Buckle Up or Slow Down Revisited: Results That Don't Stand the Test of Time

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ABSTRACT

This paper reanalyzes a time series on traffic fatalities from 1947-85 that originally appeared in Chirinko and Harper's paper, "Buckle up or slow down? New estimates of offsetting behavior and their implications for automobile safety regulations," published in the *Journal of Policy Analysis and Management*. Those authors estimated two equations finding positive relationships between improvements in motor vehicle safety (largely in occupant safety or crashworthiness) and increased crashes and pedestrian fatalities. They claimed that these estimated relationships provided support for the hypothesis that increased crashworthiness may be offset by driver behavioral changes including more risk taking. This reanalysis shows that the positive relationship between crashworthiness and pedestrian fatalities is largely an artifact of the starting year of the time series; in fact, when the series starts in 1950, increased crashworthiness is associated with a decrease in pedestrian fatalities. Similarly, a later start for the authors' accident rate equation deprives the model of all explanatory power, implying misspecification of this equation or dependence of the results on a few extreme values. Influence statistics and other diagnostic measures show that observations for 1947-49 represent unusual observations.

INTRODUCTION

Since the end of World War II, motor vehicle crash deaths per registered vehicle and per vehicle mile have generally followed a downward trend. In 1950 there were 7.6 deaths per 100 million vehicle miles traveled and 7.1 deaths per 10,000 motor vehicles, while in 1993 comparable figures were 1.8 deaths per 100 million miles and 2.1 deaths per 10,000 motor vehicles (National Safety Council, 1994). In the mid-1960s the federal government began regulating the safety of motor vehicles. The extent that the decreased death rates were attributable to federal motor vehicle safety standards for new passenger vehicles or might have occurred without these regulations has been questioned using assumptions based on the "offsetting behavior" hypothesis.

The offsetting behavior hypothesis suggests that drivers calibrate their risk taking to the perception of danger. This hypothesis implies better road design and more protective cars will reduce crash losses less than expected because of changes in driver behavior. That is, people forced to consume more safety than they ordinarily would, drive more riskily to compensate. As an abstract theory, offsetting behavior can be deduced from utility maximization with assumptions about the substitution of driver safety effort with government safety regulation, diminishing marginal returns of effort and regulation on expected crash losses, and driver perception of risk. See Blomquist (1986; 1988) for formal models. There is also anecdotal evidence addressing the universality of offsetting behavior, or, in more general terms, behavioral adaptation in response to changes in the environment. For example, typists are claimed to be more careless about spelling when a spelling checker is provided with their word processor (Chirinko, 1994). Like many analogies and anecdotes, these may be inaccurate when comparing frequent painless spelling errors with infrequent and extremely inconvenient vehicle crashes.

These analogies and the assumptions involved in the utility maximization model may provide for interesting debates, but they are unlikely to settle the more important question. This is not whether offsetting behavior exists (or more correctly whether it can be proved not to exist) but the specific circumstances when it is likely to be found and the magnitude of the effect. Is the offsetting behavior substantial and measurable or is it at the noise level and inconsequential? For this reason, empirical analyses are critical.

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Peltzman (1975) was one of the first to claim empirical support for offsetting behavior. There have been many articles published since then with mixed results. See Graham and Garber (1984), Lund and Zador (1984), Garbacz (1985), Lund and O'Neill (1986), Evans (1986), Blomquist (1988), and Keeler (1994) among others. Except for Peltzman no evidence has appeared suggesting that offsetting behavior is of such a magnitude to have eliminated the increased safety provided by safety regulations. Some research has concluded that offsetting behavior has displaced fatalities from occupants to nonoccupants. The evidence again is mixed. For example Crandall, Gruenspecht, Keeler, and Lave (1986) and Garbacz (1992) reported that mandatory seat belt use laws are associated with an increase in pedestrian fatalities. Graham and Evans (1991) found that seat belts laws were postively associated with nonoccupant fatalities for three categories of nonoccupants, motorcyclists, and pedestrians. However, the "...absolute sizes of the coefficients are larger for secondary than primary laws in the motorcycle [they probably meant pedestrian, see footnote 1 below] and bicycle regressions, a pattern that is not predicted by the risk-compensation hypothesis..." (page 70).[1] The inconsistency arises because one would expect more offset where there is stronger enforcement. Graham and Evans also found that the decrease in occupant fatalities agreed with that predicted in other studies. They wrote, "the results of this study provide some evidence of a substantial short-term benefit from mandatory belt-use laws..." (p. 71).

Recent empirical findings supporting the offsetting behavior hypothesis are reported in "Buckle Up or Slow Down? New Estimates of Offsetting Behavior and Their Implications for Automobile Safety Regulation" by Chirinko and Harper (1993). In their article Chirinko and Harper concluded that "...while imprecisely estimated, offsetting behavior is quantitatively important and attenuates the effects of safety regulation on total motor vehicle fatalities..." (1993, p. 270). They reported that motor vehicle safety regulations during the late 1960s, while associated with a decrease in occupant fatalities per vehicle mile, may have been associated with an increase in the motor vehicle crash rate and the pedestrian fatality rate over what might have been expected without such regulation. The authors argued that their findings support the offsetting behavior hypothesis. They suggested this should lead to "...a serious reassessment of the current direction of highway safety policy..." (p. 293).

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[1]In primary belt use states, police can issue traffic tickets upon observing unbelted drivers. Secondary states only allow tickets when stopping an unbelted driver for some other reason. Also, we believe that the authors meant to write "pedestrian" instead of "motorcycle" when describing the coefficients. Their table 6, page 69, shows primary and secondary belt use coefficients for motorcycle fatalities as .080 and .007 respectively, while that for pedestrian fatalities were .061 (primary) and .103 (secondary).

