correlation between the residuals from the two estimated equations (3) and (4). The appropriate *z*-statistic to use for this test is

$$z = \frac{z_r - 0}{\sqrt{1/(n-3)}},$$

where $z_r$ denotes the Fisher transformed value of the computed value of $\hat{\rho}$.

Under 3SLS with the dependent variables of pedestrian fatalities caused by cars during summer months and VMT in cars, $\hat{\rho}$ is equal to 0.775 using average daily snow depth as the instrument for VMT in equation (1), and 0.595 when using maximum daily snow depth as the instrument. The test statistics are $z$ = 20.43 and $z$ = 13.55, both of which are greater than the cutoff values of $z_{.05} = 1.96$ and $z_{.01} = 2.58$. When the dependent variables are pedestrian fatalities caused by light trucks during summer months and VMT in light trucks, $\hat{\rho}$ is equal to 0.320 when using the IV of average daily snow depth and .250 when using the IV of maximum daily snow depth. The corresponding test statistics are z = 6.57 and $z$ = 5.04. Again, both of these are higher than the cutoff values, so we can reject $H_0$ and conclude that the errors are correlated in each of the sets of equations.

Hausman (1978) presents a test for specification error arising from correlated error terms within a system of equations. The Hausman test compares the asymptotic covariance matrix of the estimator obtained under OLS with that obtained under IV estimation to determine whether the regressors under OLS are measured with error, and are thus inconsistent. Under the null hypothesis, both estimators are consistent, but under the alternative, only the IV estimator is consistent. If the Hausman statistic is significantly different from zero, then we conclude that OLS estimates are inconsistent due to specification error. The Hausman statistic employed in this analysis is

$$H = \frac{\left(\hat{\beta}_{2SLS} - \hat{\beta}_{OLS}\right)' \left\{Est.Asy.Var\left[\hat{\beta}_{2SLS}\right] - Est.Asy.Var\left[\hat{\beta}_{OLS}\right]\right\}^{-1} \left(\hat{\beta}_{2SLS} - \hat{\beta}_{OLS}\right)}{s_{OLS}^{2}}.$$

In the above formula, $\hat{\beta}_{2SLS}$ refers to the coefficient estimator found under 2SLS, $\hat{\beta}_{OLS}$ is the coefficient estimator found under OLS, and $s_{OLS}^{2}$ is the variance of the residual under OLS. According to Staiger and Stock (1997), this form of the Hausman statistic has the greatest asymptotic power even when the instrument is only weakly correlated with the endogenous variable.

For pedestrian fatalities caused by cars during summer months, the Hausman statistic is 22.79 using the IV of average daily snow depth and 17.01 using the IV of maximum daily snow depth for VMT. For pedestrian fatalities caused by light trucks during summer months, the Hausman statistics are 3.41 and 5.91 respectively. There is 1 degree of freedom, and the chi-squared 95 percent critical value is 3.84 and the 99 percent critical value is 6.63. Therefore, the hypothesis that there is no correlation between the error terms is rejected for cars, but it is not rejected for light trucks when using average daily snow depth as the instrument for VMT.

There is general evidence from both the direct correlation test and the Hausman test that the errors of the two equations in the system are not uncorrelated. The important conclusion is that if the assumption of uncorrelated errors does not hold, the model is not identified under either OLS or SUR. It is possible that the original triangular model that has been discussed so far is not defined properly to draw conclusions on driver offsetting behavior. If this is the case, then coefficient estimates will be biased and conclusions will be incorrect. In the following section, a new model will be constructed that will capture the offsetting behavior effect between

the two vehicle types. The underlying assumptions and hypotheses of this new model will be discussed.

**Section 3.B: Proposed Model and Empirical Methods**

Using a theoretical framework on driver behavior, the model will be re-specified in order to test for the presence of driver offsetting behavior between the two vehicle types. This model is similar to Dickie and Gerking (1997), as well as others in the literature. It is assumed that an individual maximizes a utility function

$$\max_{X, T_L, M} U(X, T_L, r),$$

where *X* is a composite consumption good, $T_L$ is time spent at leisure activities, *M* is vehicle miles traveled (VMT), i.e., $M = S \times T_D$, where *S* is vehicle speed and $T_D$ is time spent driving, and *r* is the risk that the driver will cause an accident during the course of operating his or her vehicle, which is a measure of driver recklessness. It is assumed that $U(\bullet) \in C^{(2)}$ on $\Re_{++}$ and that $U_X > 0$, $U_{T_L} > 0$, and $U_r > 0$, the latter indicating that drivers have a propensity for aggressive driving.

The recklessness function, or risk of causing an accident, is

$$r = R(G, M, UE, \theta, C, \Omega),$$

where *G* is a safety good, which in this case pertains to the type of vehicle chosen and it is assumed that light trucks are safer than cars. If the offsetting behavior hypothesis holds, then there will be more reckless driving in safer vehicles, thereby implying that $R_G > 0$, but in this model, the effect of *G* will be accounted for by running separate equations for cars and light trucks. Naturally, more VMT should lead to more accidents, implying that $R_M > 0$ holds. *UE* denotes the unemployment rate of the state in which the individual resides, which affects exposure to collisions according to Evans and Graham (1991). Since unemployed individuals

spend less time on roads which should lead to fewer accidents, it is expected that $R_{UE} < 0$. The vector $\theta$ refers to attitudes toward driving recklessly determined by the age and gender of the individual. Following Traynor (1993), younger drivers, especially males, typically engage in more aggressive driving behavior than older drivers and female drivers. $C$ is a control where 1 refers to urban road type and 0 refers to rural road type, with the assumption that urban roads have greater congestion than rural roads leading to greater chances for accidents, and it follows that $R_C > 0$. It has been suggested that the recklessness of drivers can be constrained by lower speed limits. Controls for increasing speed limit increments above 55 MPH are denoted by $\Omega$, so it is expected that $R_{\Omega} > 0$.

In this analysis, pedestrian fatalities and pedalcyclist fatalities caused by cars and light trucks are used to proxy the level of recklessness, or accident risk, of drivers. The measure of recklessness is based on fatalities rather than accidents because collection of data on accidents across different states is difficult and imprecise. What constitutes an "accident" or an "injury" and what is actually reported varies from one jurisdiction to another. The only reliable determinant of whether a traffic accident has occurred is if there is a fatality, since accident victims who die within 30 days from sustained injuries must be reported by all jurisdictions. The Fatality Analysis Reporting System (FARS) categorizes data on fatal crashes across the United States, with many particular factors also reported, such as vehicle types, number of vehicles involved, road type, time of day, location, and the like.