In this paper, as in Chirinko and Harper, the term "regulation" refers to the federal motor vehicle safety standards for new cars issued under the National Traffic and Motor Vehicle Safety Act of 1966 (PL 89-563). Regulations under the Act are issued by the National Highway Traffic Safety Administration and are organized into three categories, crash prevention (100 series), injury protection (200 series), and post-crash protection (300 series). Examples of crash prevention standards include standards for tires (110,117) and hydraulic brakes (105,106); injury protection standards include head restraints (202) and occupant restraints (208-210); the post-crash category includes fuel system integrity (301) and flammability (302). Standards issued during the period studied by Chirinko and Harper had effective dates beginning in January 1968. (See General Accounting Office (1976) for a listing of standards and effective dates.)

The purpose of this paper is to reexamine the findings in Chirinko and Harper. The authors provided us with their data. The main results in Chirinko and Harper were based on two equations estimated on an annual series on traffic fatalities, vehicle miles traveled, various economic variables, and an index of the improvement in auto safety associated with federal regulation. This safety index (Graham, 1983) measures the proportion of the passenger car fleet in any given year that was affected by the National Traffic and Motor Vehicle Safety Act of 1966.

We find that Chirinko and Harper's results supporting offsetting behavior do not hold up. The positive relationship between the safety index and pedestrian fatalities is an artifact of the starting point of the time series. Influence diagnostics (Belsley, Kuh, and Welch, 1980) show that 1947-49 are unusual observations. Reanalysis of the authors' pedestrian fatality equation where the time series starts at least two years later, and the observations are not outliers, results in a negative relationship between safety and pedestrian fatalities. One could then argue that safety regulation was associated with a decrease in pedestrian fatalities, a conclusion at variance with offsetting behavior. Similarly, a later start for the authors' "accident rate" equation deprives the model of all explanatory power suggesting possible misspecification of that equation. Thus the models do not stand the test of different time periods.

The remainder of the paper reconsiders the empirical findings. The Appendix discusses the quality of the data used in that analysis.

EMPIRICAL FINDINGS IN "BUCKLE UP OR SLOW DOWN"

The authors present estimates for five equations in the paper, two for occupant fatality rates (FR_{occ}), one for pedestrian fatality rates (FR_{ped}), one for the probability of a fatality given a crash (vulnerability rate or VR), and the last for the vehicle accident rate (AR). In their paper, the category of pedestrians also includes pedalcyclists. They are occasionally referred to as "nonoccupants." Rates are defined per million vehicle miles traveled. Data used in the paper were obtained from the National Safety Council (see National Safety Council, 1994) and the National Highway Traffic Safety Administration.[2]

Accident and vulnerability rates are factors of the occupant fatality rate ($FR_{occ} = AR * VR$). This decomposition was proposed in Evans and Graham (1991), although they did not obtain estimates. Chirinko and Harper argued that decreases in occupant fatalities, FR_{occ}, would largely result from improvements in survivability given a crash (VR) rather than changes in accident rates (AR), because in their view the federal motor vehicle safety standards primarily improved survivability.[3] Thus an obvious manifestation of offsetting behavior would be increases in accident rates when vulnerability decreases. Extracting accident rates removes the masking effect of known increases in survivability.

There are nine explanatory variables in the models. (Details of these variables are found in Chirinko and Harper, 1992.) SAF is Graham's (1983) estimate of vehicle safety relative to 1965 cars. Graham estimated improvements in 1966-67 cars of 4 percent, 1968-69 of 19 percent, 1970-71 at 24 percent, 1972-73 of 28 percent, and 1974 and later 34 percent. The index is adjusted to reflect the proportion of cars in the fleet of each year so that it gradually rises from zero in 1965 to 34 percent during the 1980s. SAF has been used in other analyses (for example Crandall, Gruenspecht, Keeler, and Lave, 1986). LAW55 is a dummy variable equal to zero before the 55 mile per hour national speed limit in 1974 and one thereafter. PERMY is a five-year moving average of real total per capita consumption expenditures. PGAS is the ratio of the CPI price of gasoline to the overall CPI scaled to the 1967 value. PRPR is the relative price of automobile and medical repairs weighted 40 and 60 percent, respectively, and also scaled to 1967. YOUNG is the proportion of young and inexperienced drivers on the road. ALCHL is the per capita consumption of alcohol. MCYCLE is the share of motorcycles in total

[2]Since 1975, the National Highway Safety Administration has maintained the Fatal Accident Reporting System (FARS), a source of detailed data on fatal crashes in the U.S.. According to Baker, O'Neill, Ginsburg, and Li (1992, p. 214) total deaths in FARS and National Center for Health Statistics (the source for the National Safety Council total deaths) closely agree. FARS contains greater detail than the NCHS data, especially whether the victim was an occupant or not. The National Safety Council provides estimates for pedestrian and pedalcyclist fatalities based on reports by some of the states. These estimates are rounded to the nearest 1000 or 100.

The authors do not indicate the source for the accident data; however, they suggest it is of lower quality than the series on fatalities. See their footnote 24.

A more detailed discussion of the data is found in the Appendix to this paper. It is shown there that there is a high correlation between total fatalities in FARS and National Safety Council data between 1975 and 1993 and a slightly lower correlation between non occupant fatalities during the same period. It is also shown that roundoff in the National Safety Council has implications for the amount and pattern of error in the regressions.

[3] This point is arguable. Many standards address crash avoidance such as 108 (lamps, reflectors, and devices), and 109-110 (tires).

registrations. TRUCK is the share of total vehicle miles driven by trucks. MCYCLE and TRUCK are included to account for the contribution of motorcycles and trucks to occupant fatalities rates because the data do not allow direct calculation of the automobile fatalities apart from truck and motorcycle fatalities. Neither SAF nor LAW55 are transformed to logs in any specification. LAW55 is omitted from the pedestrian fatality equation because most of these fatalities occur on urban roads largely unaffected by the 55 mile per hour speed limit.

All specifications in Chirinko and Harper are differences of logarithms except one occupant fatality rate equation in logarithms. Chow tests for model stability indicated a preference for the differenced log form.

The authors characterized their findings about pedestrian fatalities as follows:

> In all four models (logarithmic and levels, both undifferenced and differenced), the safety regulation variable is positive, though it is significant only in the undifferenced levels equation. In addition, the very low Durbin-Watson statistics characterizing all but the differenced logarithmic equation (displayed in column 3) temper the conclusions to be drawn from these estimates. Nonetheless, these positive effects of SAF on FR_{ped}, coupled with the insignificant effects of SAF in some of the FR_{occ} equations, suggest the possibility of offsetting behavior and the need for further evidence. (p. 275)

For the AR equation, they wrote the following:

> In response to more crashworthy cars, motorists may increase their level of driving intensity. Under the OBH (offsetting behavior hypothesis), we would expect to find the accident rate positively related to SAF...In all four models, the coefficients on SAF are positive, though statistically significant only in the undifferenced levels equation. These results suggest the possibility of offsetting behavior but, as with the results for FR_{occ} and FR_{ped}, conclusions about the OBH depend on which of the four specifications is appropriate. (p. 283)

The empirical evidence fails to support the offsetting behavior hypothesis for the following reasons:

1. The positive sign on the SAF variable in the pedestrian fatality and accident rate equations disappear for different starting points for the time series.
2. Some of the signs of other estimates are inconsistent with theory and suggest that the equations might be misspecified.
3. Measures of goodness of fit for the AR equation suggests it is a poor fit to the data.

The following discussion focuses on the FR_{ped} and AR equations because only they impinge on the offsetting behavior hypothesis. Chirinko and Harper present two other equations, one for occupant fatalities (FR_{occ}) and the second for vulnerability rate (VR) or fatalities per crash. In this examination both FR_{occ} and VR equations survive different starting periods with a negative and significant coefficient on the SAF variable. The results suggest regulation has improved vehicle crashworthiness.

The Pedestrian Fatality Rate Equation(FR_{ped})

The FR_{ped} equation uses pedestrian (plus pedalcycle) fatalities per vehicle mile traveled as related to SAF, PERMY, YOUNG, PGAS, PRPR, MCYCLE, and TRUCK. Evidence for offsetting behavior would be found in a positive coefficient on SAF because increased protection afforded by a safer car would to some degree be offset by more risky driving.

Estimates for the FR_{ped} equation from Chirinko and Harper are shown in Table 1, column 1. The form of the equation is differenced logarithms for all variables except SAF that is just differenced.[4] Years shown in the table represent the ending point of the difference; that is, 1948 the first year of the series represents the equation estimated using the 1947-48 difference as the first year. For shorthand, references to 1948 below mean the time series beginning with the 1947-48 difference. Columns 2 through 5 represent the estimates for the equation with later starting years; for example, column 2 excludes 1948 and begins the series with 1949 (the 1948-49 difference). T-statistics in parentheses were computed using White's procedure for heteroscedasticity corrected standard errors (White, 1980). Column 1 shows the estimate for SAF using the authors' starting point of 1948-85 as 0.424; although insignificant, it suggests that pedestrian fatalities increase with increases in automobile safety. This estimate forms the major part of the paper's evidence supporting the offsetting behavior hypothesis.

[4] FR_{ped} is actually log ($FR_{ped,t}/FR_{ped,t-1}$), SAF is SAF_t - SAF_{t-1}.

Table 1
Stability of the Coefficients in the FR_{ped} Equation

Coefficient	1948-1985	1949-1985	1950-1985	1951-1985	1952-1985
SAF	0.424	0.112	-0.444	-0.725	-0.747
	(0.551)	(0.136)	(-0.610)	(-1.062)	(-1.095)
PERMY	-0.166	0.785	2.348	2.735	2.769
	(-0.137)	(0.552)	(1.993)	(2.417)	(2.454)
ALCHL	0.235	0.032	-0.199	0.104	0.146
	(0.993)	(0.120)	(-0.760)	(0.437)	(0.608)
PGAS	-0.198	-0.213	-0.147	-0.202	-0.230
	(-1.039)	(-1.211)	(-0.964)	(-1.331)	(-1.442)
PRPR	-0.772	-0.894	-0.707	-0.934	-1.104
	(-2.359)	(-2.777)	(-2.655)	(-3.228)	(-3.288)
YOUNG	0.596	0.597	0.702	0.500	0.495
	(1.685)	(1.685)	(2.185)	(1.645)	(1.672)
MCYCLE	-0.011	-0.017	-0.110	-0.166	-0.197
	(-0.089)	(-0.132)	(-1.017)	(-1.654)	(-1.964)
TRUCK	0.337	0.351	0.273	0.339	0.310
	(2.327)	(2.454)	(2.325)	(2.775)	(2.598)
CONSTANT	-0.032	-0.041	-0.063	-0.062	-0.056
	(-1.676)	(-1.942)	(-3.460)	(-3.614)	(-3.318)
R^2 - adjusted	0.171	0.176	0.156	0.264	0.273

Notes: Each column represents estimates for the FR_{ped} equation using the differenced log functional form. All variables are in logarithms except SAF that are in levels. The starting point is each column different with the second year given in the column. The 1948 column, for example represents the 1947-48 difference. Coefficients are given with t-statistics below in parentheses. The t-statistics us`e the heteroscedastic correction from White (1980).