Pedestrian and pedalcyclist fatalities are used because it is assumed that all pedestrians and pedalcyclists face the same risk of fatal injury from vehicle crashes. Wearing only minimal protective gear such as a helmet or no protection at all, pedestrians and pedalcyclists are

completely vulnerable to vehicle crashes. It is assumed that both cars and light trucks have an equal potential to kill a pedestrian or pedalcyclist if struck simply due to the fact that all vehicles outweigh individuals by a considerable margin. The level of recklessness is not based on vehicle driver or occupant fatalities because they are insulated during crashes by the vehicles in which they are traveling, which offer various levels of protection due to model-specific features. The presence or absence of such safety equipment may actually have a more significant effect on fatalities than the vehicle type causing the crash. Occupants may or may not wear seat belts, and vehicle maintenance can also play a part in the severity of occupant injuries in a crash. With so many exogenous factors determining the risk of death in a crash, estimation based on driver or occupant fatalities has a serious potential to produce biased results.

The individual driver is a consumer, who maximizes utility subject to a money budget constraint,

$$I = p_X X + p_G G,$$

where *I* is income, and $p_X$ and $p_G$ are prices of goods *X* and *G*, respectively. The individual's time constraint is

$$T = t_X X + t_G G + T_W + T_D + T_L.$$

Here, $t_X$ and $t_G$ are the shares of time spent consuming goods *X* and *G*, and time spent working is denoted as $T_W$. Noting that $I = wT_W$, where *w* is the wage per hour worked, the full-income budget constraint then becomes

$$wT = q_X X + q_G G + wT_D + wT_L,$$

where $q_X \overset{def}{=} p_X + wT_X$ and $q_G \overset{def}{=} p_G + wT_G$ reflect the time-inclusive prices of the two goods according to Becker (1965).

The utility maximization problem, where time spent driving is expressed in terms of VMT and vehicle speed, is therefore given by

$$U^*(\alpha) \overset{def}{=} \max_{X, T_L, M} \left\{ U\left(X, T_L, R(G, M, UE, \theta, C, \Omega)\right) \text{ s.t. } wT = q_X X + q_G G + wMS^{-1} + wT_L \right\}.$$

The parameters in the utility maximization problem are

$$\alpha \overset{def}{=} \left(w, q_X, q_G, G, UE, \theta, C, \Omega, T, P\right).$$

The amounts of *X*, $T_L$, and *M* chosen to maximize utility depend on the budget variables as well as those that affect the individual's time and distance traveled, including unemployment, age- and gender-related factors, driving environment, traffic laws, and total time. Since the data in this analysis are based on aggregate figures, there is also a variable for the total population of each state, which is listed as *P*.

The Lagrangian function for the utility maximization problem faced by drivers of both vehicle types is

$$L = U\left\{X, T_L, R(G, M, UE, \theta, C, \Omega)\right\} + \lambda\left[-q_X X - q_G G - wMS^{-1} - wT_L + wT\right].$$

The first-order necessary conditions are

$$\frac{\partial L}{\partial X} = U_X - \lambda q_X = 0,$$

$$\frac{\partial L}{\partial T_L} = U_{T_L} - \lambda w = 0,$$

$$\frac{\partial L}{\partial M} = U_r \frac{\partial R}{\partial M} - \lambda w S^{-1} = 0,$$

$$\frac{\partial L}{\partial \lambda} = -q_X X - q_G G - wMS^{-1} - wT_L + wT = 0\,.$$

Solving the first-order necessary conditions and assuming that second-order sufficient conditions hold for a maximum, the solutions are $X = X^*(\alpha)$, $T_L = T_L{}^*(\alpha)$, $M = M^*(\alpha)$, and $\lambda = \lambda^*(\alpha)$.

Evidence to support the offsetting behavior hypothesis can be found by taking the difference of the VMT coefficients in the recklessness functions for cars and light trucks. If the VMT coefficient in the light truck recklessness equation is significantly larger than that in the car recklessness equation, then it can be concluded that drivers of light trucks fatally injure more pedestrians per vehicle mile traveled than drivers of cars, holding all else constant, implying that

$$\frac{\partial R_j}{\partial M_j} - \frac{\partial R_i}{\partial M_i} > 0\,,$$

where *j* refers to light trucks and *i* refers to cars. If this intuition is true, then it is likely that a difference in driver behavior is responsible for the larger number of pedestrian crash fatalities caused by light trucks.

VMT is represented in the utility maximization problem as

$$M = M^*\left(w, q_X, q_G, G, UE, \theta, C, \Omega, T, P\right).$$

In the original model, the VMT equation does not include variables for prices, income, or total state population, but by the theoretical implications, they are necessary determinants. The population variable and the controls for increasing speed limits should be positively related to VMT, so it is expected that $\partial M^*/\partial P > 0$ and $\partial M^*/\partial \Omega > 0$. The variation in $q_X$, $q_G$, and *w* are mainly due to variation in prices and income. Real gross state product for each state was obtained from the Bureau of Economic Analysis (BEA), which was divided by state population

figures to reach an estimate of per capita income. Population was then included as a separate variable. To estimate a price effect that must be paid by all drivers, a variable for per-gallon gasoline tax in each state was also included. Since all individuals have the same amount of total time available (24 hours per day), no variable is included for time. The estimated triangular model then becomes

$$r = R(G, M, UE, \theta, C, \Omega), \tag{10}$$

$$M = \mu^*(G, I, GTAX, UE, \theta, C, \Omega, P), \tag{11}$$

where *I* and *GTAX* are income and gasoline taxes, respectively.

The functional form of equations (10) and (11) is again assumed to be linear, just as equations (1) and (2). Therefore, the actual triangular system of equations to be estimated in order to determine the recklessness of drivers of each vehicle type then becomes

$$r_{jst} = M_{jst}\delta_j + x'_{jst}\beta_j + \varepsilon_{jst}, \tag{12}$$

$$M_{jst} = x'_{jst}\pi_j + I_{jst}\phi_j + GTAX_{jst}\vartheta_j + P_{jst}\gamma_j + \eta_{jst}. \tag{13}$$

Here, $r_{jst}$ is the recklessness indicated by pedestrian or pedalcyclist fatalities caused by vehicle type *j* in state *s* and year *t*. The set of observed characteristics in the vector $x'_{jst}$ in equations (12) and (13) is the same as those in equations (1) and (2).

By leaving the first equation in the original triangular system alone and adding three additional variables to the second equation, the initial specification problem is eliminated. The new model takes into account the effects of necessary variables that were omitted in the original model, and consistent estimation no longer depends on uncorrelated error terms. Since both SUR and 3SLS can provide a gain in efficiency over using OLS, the question remains of which method is the best one to use for estimating this model. Lahiri and Schmidt suggest using the

method of SUR to estimate the triangular system based on the fact that the SUR estimator and the full-information maximum likelihood (FIML) estimator are equivalent. However, Prucha (1987) points out that SUR does not provide a consistent estimator of the asymptotic covariance matrix of the FIML estimator, a technicality that is not explored by Lahiri and Schmidt. In this analysis, the method of 3SLS is employed since it yields an asymptotically efficient estimate of the FIML estimator. Results under both SUR and 3SLS are included in the tables in the appendix section, but results under 3SLS will be regarded as superior based on consistent standard error estimates. When using 3SLS, the variables in the second equation are used to identify the first equation without the need for exogenous IVs.