Further inspection of the table (second column) shows that the coefficient on SAF is still positive when the series begins in 1949. Using 1950 as a starting point causes the coefficient on SAF to become negative. It remains negative in the next two years as shown in the table and for all starting years explored up to 1960. Negative coefficients suggest that the pedestrian fatality rate drops with increasing safety. The question then becomes whether there is something pathological in 1947-49 so that a more appropriate starting point is later. Which series is better?

The year, 1947, seems to be a traditional starting point. Peltzman (1975) and Crandall et al. (1986) used 1947 as the beginning of their time series.[5] But the period 1947-50 contains extreme observations. These few years exert undue influence on the estimates and distort their values. The fit of the equation improves markedly when these years are discarded. A more appropriate starting point would be 1950 or 1951.

The years up to 1949 were at the end of a period where the pedestrian death rate was falling quickly. National Safety Council estimates used in Chirinko and Harper show that pedestrian deaths peaked in 1937 at 16,200. See Table 2. During World War II, the number of deaths dropped slightly but rates jumped to a high of 49.76 deaths per billion miles primarily due to a sharp drop in vehicle miles traveled. The last column of Table 2 shows the percentages change in death rates between adjacent years, a quantity that is the exponentiated difference of logs used in the FR_{ped} equation. For example, the death rate in 1938 was 83.46 percent (100% * 50.07/60) of the death rate in 1937. There is a very sharp decrease from 1948 to 1949 and a very sharp increase from 1949 to 1950. In fact, the value in 1949 of 83.99 is the lowest percent difference observed in the complete series between 1948 and 1985.

Although possibly unusual observations, are the values of FR_{ped} inconsistent with the regressors (explanatory variables) for those years? One approach is to delete those observations and repeat the regressions as shown in Table 1 and discussed above. A more exact approach uses residual analysis and influence diagnostics based on single point deletion. For the series beginning with the 1947-48 difference, the first three years show large studentized residuals of -1.59, -1.88, and -1.93; such values are approximately t-statistics with p values between 0.05 and 0.10 for both 1949 and 1950.[6] The hat matrix diagonal elements measures if the regressors are outliers. For the first three years values were 0.41, 0.31, and 0.52 all around the cutoff for high leverage points of 2p/n=.474 (Belsley, Kuh, and Welch, 1980).[7] It appears therefore that both the response variable, FR_{ped}, and the regressors are outliers.

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[5]Without any strong justification, Garbacz's (1985) reanalysis of Peltzman began with the year 1952. He found little or no offsetting effect.

[6]Other large studentized residuals are found in the 1948 equation for the 1974 difference (-3.68) and 1979 (2.57). Both of these were years where vehicle miles traveled (VMT) dropped rather than increased. In 1974 VMT dropped to 1.29 trillion from 1.31 trillion in 1973 and rose to 1.33 trillion in 1975. VMT figures for 1978-80 were 1.55, 1.53 and 1.52 trillion respectively. In all other years, VMT increased over the previous year.

[7] In this context, the symbol, p, denotes the number of variables, 9, and n is the number of observations, 38.

Table 2
Pedestrian and Pedalcycle Deaths 1937-1955

Year	Total Deaths	Vehicle Miles (Billion)	Deaths per Billion Miles	Percent of Previous Year
1937	16200	270	60.00	-
1938	13570	271	50.07	83.46
1939	13110	285	46.00	91.86
1940	13450	302	44.54	96.82
1941	14460	334	43.29	97.21
1942	11300	268	42.16	97.39
1943	10350	208	49.76	118.01
1944	10300	213	48.36	97.18
1945	11500	250	46.00	95.13
1946	12140	341	35.60	77.39
1947	11000	371	29.65	83.28
1948	10450	398	26.26	88.56
1949	9350	424	22.05	83.99
1950	9440	458	20.61	93.47
1951	9540	491	19.43	94.27
1952	9330	514	18.15	93.42
1953	9170	544	16.86	92.86
1954	8380	562	14.91	88.46
1955	8610	606	14.21	95.28

Source: National Safety Council (1994)

The primary effect of these three years is on the coefficient of the SAF term. This effect is strongly positive with DFBETA values of 0.434, 0.422, and 0.453, all in excess of the suggested cutoff of (2 divided by the square root of n =) .324. These values indicate that deletion of each of these years would cause a substantial decrease in the estimate for the coefficient of SAF. Turning again to Table 1, it can be observed that deletion of the first year in the series reduces the coefficient on SAF and also improves the fit of the model to the data (adjusted R^2=.176). Finally, removal of 1950 seems to settle down the process with a negative estimate for SAF, no serious outliers around that range, and a major improvement in fit.

How could the values of the permanent income, repair price, alcohol consumption, and proportion of young drivers in the years 1947-49 have such an influence on the relationship between safety (SAF) and pedestrian fatalities in the full regression model? Mathematically, the regression engine tries to fit a surface to all the data; with SAF being constant over the first 20 years its contribution to the fit is minimized. This would be appropriate if the relationship between all other variables and pedestrian fatalities remained the same before and after 1965. It would mean that the variability in pedestrian fatalities in both periods could be explained by changes in other variables than SAF. However, different patterns before 1965 and after seem to be the case for the pedestrian fatality equation. Only the differenced log form survives the author's Chow tests with a weak p-value of 0.138 (see the authors' Table 2, p. 284). It is important not to take too much comfort from such a test because it can only confirm instability, that is failing to reject the null hypothesis of stability.

The negative coefficient on PERMY also indicates a problem with the 1948 start. This coefficient switches to positive in 1949, positive and significant in 1950. The literature is not unanimous about the sign of variable, but it should not change sign during the first few years.

The entire time series for three key variables is shown in Figures 1a and 1b. These include differenced log FR_{ped} (thick line), differenced SAF, and differenced log PRPR (repair and medical price index). PRPR tends to be strongly correlated with pedestrian fatalities. In these figures, all variables have been standardized (to mean 0 and variance 1) in order to plot them on the same scale. A vertical line is drawn at 1966 marking the passage of the National Traffic and Motor Safety Act; the first year where SAF is greater than zero.

It is obvious from Figure 1a that SAF cannot absorb any of the variability in pedestrian fatality rates during the 1950s and early 1960s.[8] The repair price variable can absorb this variability and it seems to move oppositely from pedestrian fatalities. This movement is especially pronounced during 1948-50 where pedestrian fatalities make a sharp decrease followed by a steep increase while the repair price index makes a sharp increase followed by a sharp decrease. Such covariation is highly influential on the regression coefficients as discussed above and is shown by removing the years from the series.

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[8]Recall SAF is actually $SAF_t - SAF_{t-1}$. The difference is 0 until 1966 because SAF_t=0 for all values of $t < 1966$.