The previous literature concerning offsetting behavior has not considered pedalcyclists, but since it has been assumed that they are equally as vulnerable to deaths from vehicle accidents as pedestrians, estimating the model with data on pedalcyclist fatalities could further support the offsetting behavior hypothesis.

# CHAPTER FOUR: ESTIMATION RESULTS

This chapter discusses the results obtained from estimating the theoretical model developed in chapter 3. Empirical results are presented in tabular form in the appendix section. Table 1 shows the results for pedestrian fatalities using the method of SUR to estimate the model, while table 2 shows the results for pedestrian fatalities using the method of 3SLS. In both cases, the model was estimated a total of ten times, five for each vehicle type, with yes or no indicators for the various fixed effects that were included in the estimations. The first column indicates that the equations were estimated without any of the fixed effects present. In the other columns, combinations of state fixed effects and year effects are added to strengthen the results. There is a state linear time trend which is added in the last column to account for any variables that may vary across states over time, such as unemployment levels and speed limits.

The upper panels of each table consist of estimations where the dependent variables are car crashes with pedestrians and vehicle miles traveled in cars. The dependent variables in the lower panel estimations are light truck crashes with pedestrians and vehicle miles traveled in light trucks. In each estimated model, results from the accident risk equation are listed above those from the corresponding VMT equation. The coefficients and standard errors for VMT in the risk equations are reported. For the speed limit controls and population variables in both equations, only t-statistics are listed with superscripts a, b, and c to indicate significance at the 1 percent, 5 percent, and 10 percent levels of a two-sided test, respectively. $R^2$ coefficients are shown only for the risk equations. Results for the other independent variables in the equations are not shown in the tables because these variables were generally not significant or did not point to interesting conclusions. Table 3 is a reduced-form OLS estimation which will be discussed

later.  Tables 4, 5, and 6 present similar estimations of models concerning pedalcyclist fatalities by vehicle type.

Considering the construction of the model, t-statistics for the population variable in the VMT equations generally indicate very high levels of significance.  The number of aggregate vehicle miles traveled in both vehicle types increases with state population, which is consistent with the theoretical prediction.  Population is highly significant in all estimations except for pedestrian fatalities caused by cars under 3SLS with state fixed effects added.  There is evidence that the original model structure could produce biased results since the effect of state population should be included in the VMT equation in order to correctly specify this model.  Gasoline tax and per capita income lost significance when the fixed effects were added.

The bottom row of each table shows the t-statistics for the test for driver offsetting behavior.  The hypothesis test in this case focuses on the VMT coefficients from the accident risk equations for each vehicle type.  If there is offsetting behavior associated with the drivers of light trucks, then we should see a higher number of pedestrians or pedalcyclists fatally injured by drivers of light trucks per vehicle mile traveled, holding all else constant.  Using the VMT coefficients from equation (12), the appropriate test is:

$$H_0 : \delta_j = \delta_i ,$$

$$H_a : \delta_j > \delta_i .$$

where *i* refers to cars and *j* refers to light trucks.  In this case, the t-statistics are compared with the appropriate table value for the 1 percent level of a one-sided test, and significance is indicated by superscript a.  All t-statistics for this test were found to be significant for pedestrian and pedalcyclist fatalities using both SUR and 3SLS.  Therefore, we can reject $H_0$ and conclude

that drivers of light trucks are overall more reckless than drivers of cars holding VMT and all else constant. This confirms Peltzman's hypothesis on offsetting behavior.

The data on pedalcyclist fatalities was obtained from FARS. Each pedalcyclist crash casualty resulted from being struck by either a car or a light truck. Unlike the data on pedestrian fatalities by vehicle type, FARS did not separate pedalcyclist fatalities by those occurring on urban and rural road types, so the data set was modified accordingly before estimating the model. This reduces the number of total observations from 394 in the pedestrian fatalities data set to 199 in the pedalcyclist data set. With the exception of road types to proxy congestion levels, the same set of independent variables was used in the pedalcyclist equations. There is significant evidence from the pedalcyclist equations to support driver offsetting behavior in light trucks.

The extent to which drivers of light trucks are actually offsetting the safety benefits associated with driving larger vehicles cannot be determined from this analysis. If light trucks are in fact safer than cars, then the benefits of added protection only accrue to their drivers and occupants, not to pedestrians or pedalcyclists. If a greater number of light truck occupants are injured in at-fault crashes than car occupants, then drivers of light trucks are more than fully offsetting the safety benefits by driving more aggressively. Following Blomquist (1988), this would be an example of the lulling effect. If there is no difference between injuries of car occupants and light truck occupants in at-fault collisions, then drivers of light trucks are assuming a level of risk that exactly offsets the effect of safety, or what is known as risk homeostatis. In the technological approach, driver behavior remains the same between cars and light trucks, and the occupants of light trucks experience fewer injuries from crashes. While the presence of offsetting behavior discovered here appears to suggest either the lulling effect or risk homeostatis, it can only be concluded from this analysis that drivers of light trucks are

significantly more aggressive overall than drivers of cars, with pedestrian and pedalcyclist fatalities cited as evidence of this.

Although the offsetting behavior result is clearly expected based on intuition developed from the earlier literature, there is an unexpected negative relationship between speed limits and pedestrian fatalities. In the accident risk function estimated under both SUR and 3SLS, significant speed limit coefficients are negatively related to pedestrian fatalities. However, it is important to note that the significant coefficients for speed limits in the VMT equations are positive, which follows from the premise that as speed increases, vehicles will travel more miles. Due to the triangular construction of the model, the VMT equation is part of the accident risk function, and both pedestrian fatalities and VMT are dependent on speed limits. Since the speed limit coefficients are negative for pedestrian fatalities and positive for VMT, the net effect of increased speed limits on pedestrian fatalities is unclear.

To determine the direct relationship between speed limits and driver recklessness, the total derivative of recklessness equation (10) is taken with respect to speed limits using the chain rule. However, this total derivative is equal to running the reduced-form driver recklessness function under OLS and taking the partial derivative with respect to speed limits. The recklessness function in reduced form is

$$r = f\left(G, I, GTAX, UE, \theta, C, \Omega, P\right).$$

Results for the estimated reduced-form equation are included in Table 3. The corresponding t-statistics are shown in parentheses and they reflect the heteroskedasticity-robust covariance matrix found under the method proposed by White (1980). In the reduced-form OLS estimation with fixed effects added for states and years, significant speed limit coefficients are positive for cars and negative for light trucks, indicating that drivers of light trucks are causing fewer

pedestrian fatalities when speed limits increase while drivers of cars are causing more fatalities with increased speed limits.