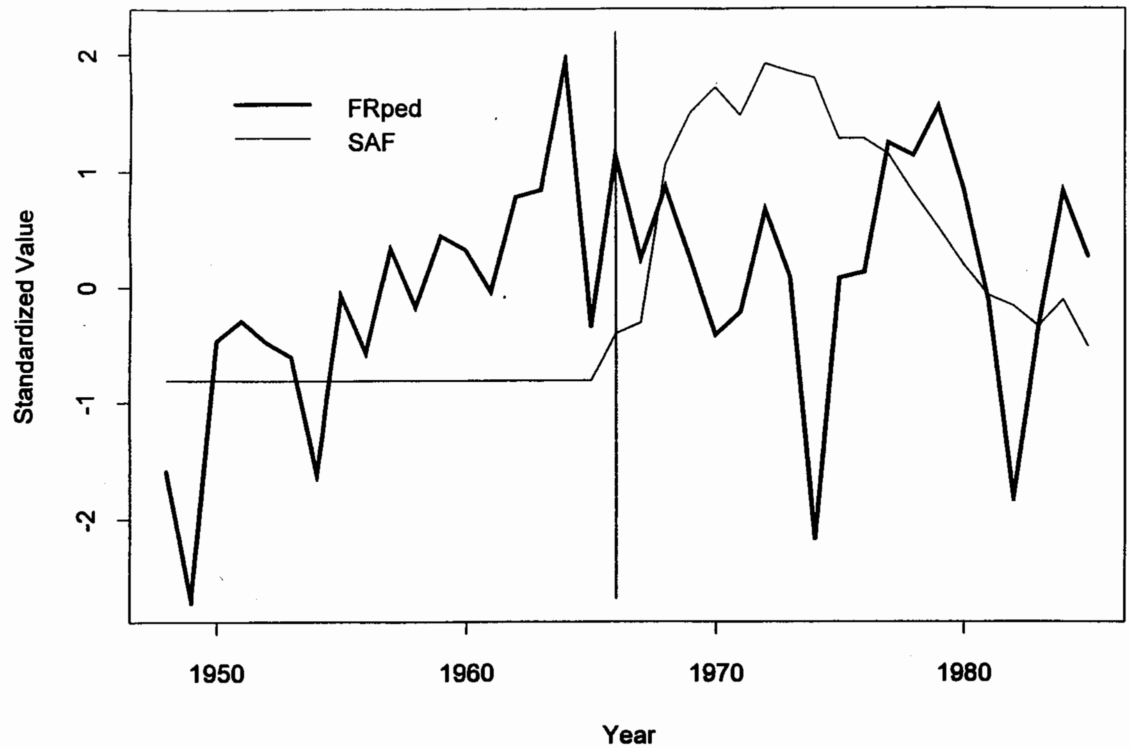

Figure 1a: Pedestrian Fatalities and Safety Index 1948-1985

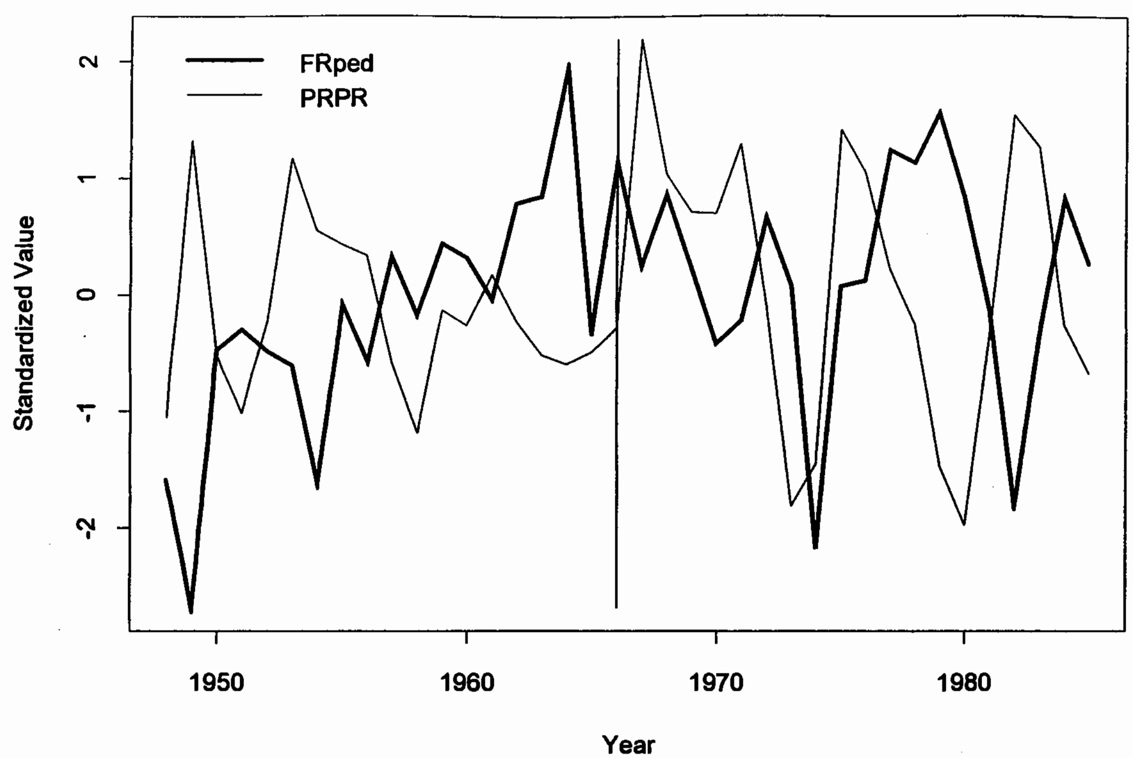

Figure 1b: Pedestrian Fatalities and Repair Price Index 1948-1985

During all these early swings SAF stays flat. When SAF begins to move upward in 1966 (the 1965-66 difference), the effect on FR_{ped} in Figure 1a is immediate. Between 1966 and about 1976, the FR_{ped} curve shifts downward and looks like the reverse of the SAF curve.[9] This dramatic negative relationship between the two variables suggests an increase in occupant safety and a decrease in pedestrian fatalities. This pattern continues to about the mid-1970s where the pattern reverses and both curves go into decline. Values of SAF after 1974 do not represent any improvements, instead the variable measures the decreasing number of pre-1966 cars in the fleet. The problem at the end of the series is much like that at the beginning; i.e., there is not enough variability in SAF to capture changes in the response variable.

The pattern also reverses in Figure 1b. The repair price index, PRPR, moves counter to pedestrian fatalities during much of the series (and thereby earns a negative coefficient) before 1966 and after the mid-1970s. Between 1966 and 1976, the pattern reverses with changes in repair price index and pedestrian fatalities both in decline. (Recall that 60 percent of the repair price index is medical costs.) These costs were changing rapidly during the late 1960s with the introduction of medicare and medicaid.

What can be concluded from these trends? It is clear that immediately following passage of the National Traffic and Motor Vehicle Safety Act pedestrian fatalities declined. The strongest evidence favors a negative sign on SAF, i.e., that the safety regulation decreased pedestrian fatalities. This evidence is at variance with the offsetting behavior hypothesis.

The Accident Rate Equation (AR)

Table 3 examines the stability of the coefficients in the AR equation. The offsetting behavior hypothesis suggests that SAF will be positive for this equation indicating that drivers assume an increased chance of a crash when the vehicle becomes safer. To summarize the results, the coefficient on SAF is positive and insignificant when the series begins with the 1947-48 or 1948-49 difference. It is also positive, but much smaller with 1952 as the starting point (see the last column of Table 3), also for 1953 (0.028) and 1954 (0.011). For all other starting years this coefficient is negative and insignificant.

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[9] The sharp drop in pedestrian fatalities in Figure 1a occurs in the 1973-74 difference. This was undoubtedly a result of large decreases in vehicle miles in 1974. The 1974-75 difference shows a recovery. The 55 mph speed limit was also introduced in 1974.

Table 3
Stability of the Coefficients in the AR Equation

Coefficient	1948-1985	1949-1985	1950-1985	1951-1985	1952-1985
SAF	0.582	0.487	-0.063	-0.076	0.029
	(1.009)	(0.753)	(-0.122)	(-0.137)	(0.056)
55LAW	-0.058	-0.054	-0.037	-0.036	-0.044
	(-2.454)	(-2.152)	(-1.890)	(-1.754)	(-2.463)
PERMY	-2.079	-1.825	-0.414	-0.396	-0.563
	(-2.718)	(-1.732)	(-0.726)	(-0.612)	(-0.792)
ALCHL	0.529	0.478	0.274	0.283	0.188
	(5.045)	(3.060)	(3.176)	(2.022)	(1.520)
PGAS	-0.057	-0.065	-0.036	-0.038	0.040
	(-0.633)	(-0.754)	(-0.479)	(-0.462)	(0.665)
PRPR	-0.284	-0.313	-0.166	-0.173	0.240
	(-0.665)	(-0.734)	(-0.430)	(-0.414)	(0.735)
YOUNG	-0.227	-0.225	-0.134	-0.140	-0.130
	(-1.112)	(-1.121)	(-0.757)	(-0.785)	(-0.741)
MCYCLE	0.118	0.116	0.037	0.035	0.112
	(1.352)	(4.104)	(0.450)	(0.370)	(1.427)
TRUCK	0.097	0.102	0.049	0.051	0.117
	(0.747)	(0.805)	(0.433)	(0.506)	(1.327)
CONSTANT	0.017	0.014	-0.005	-0.005	-0.018
	(1.014)	(0.760)	(-0.360)	(-0.363)	(-1.426)
R^2	0.203	0.085	-0.136	-0.179	-0.081

Notes: Each column represents estimates for the AR equation using the differenced log functional form. All variables are in logarithms except 55LAW and SAF that are in levels. The starting point is each column different with the second year given in the column. The 1948 column, for example represents the 1947-48 difference. Coefficients are given with t-statistics below in parentheses. The t-statistics use the heteroscedastic correction from White (1980).

Among other variables shown in that table, PERMY remains negative but becomes insignificant; PGAS, PRPR, and YOUNG remain negative; ALCHL stays positive and significant. Of these, the negative sign on YOUNG is unexpected because young drivers are normally associated with higher crash rates.[10]

[10]YOUNG is positive in the FR_{occ} and FR_{ped} equations as might be expected. It is unexpectedly positive in the VR (vulnerability rate) equation as one might normally expect young drivers to have a larger chance of survival, although young drivers could be likely to have more serious, less survivable crashes.

The major problem with the AR equation is the poor fit. The fit seems largely grounded in the early possible outlier years. Table 3 shows that the value for adjusted R^2 drops off to 0.085 when the series begins in 1949 and then goes negative when the series starts with 1950, 1951, or 1952. All starting points in the series from 1950 through 1960 have negative values for adjusted R^2.

A closer look at outlier diagnostics for the series starting with the 1947-48 difference shows unusual values in the first three years. The hat diagonal for 1948 is 0.4331 and for 1950 is 0.5330 (against the suggested cutoff of 0.526), and the covariance ratios are large (2.3024 and 3.0805 -- threshold of 1.789), which indicates that 1948 and 1950 are high leverage points in the regressor space. For these two years, the studentized residuals are -0.5138 and 0.0137, neither indicating any problem with fit. AR is extreme for 1948 (-2.16 standard deviations below the mean). The large hat diagonal/covariance ratio and low studentized residual suggests that 1948 and 1950 are extreme in terms of the regressors but the value for AR is close to the regression line. The year 1948 has an extreme value for permanent income (PERMY) of 1.53 (SD's above the mean); with a regression coefficient of -2.08, the value of PERMY helps in fitting to the standardized value for AR of -2.16. Things are not quite as bad in 1950, but both of these years contribute strongly to the quality of the regression fit.

In 1949, the outlier diagnostics are somewhat different. The standardized residual is large (-2.59) and the standardized value of AR is -3.46, an extreme outlier. The DFBETA for SAF is 0.6383 for this year, the largest single value in the dataset. This indicates a point that is poorly fit by the regression plane, but is extremely influential on the coefficient on SAF.

Figure 2 shows the relationship between AR and SAF over time. The pattern is similar to that in Figures 1a and 1b. The onset of regulation in the 1960s is associated with a sharp decrease in the accident rate as the two variables appear to move oppositely from each other. Later in the period as an increasing number of cars conform to safety regulations, both measures appear to move together in a negative direction.

The AR equation does not appear to fit the data well enough to be useful. The relationship is primarily structured during the first two or three years, where extreme observations define the quality of the fit. When the series is started a few years later, the fit becomes unacceptable. With respect to the relationship between SAF and AR, the pattern is similar to the FR_{ped} equation, that is, a negative relationship between 1966 to the mid-1970s and a positive relationship thereafter. During the introduction of the new safety equipment, crash rates fall. This is unequivocal. Nothing in these data confirms the offsetting behavior hypothesis.