There are a few explanations for why these results diverge from the logical expectation that higher speed limits will always result in more fatalities regardless of vehicle type. First, areas with the highest speed limits are usually those with the lowest population densities. Raising the speed limit to 70 MPH or 75 MPH would only affect roads in the least populated areas, such as rural highways. These roads would have very few chances for fatal crashes to occur between vehicles and pedestrians, which is evidenced by the fact that the control for urban roads is significant and positive in both reduced-form estimations. This indicates that there are more pedestrian fatalities caused by both vehicle types on urban roads than on rural roads. When speed limits are increased on highways, they become capable of handling greater traffic volumes and become more attractive to motorists who are likely to drive recklessly, such as drivers of light trucks. This takes many light trucks off of city streets where they would come into contact with pedestrians, and subsequently lowers their fatality numbers. Despite the increased speed limits on highways, drivers of cars, who are less likely to drive recklessly, will use surface streets where there are more pedestrians. Cars will then become responsible for more pedestrian deaths than they were previously.

A second explanation for the negative relationship between speed limits and pedestrian fatalities caused by light trucks was offered in a study by Lave (1985), which concludes that it is not vehicle speed alone that causes most accidents. Rather, the cause of most crashes is the speed variance between the slowest and the fastest vehicles that are sharing a roadway. When speed limits are set at 55 MPH, there are drivers who are obeying the limit while others are traveling much faster, leading to a large speed variance that can be dangerous. As the posted

speed limit is increased, the speed variance decreases and we should expect a subsequent decline in the accident rate. Keeler (1994), Alexander (1992), and a traffic engineering study by Garber and Gadiraju (1988), all support this finding. Since light trucks are more likely to become involved in serious collisions than cars because of differences in driver behavior, light trucks become even more deadly when the speed variance is high. A situation where a pickup or sport-utility vehicle is being driven at a speed that is significantly higher than the surrounding traffic would pose a far greater risk to other road users than a situation where a car is being driven too fast, based on the added size and weight of the light truck. With drivers of light trucks being generally more reckless than drivers of cars, they are naturally more likely to be at the higher end of the speed variance. We must consider that as the posted speed limit increases to 70 MPH, the speed variance gap begins to close which makes trucks relatively safer in traffic. But as the limit goes as high as 75 MPH, the speed of cars will increase and they will inevitably become responsible for more pedestrian deaths than they were initially, a plausible explanation for the positive relationship between speed limits and pedestrian deaths caused by cars.

Controls for speed limits are generally not significant in the SUR and 3SLS estimations, especially after adding state and year fixed effects. It is possible that including state effects yields estimates that are not significant because of the small numbers of pedalcyclist fatalities in many states during the observed five-year period. In fact, some states reported zero pedalcyclist fatalities, and most reported fewer than ten in any given year. Regardless, there is still evidence to support the conjecture that light trucks pose a greater risk to pedalcyclists than cars, which must be attributed to the more aggressive manner in which they are driven. This conclusion strengthens the offsetting behavior hypothesis relating to drivers of light trucks beyond previous studies.

# CHAPTER FIVE: CONCLUSIONS

This analysis presents an econometric model that is specified on the basis of Peltzman's offsetting behavior hypothesis to test the response of drivers of light trucks to their higher perceived safety benefits. Results offer substantial evidence supporting the contention that drivers are operating light trucks more dangerously than they would operate cars. The results are based on examining data on pedestrian fatalities caused by light trucks and those caused by cars across the United States over the 5-year period from 1994 – 1998. Analyzing pedalcyclist fatalities across the United States over the same time period also confirms the offsetting behavior hypothesis.

With the trend towards heavier trucks used as personal vehicles, there is a cause for concern on our nation's roads if light trucks are inducing reckless behavior which is leading to more accidents. Relaxed fuel consumption and safety standards for light trucks have made them profitable to design and build, while consumers have been attracted by the illusion of increased safety and the ability to drive off-road if necessary. The truth about safety benefits of light trucks is a two-sided coin. Drivers and occupants of the trucks might be safer on average, but occupants of other vehicles, pedestrians, and pedalcyclists, are more at risk.

The policy decisions that have led to weaker standards for light trucks were intended to help the domestic auto industry. However, it is likely that these policy decisions have created a negative externality, a rise in accident fatalities due to more aggressive driving in light trucks. To reduce the potential for driver offsetting behavior, more information regarding the dangers of operating light trucks must be made available to the public. In order for offsetting behavior to exist, there must be a perception of safety. Without this misguided safety perception, drivers

may not be inclined to drive light trucks more aggressively, or even purchase them in the first place. In addition, loopholes in regulations where light trucks are concerned must be closed in an effort to promote the manufacturing of safer cars.

Since drivers of light trucks tend to be more reckless than drivers of cars, they will want to drive at higher speeds and will naturally gravitate toward open highways where speed limits are set at 65 MPH or above. There is evidence that high speed limits will take light trucks off of city streets and place them on highways where there are fewer pedestrians, thereby reducing pedestrian fatalities caused by light trucks. Meanwhile, drivers of cars who are often less hazardous will choose to leave the highways and drive where the speed limit is lower, so there will be more car traffic on city streets increasing the chances for drivers of cars to cause pedestrian fatalities.

Speed limits that were set at 55 MPH and were originally thought to reduce offsetting behavior by prohibiting high-speed driving may have just the opposite effect. Previous studies have indicated that low speed limits create such a high speed variance between the slowest and the fastest vehicle that there may be an increased potential for accidents. When light trucks are at the high end of the speed variance, a frequent occurrence given that drivers of light trucks tend to be aggressive, they are posing a tremendous threat to the other road users. This risk could start to diminish as the speed variance gap closes, which makes a case for higher speed limits. On the other hand, raising the speed limit will close the variance gap by increasing the speed of cars, inevitably resulting in more pedestrian fatalities caused by cars.

The degree to which drivers of light trucks are actually offsetting the large vehicle safety benefits is unclear, but the amount is great enough to cause considerable risk to pedestrians who do not have the insulation level from collisions afforded by even the most unsafe car. Traffic policy

decisions and vehicle designs should focus on the welfare of these most vulnerable road users since it is evident that greater vehicle occupant protection offered by light trucks does not translate into safer roads overall.

# APPENDIX: TABLES

Table 1: Estimated SUR models for pedestrian fatalities by vehicle type:

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Pedestrian fatalities caused by cars | | | | | |
| Vehicle miles traveled (millions) | 0.00180[a] | 0.00085[a] | 0.00180[a] | 0.00085[a] | 0.00197[a] |
| | (0.000040) | (0.000050) | (0.000040) | (0.000051) | (0.000045) |
| *R*-squared | 0.8815 | 0.8206 | 0.8821 | 0.8206 | 0.9197 |
| Limit65 | -2.426[b] | 0.011 | -2.317[b] | 0.020 | -2.227[b] |
| Limit70 | -3.273[a] | -2.508[b] | -2.766[a] | -2.421[b] | -2.457[b] |
| Limit75u | -1.860[c] | 0.848 | -1.543 | 0.826 | -1.760[c] |
| VMT in cars | | | | | |
| Limit65 | 1.953[c] | 2.477[b] | 1.871[c] | 2.484[b] | 2.548[b] |
| Limit70 | -0.254 | -0.856 | -0.404 | -0.771 | -1.057 |
| Limit75u | 2.576[a] | 3.414[a] | 2.367[b] | 3.363[a] | 3.652[a] |
| Population | 26.277[a] | 3.973[a] | 26.139[a] | 3.977[a] | 15.135[a] |
| Pedestrian fatalities caused by light trucks | | | | | |
| Vehicle miles traveled (millions) | 0.00576[a] | 0.00702[a] | 0.00576[a] | 0.00701[a] | 0.00531[a] |
| | (0.000176) | (0.000246) | (0.000176) | (0.000245) | (0.000206) |
| *R*-squared | 0.7338 | 0.8874 | 0.7356 | 0.8884 | 0.8430 |
| Limit65 | -1.161 | -3.157[a] | -1.347 | -3.287[a] | -1.405 |
| Limit70 | -2.827[a] | -3.951[a] | -3.124[a] | -4.135[a] | -3.211[a] |
| Limit75u | -1.688[c] | -3.251[a] | -2.010[b] | -3.467[a] | -1.449 |
| VMT in light trucks | | | | | |
| Limit65 | 1.010 | 2.591[a] | 1.006 | 2.587[a] | 2.089[b] |
| Limit70 | 1.026 | -0.636 | 0.915 | -0.575 | -1.389 |
| Limit75u | 2.506[b] | 3.601[a] | 2.412[b] | 3.561[a] | 3.463[a] |
| Population | 24.784[a] | 2.340[b] | 24.654[a] | 2.326[b] | 16.731[a] |
| State fixed effects | No | Yes | No | Yes | No |
| Year indicators | No | No | Yes | Yes | Yes |
| State-specific linear time trend | No | No | No | No | Yes |
| Offsetting behavior effect | 21.94[a] | 24.58[a] | 21.94[a] | 24.62[a] | 15.84[a] |

Notes: The first panel consists of SUR estimations where the dependent variables are pedestrian fatalities caused by car crashes and VMT in cars. The dependent variables in the second panel of SUR estimations are pedestrian fatalities caused by light truck crashes and VMT in light trucks. Additional independent variables included in both regression equations are unemployment rate, speed limit indicators, controls for urban and rural road types, and percentages of the population of each state who are men age 65 and over, women age 65 and over, men between the ages of 15-29, and women between the ages of 15-29. The vehicle miles traveled equations also contain real per capita income (measured as real per capita gross state product), state population, and gasoline tax. Coefficients and standard errors are reported for VMT in each vehicle type. For the speed limit indicators, population estimates, and offsetting behavior effects, t-statistics are reported. Superscripts a, b, and c denote significance at the 1%, 5%, and 10% levels of the appropriate tests, respectively. Data were collected over 46 states during the five year period from 1994-1998, with the exceptions of DC, MN, NV, VA, and IA for which data were unavailable. There are both urban and rural road types, but some states did not report the VMT data for both road types for each year. There are 116 missing observations, so the total number of observations included in each regression equation is 394.

Table 2: Estimated 3SLS models for pedestrian fatalities by vehicle type:

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Pedestrian fatalities caused by cars | | | | | |
| Vehicle miles traveled (millions) | 0.00182[a] | -0.00077 | 0.00182[a] | -0.00083 | 0.00201[a] |
| | (0.000052) | (0.002185) | (0.000052) | (0.002251) | (0.000077) |
| *R*-squared | 0.8830 | 0.3903 | 0.8836 | 0.3707 | 0.9209 |
| Limit65 | -2.543[b] | 0.643 | -2.432[b] | 0.652 | -2.307[b] |
| Limit70 | -3.384[a] | -1.506 | -2.874[a] | -1.415 | -2.430[b] |
| Limit75u | -1.963[b] | 0.861 | -1.639 | 0.855 | -1.892[c] |
| VMT in cars | | | | | |
| Limit65 | 1.929[c] | 2.492[b] | 1.846[c] | 2.509[b] | 2.562[b] |
| Limit70 | -0.309 | -0.658 | -0.458 | -0.559 | -0.956 |
| Limit75u | 2.597[a] | 3.462[a] | 2.385[b] | 3.418[a] | 3.527[a] |
| Population | 25.907[a] | 1.384 | 26.768[a] | 1.339 | 15.026[a] |
| Pedestrian fatalities caused by light trucks | | | | | |
| Vehicle miles traveled (millions) | 0.00575[a] | 0.00709[a] | 0.00575[a] | 0.00708[a] | 0.00531[a] |
| | (0.000229) | (0.000206) | (0.000229) | (0.002032) | (0.000319) |
| *R*-squared | 0.7341 | 0.8872 | 0.7359 | 0.8883 | 0.8431 |
| Limit65 | -1.137 | -2.179[b] | -1.321 | -2.271[b] | -1.393 |
| Limit70 | -2.751[b] | -3.296[a] | -3.052[a] | -4.122[a] | -3.209[a] |
| Limit75u | -1.665[c] | -1.815[c] | -1.986[b] | -1.959[c] | -1.428 |
| VMT in light trucks | | | | | |
| Limit65 | 1.007 | 2.591[a] | 1.004 | 2.587[a] | 2.089[b] |
| Limit70 | 1.022 | -0.636 | 0.912 | -0.575 | -1.389 |
| Limit75u | 2.505[b] | 3.602[a] | 2.411[b] | 3.561[a] | 3.463[a] |
| Population | 24.456[a] | 2.333[b] | 24.331[a] | 2.320[b] | 16.698[a] |
| State fixed effects | No | Yes | No | Yes | No |
| Year indicators | No | No | Yes | Yes | Yes |
| State-specific linear time trend | No | No | No | No | Yes |
| Offsetting behavior effect | 16.74[a] | 3.58[a] | 16.74[a] | 2.61[a] | 10.06[a] |

Notes: The first panel consists of 3SLS estimations where the dependent variables are pedestrian fatalities caused by car crashes and VMT in cars. The dependent variables in the second panel of 3SLS estimations are pedestrian fatalities caused by light truck crashes and VMT in light trucks. Additional independent variables included in both regression equations are unemployment rate, speed limit indicators, controls for urban and rural road types, and percentages of the population of each state who are men age 65 and over, women age 65 and over, men between the ages of 15-29, and women between the ages of 15-29. The vehicle miles traveled equations also contain real per capita income (measured as real per capita gross state product), state population, and gasoline tax. Coefficients and standard errors are reported for VMT in each vehicle type. For the speed limit indicators, population estimates, and offsetting behavior effects, t-statistics are reported. Superscripts a, b, and c denote significance at the 1%, 5%, and 10% levels of the appropriate tests, respectively. Data were collected over 46 states during the five year period from 1994-1998, with the exceptions of DC, MN, NV, VA, and IA for which data were unavailable. There are both urban and rural road types, but some states did not report the VMT data for both road types for each year. There are 116 missing observations, so the total number of observations included in each regression equation is 394.

Table 3: Reduced-form OLS estimation for pedestrian fatalities by vehicle type:

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Pedestrian fatalities caused by cars | | | | | |
| Limit65 | 0.295 | 4.452 | 0.284 | 4.569 | 4.271 |
| | (0.085) | (1.104) | (0.073) | (1.149) | (1.201) |
| Limit70 | -12.662[c] | -12.788 | -12.720 | -12.527 | -15.917 |
| | (-1.762) | (-1.340) | (-1.520) | (-1.291) | (-1.547) |
| Limit75u | 8.536[b] | 13.810[a] | 8.608[c] | 14.064[a] | 16.270[a] |
| | (2.292) | (3.070) | (1.693) | (3.134) | (3.800) |
| Urban | 21.165[a] | 23.828[a] | 21.656[a] | 23.969[a] | 23.692[a] |
| | (6.913) | (6.858) | (5.863) | (7.049) | (7.150) |
| Population | 0.0000046[a] | -0.000004 | 0.0000046[a] | -0.000004 | 0.0000049[a] |
| | (5.731) | (-0.119) | (5.798) | (-0.116) | (2.974) |
| $R$-squared | 0.5791 | 0.6359 | 0.5794 | 0.6359 | 0.6193 |
| Pedestrian fatalities caused by light trucks | | | | | |
| Limit65 | -0.209 | 0.771 | -0.633 | 0.570 | 1.281 |
| | (-0.093) | (0.388) | (-0.252) | (0.283) | (0.672) |
| Limit70 | -4.732 | -10.462[c] | -6.301 | -10.970[b] | -12.345[b] |
| | (-1.129) | (-1.931) | (-1.232) | (-1.973) | (-2.065) |
| Limit75u | 2.962 | 4.293[c] | 1.686 | 3.180 | 5.678[b] |
| | (1.303) | (1.715) | (0.522) | (1.447) | (2.295) |
| Urban | 10.111[a] | 9.826[a] | 9.488[a] | 9.563[a] | 10.021[a] |
| | (5.371) | (5.763) | (4.227) | (5.597) | (5.762) |
| Population | 0.0000027[a] | 0.0000116 | 0.0000027[a] | 0.0000115 | 0.0000025[a] |
| | (6.330) | (0.709) | (6.484) | (0.697) | (3.168) |
| $R$-squared | 0.6027 | 0.6782 | 0.6048 | 0.6785 | 0.6656 |
| State fixed effects | No | Yes | No | Yes | No |
| Year indicators | No | No | Yes | Yes | Yes |
| State-specific linear time trend | No | No | No | No | Yes |

Notes: The first panel consists of an OLS estimation where the dependent variable is pedestrian fatalities caused by car crashes. The second panel is an OLS estimation where the dependent variable is pedestrian fatalities caused by light truck crashes. Additional independent variables included in both regression equations are unemployment rate, speed limit indicators, controls for urban and rural road types, and percentages of the population of each state who are men age 65 and over, women age 65 and over, men between the ages of 15-29, and women between the ages of 15-29, real per capita income (measured as real per capita gross state product), state population, and gasoline tax. For the speed limit indicators and population estimates, coefficients are reported with t-statistics in parentheses. All reported t-statistics reflect the heteroskedasticity-robust covariance matrix. Superscripts a, b, and c denote significance at the 1%, 5%, and 10% levels of a 2-sided test, respectively. Data were collected over 46 states during the five year period from 1994-1998, with the exceptions of DC, MN, NV, VA, and IA for which data were unavailable. There are both urban and rural road types, but some states did not report the VMT data for both road types for each year. There are 116 missing observations, so the total number of observations included in each regression equation is 394.

Table 4: Estimated SUR models for pedalcyclist fatalities by vehicle type:

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Pedalcyclist fatalities caused by cars | | | | | |
| Vehicle miles traveled (millions) | 0.00034[a] | -0.00122[a] | 0.00034[a] | -0.00119[a] | 0.00040[a] |
| | (0.000018) | (0.000204) | (0.000018) | (0.000205) | (0.000022) |
| *R*-squared | 0.7279 | 0.9314 | 0.7302 | 0.9338 | 0.8642 |
| Limit65 | 1.940[c] | -0.250 | 1.938[b] | -0.522 | 1.821[c] |
| Limit70 | 1.061 | -0.852 | 1.340 | -1.465 | 0.004 |
| Limit75u | 0.175 | 0.315 | 0.458 | -0.558 | 1.287 |
| VMT in cars | | | | | |
| Limit65 | 0.291 | 0.389 | 0.136 | 0.346 | 1.955[c] |
| Limit70 | 1.593 | 1.324 | 1.034 | 0.518 | 0.842 |
| Limit75u | 0.096 | 0.756 | -0.216 | -0.217 | 0.753 |
| Population | 75.569[a] | 15.008[a] | 75.786[a] | 15.687[a] | 77.645[a] |
| Pedalcyclist fatalities caused by light trucks | | | | | |
| Vehicle miles traveled (millions) | 0.00139[a] | 0.00051[b] | 0.00140[a] | 0.00067[a] | 0.00135[a] |
| | (0.000063) | (0.000251) | (0.000063) | (0.000256) | (0.000074) |
| *R*-squared | 0.6177 | 0.9517 | 0.6181 | 0.9526 | 0.8476 |
| Limit65 | 0.673 | 0.374 | 0.631 | 0.705 | 1.244 |
| Limit70 | -0.305 | -0.369 | -0.289 | 0.113 | -0.289 |
| Limit75u | -1.097 | 0.197 | -1.040 | 0.784 | 0.238 |
| VMT in light trucks | | | | | |
| Limit65 | 0.989 | 0.395 | 1.234 | 0.693 | 0.607 |
| Limit70 | 2.772[a] | 0.503 | 3.055[a] | 0.407 | 0.387 |
| Limit75u | 1.382 | -0.468 | 1.795[c] | -0.465 | 0.456 |
| Population | 28.474[a] | 7.763[a] | 28.445[a] | 8.250[a] | 29.881[a] |
| State fixed effects | No | Yes | No | Yes | No |
| Year indicators | No | No | Yes | Yes | Yes |
| State-specific linear time trend | No | No | No | No | Yes |
| Offsetting behavior effect | 16.03[a] | 5.35[a] | 16.18[a] | 5.67[a] | 12.31[a] |

Notes: The first panel consists of SUR estimations where the dependent variables are pedalcyclist fatalities caused by car crashes and VMT in cars. The dependent variables in the second panel of SUR estimations are pedalcyclist fatalities caused by light truck crashes and VMT in light trucks. Additional independent variables included in both regression equations are unemployment rate, speed limit indicators, and percentages of the population of each state who are men age 65 and over, women age 65 and over, men between the ages of 15-29, and women between the ages of 15-29. The vehicle miles traveled equations also contain real per capita income (measured as real per capita gross state product), state population, and gasoline tax. Coefficients and standard errors are reported for VMT in each vehicle type. For the speed limit indicators, population estimates, and offsetting behavior effects, t-statistics are reported. Superscripts a, b, and c denote significance at the 1%, 5%, and 10% levels of the appropriate tests, respectively. Data were collected over 46 states during the five year period from 1994-1998, with the exceptions of DC, MN, NV, VA, and IA for which data were unavailable. Data separating pedalcyclist fatalities by road type were not available through FARS, so this control is not included in the equations. The total number of observations included in each regression equation is 199.

Table 5: Estimated 3SLS models for pedalcyclist fatalities by vehicle type:

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Pedalcyclist fatalities caused by cars | | | | | |
| Vehicle miles traveled (millions) | 0.00034[a] | -0.00121[a] | 0.00034[a] | -0.00194[a] | 0.00040[a] |
| | (0.000018) | (0.000304) | (0.000018) | (0.000276) | (0.000023) |
| *R*-squared | 0.7279 | 0.9316 | 0.7302 | 0.9201 | 0.8642 |
| Limit65 | 1.943[c] | -0.245 | 1.941[b] | -0.828 | 1.814[c] |
| Limit70 | 1.067 | -0.853 | 1.345 | -1.300 | 0.000 |
| Limit75u | 0.178 | 0.316 | 0.460 | -0.737 | 1.284 |
| VMT in cars | | | | | |
| Limit65 | 0.282 | 0.390 | 0.125 | -0.589 | 1.969[b] |
| Limit70 | 1.586 | 1.324 | 1.026 | 0.702 | 0.852 |
| Limit75u | 0.084 | 0.756 | -0.228 | -0.461 | 0.760 |
| Population | 75.594[a] | 14.180[a] | 75.807[a] | 22.729[a] | 77.656[a] |
| Pedalcyclist fatalities caused by light trucks | | | | | |
| Vehicle miles traveled (millions) | 0.00135[a] | 0.00048 | 0.00135[a] | 0.00066 | 0.00130[a] |
| | (0.000077) | (0.000503) | (0.000078) | (0.000509) | (0.000087) |
| *R*-squared | 0.6281 | 0.9518 | 0.6293 | 0.9527 | 0.8513 |
| Limit65 | 0.782 | 0.369 | 0.750 | 0.700 | 1.398 |
| Limit70 | -0.090 | -0.362 | -0.068 | 0.115 | -1.880 |
| Limit75u | -1.027 | 0.192 | -0.959 | 0.776 | 0.317 |
| VMT in light trucks | | | | | |
| Limit65 | 0.797 | 0.392 | 1.015 | 0.693 | 0.228 |
| Limit70 | 2.579[a] | 0.500 | 2.829[a] | 0.407 | 0.136 |
| Limit75u | 1.241 | -0.472 | 1.627 | -0.465 | 0.277 |
| Population | 26.911[a] | 7.723[a] | 26.892[a] | 8.188[a] | 29.336[a] |
| State fixed effects | No | Yes | No | Yes | No |
| Year indicators | No | No | Yes | Yes | Yes |
| State-specific linear time trend | No | No | No | No | Yes |
| Offsetting behavior effect | 12.77[a] | 12.88[a] | 12.62[a] | 4.49[a] | 10.00[a] |

Notes: The first panel consists of 3SLS estimations where the dependent variables are pedalcyclist fatalities caused by car crashes and VMT in cars. The dependent variables in the second panel of 3SLS estimations are pedalcyclist fatalities caused by light truck crashes and VMT in light trucks. Additional independent variables included in both regression equations are unemployment rate, speed limit indicators, and percentages of the population of each state who are men age 65 and over, women age 65 and over, men between the ages of 15-29, and women between the ages of 15-29. The vehicle miles traveled equations also contain real per capita income (measured as real per capita gross state product), state population, and gasoline tax. Coefficients and standard errors are reported for VMT in each vehicle type. For the speed limit indicators, population estimates, and offsetting behavior effects, t-statistics are reported. Superscripts a, b, and c denote significance at the 1%, 5%, and 10% levels of the appropriate tests, respectively. Data were collected over 46 states during the five year period from 1994-1998, with the exceptions of DC, MN, NV, VA, and IA for which data were unavailable. Data separating pedalcyclist fatalities by road type were not available through FARS, so this control is not included in the equations. The total number of observations included in each regression equation is 199.

Table 6: Reduced-form OLS estimation for pedalcyclist fatalities by vehicle type:

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Pedalcyclist fatalities caused by cars | | | | | |
| Limit65 | 5.022[a] | -0.950 | 5.359[a] | -1.091 | 6.564[b] |
| | (2.602) | (-0.0774) | (2.664) | (-0.913) | (2.245) |
| Limit70 | 4.420[b] | -2.971 | 5.619[a] | -3.568[b] | 4.125 |
| | (2.453) | (-1.634) | (2.675) | (-2.126) | (1.286) |
| Limit75u | 3.334[c] | -0.365 | 4.489[c] | -1.183 | 8.018[b] |
| | (1.705) | (-0.247) | (1.942) | (-0.747) | (2.033) |
| Population | 0.0000017[a] | -0.0000092[a] | 0.0000017[a] | -0.0000090[a] | 0.0000020[a] |
| | (13.520) | (-2.699) | (13.715) | (-2.661) | (11.348) |
| *R*-squared | 0.7581 | 0.9437 | 0.7608 | 0.9444 | 0.8773 |
| Pedalcyclist fatalities caused by light trucks | | | | | |
| Limit65 | 3.116[a] | 0.756 | 3.435[a] | 0.958 | 4.505[a] |
| | (2.954) | (1.336) | (3.215) | (1.530) | (3.138) |
| Limit70 | 3.819[a] | -0.033 | 4.891[a] | 0.260 | 2.796 |
| | (3.505) | (-0.035) | (3.990) | (0.263) | (1.616) |
| Limit75u | 1.296 | 0.349 | 2.370[c] | 1.125 | 3.935[c] |
| | (1.127) | (0.444) | (1.840) | (1.141) | (1.883) |
| Population | 0.0000013[a] | 0.0000024 | 0.0000013[a] | 0.0000019 | 0.0000012[a] |
| | (18.488) | (1.258) | (18.708) | (0.983) | (14.828) |
| *R*-squared | 0.8205 | 0.9527 | 0.8244 | 0.9540 | 0.9161 |
| State fixed effects | No | Yes | No | Yes | No |
| Year indicators | No | No | Yes | Yes | Yes |
| State-specific linear time trend | No | No | No | No | Yes |

Notes: The first panel consists of an OLS estimation where the dependent variable is pedalcyclist fatalities caused by car crashes. The second panel is an OLS estimation where the dependent variable is pedalcyclist fatalities caused by light truck crashes. Additional independent variables included in both regression equations are unemployment rate, speed limit indicators, and percentages of the population of each state who are men age 65 and over, women age 65 and over, men between the ages of 15-29, and women between the ages of 15-29, real per capita income (measured as real per capita gross state product), state population, and gasoline tax. For the speed limit indicators and population estimates, coefficients are reported with t-statistics in parentheses. All reported t-statistics reflect the heteroskedasticity-robust covariance matrix. Superscripts a, b, and c denote significance at the 1%, 5%, and 10% level of a 2-sided test, respectively. Data were collected over 46 states during the five year period from 1994-1998, with the exceptions of DC, MN, NV, VA, and IA for which data were unavailable. Data separating pedalcyclist fatalities by road type were not available through FARS, so this control is not included in the equations. The total number of observations included in each regression equation is 199.

# REFERENCES


Alexander, Donald L. "Motor Carrier Deregulation and Highway Safety: An Empirical Analysis." *Southern Economic Journal* 59 (1992): 28-38.

Becker, Gary S. "A Theory of the Allocation of Time." *The Economic Journal* 75 (1965): 493-517.

Blomquist, Glenn C. *The Regulation of Motor Vehicle and Traffic Safety*. Boston: Kluwer Academic Publishers (1988).

Bradsher, Keith. *High and Mighty*. New York: PublicAffairs Books (2002).

Bureau of Economic Analysis (BEA). U.S. Department of Commerce. http://www.bea.doc.gov.

Chirinko, Robert S. and E. P. Harper, Jr. "Buckle up or Slow Down? New Estimates of Offsetting Behavior and their Implications for Automobile Safety Regulation." *Journal of Policy Analysis and Management* 12 (1993): 270-296.

Cohen, Alma and Liran Einav. "The Effect of Mandatory Seat Belt Laws on Driving Behavior and Traffic Fatalities." Working Paper. Harvard University (2001).

Crandall, Robert W. and John D. Graham. "The Effect of Fuel Economy Standards on Automobile Safety." *Journal of Law and Economics* 32 (1989): 97-118.

Dickie, Mark and Shelby Gerking. "Genetic Risk Factors and Offsetting Behavior: The Case of Skin Cancer." *Journal of Risk and Uncertainty* 15 (1997): 81-97.

Evans, William N. and John D. Graham. "Risk Reduction or Risk Compensation? The Case of Mandatory Seat-Belt Use Laws." *Journal of Risk and Uncertainty* 4 (1991): 61-74.

Fatality Analysis Reporting System (FARS). http://www-fars.nhtsa.dot.gov.

Gayer, Ted. "The Fatality Risks of Sport-Utility Vehicles, Vans, and Pickups Relative to Cars." *Journal of Risk and Uncertainty* 28 (2004): 103-133.

Garber, Nicholas J. and Ravi Gadiraju. "Speed Variance and its Influence on Accidents." Washington, DC: AAA Foundation for Traffic Safety (1988).

Godek, Paul E. "The Regulation of Fuel Economy and the Demand for 'Light Trucks.'" *Journal of Law and Economics* 40 (1997): 495-509.

Greene, William H. *Econometric Analysis*. Fifth Edition. Upper Saddle River, NJ: Prentice Hall (2003).

Hausman, J. A. “Specification Tests in Econometrics.” *Econometrica* 46 (1978): 1251-1271.

Kakwani, N. C. “The Unbiasedness of Zellner’s Seemingly Unrelated Regression Equations Estimators.” *Journal of the American Statistical Association* 62 (1967): 141-142.

Keeler, Theodore E. “Highway Safety, Economic Behavior and Driving Environment.” *American Economic Review* 84 (1994): 684-693.

Lahiri, Kajal and Peter Schmidt. “On the Estimation of Triangular Structural Systems.” *Econometrica* 46 (1978): 1217-1221.

Lave, Charles A. “Speeding, Coordination, and the 55 MPH Limit.” *American Economic Review* 75 (1985): 1159-1164.

Lave, Lester B. and W. E. Weber. “A Benefit-Cost Analysis of Auto Safety Features.” *Applied Economics* 2 (1970): 265-275.

Nader, Ralph. *Unsafe at Any Speed: The Designed-in Dangers of the American Automobile*. New York: Grossman Publishers (1965).

National Highway Traffic Safety Administration (NHTSA). “Relationship of Vehicle Weight to Fatality and Injury Risk in Model Year 1985-93 Passenger Cars and Light Trucks.” Summary Report Number DOT HS 808 569 (1997).

Peltzman, Sam. “The Effects of Automobile Safety Regulation.” *Journal of Political Economy* 83 (1975): 677-725.

Peterson, Steven, George Hoffer, and Edward Millner. “Are Drivers of Air-Bag-Equipped Cars More Aggressive? A Test of the Offsetting Behavior Hypothesis.” *Journal of Law and Economics* 38 (1995): 251-264.

Prucha, Ingmar. “The Variance-Covariance Matrix of the Maximum Likelihood Estimator in Triangular Structural Systems: Consistent Estimation.” *Econometrica* 55 (1987): 977-978.

Revankar, Nagesh S. “Some Finite Sample Results in the Context of Two Seemingly Unrelated Regression Equations.” *Journal of the American Statistical Association* 69 (1974): 187-190.

Sobel, Russell S. and Todd M. Nesbit. “Automobile Safety Regulation and the Incentive to Drive Recklessly: Evidence from NASCAR.” Working Paper. West Virginia University (2003).

Srivastava, Virendra K. and David E. A. Giles. *Seemingly Unrelated Regression Equations Models*. New York: Marcel Dekker (1987).

Staiger, Douglas and James H. Stock. "Instrumental Variables Regression with Weak Instruments." *Econometrica* 65 (1997): 557-586.

Traynor, Thomas L. "The Peltzman Hypothesis Revisited: An Isolated Evaluation of Offsetting Driver Behavior." *Journal of Risk and Uncertainty* 7 (1993): 237-247.

Viscusi, W. Kip. "The Lulling Effect: The Impact of Child-Resistant Packaging on Aspirin and Analgesic Ingestion." *American Economic Review* 74 (1984): 324-327.

White, Halbert. "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity." *Econometrica* 48 (1980): 817-838.

Yun, John M. "Offsetting Behavior Effects of the Corporate Average Fuel Economy Standards." *Economic Inquiry* 40 (2002): 260-270.

Zellner, Arnold. "An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias." *Journal of the American Statistical Association* 57 (1962): 348-368.