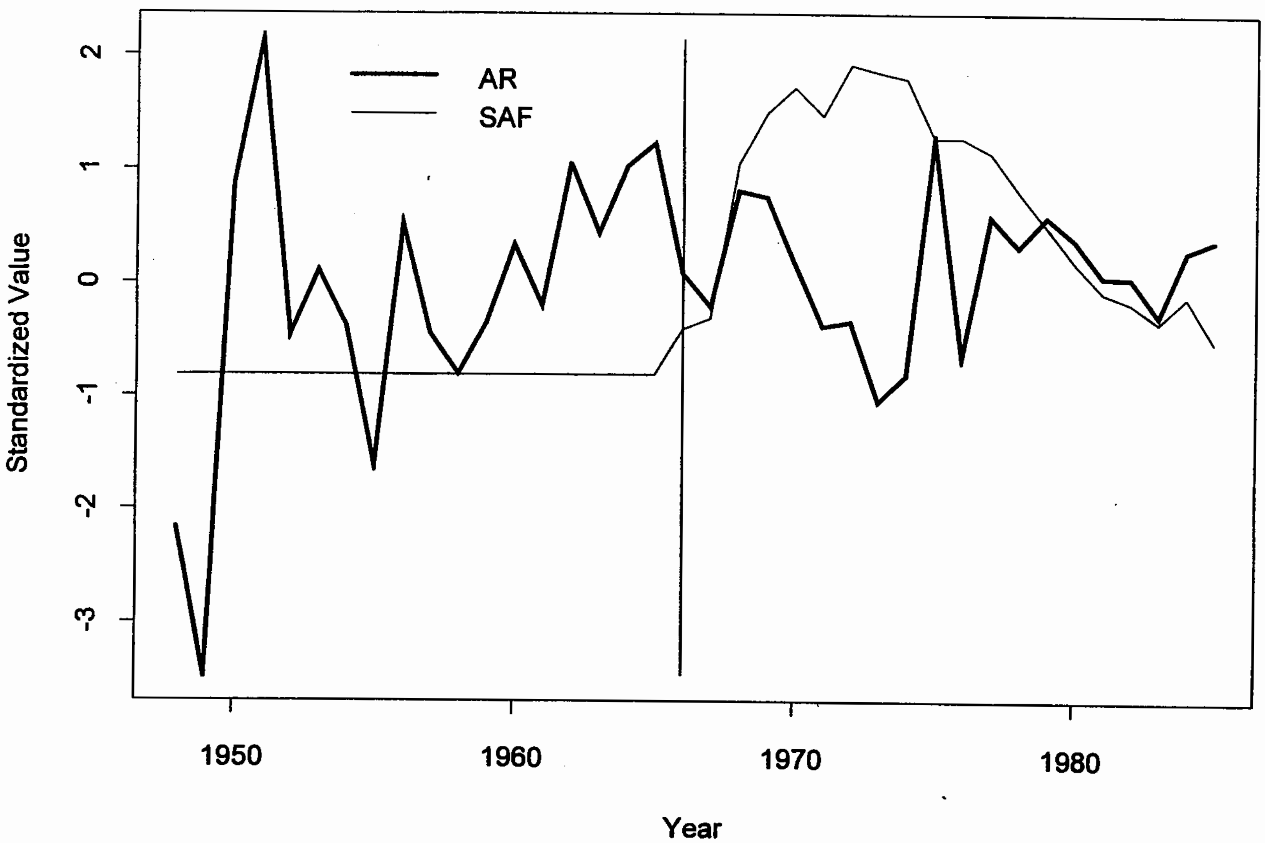

Figure 2: Accident Rate and Safety Index 1948-1985

Alternative specifications for the FR_{ped} and AR equations including levels (the original untransformed variables), differenced levels, and logs were also examined. Using starting periods from 1947-52, levels and log models for FR_{ped} were found to have Durbin-Watson (*d*) statistics under 1.0, suggesting positive serial correlation. The differenced levels model had *d* values of 0.668 and 0.966 with a 1948 start and 1949 start, respectively. Starting in 1950 for the differenced levels model brings *d* into the acceptable range of 1.577; however, the coefficient of SAF is -0.0554 (SE=.7515). The same patterns of acceptable values for *d* and negative insignificant SAF coefficients are found for the 1951 and 1952 start.

In the accident rate equation, the Durbin-Watson statistics are also low, varying between 1.09-1.25 for the levels specification and 1.11-1.28 for the log specification. The Durbin-Watson statistic is much higher for the differenced levels specification with the starting point as the 1950, 51 or 52 (i.e., $d =$ 1.865, 1.565, and 1.866, respectively), but the coefficient of SAF again becomes negative.

This leads to two conclusions. First, the undifferenced levels or logs models cannot be used because the unacceptable *d* statistic suggests positively correlated residuals that in turn suggest omitted variables. Second, for the differenced models, *d* is in the acceptable range when the SAF coefficient is negative. Thus either the specification cannot be used due to serial correlation, or the model does not support offsetting behavior.

CONCLUSION

Chirinko and Harper conclude their analysis by simulating the percentage change in the 1985 value of the dependent variables if all other regressors had remained at their 1965, pre-regulation values. They interpret the analysis to represent the change in fatality rates if safety regulation had not been imposed. Regression coefficients used in this simulation were estimated in previous sections of their paper including those positive coefficients for SAF in the AR and FR_{ped} equations. They estimated the net effect of the National Traffic and Motor Vehicle Safety Act to be a 16.2 percent reduction in total fatalities. Such a finding supports motor vehicle safety legislation and does not confirm Peltzman's finding of total offset. But Chirinko and Harper also find evidence for offsetting behavior in an estimated 21.1 per cent increase in crashes per mile and a 15 percent increase in pedestrian fatalities attributable to the Act.

These findings about increased fatalities seem far from warranted considering the evidence presented here concerning the sign and stability of the regression coefficients. The findings supporting the offsetting behavior hypothesis are related strongly to the starting point of the time series. The graphs in this paper show that in the early years of the initial safety regulations (mid-1960s) there was a strong negative effect on pedestrian fatality and accident rates. A more plausible conclusion would be that safety regulations resulted in a decrease in pedestrian fatalities. The accident rate equation fits the data so poorly that it seems inappropriate to use it for predictions.

A problem incompletely acknowledged by the authors is the basic inadequacy of the data. Prior to 1975 and FARS, total fatalities based on NCHS counts may be reasonably good, but disaggregation into categories such as passenger vehicle fatalities (excluding trucks and motorcycles), pedestrian and pedalcycle fatalities relies on using estimates based on reports from less than half the states.[11] As a result of comparing with FARS, it appears that from 1975 to the present, there is no systematic bias in

[11]For example, 1993 pedestrian deaths in *Accident Facts* were based on reports from 15 state traffic authorities. The number of states reporting varies from year to year. See National Safety Council (1994, page 69).

the pedestrian fatality data, although the data must be considered imprecise. As shown in the Appendix, roundoff error in pedestrian fatality counts introduces a pattern in the residuals that correlates strongly with time. Counts of total crashes in the AR equation, according to the Chirinko and Harper are of much lower quality. They argue that unless there is systematic bias, the lower quality data will simply inflate the standard errors of the estimated coefficients. There is no way, however, to determine if the data are free from systematic bias.

It is also important to note that Chirinko and Harper's models for accident rate and pedestrian fatalities equations are overly simplistic. Probably some of the same variables govern occupant fatalities, all crashes whether fatal or not, and nonoccupant fatalities, but there are other important variables that are left out. For example, pedestrian fatalities are more prevalent among young and old and occur primarily in urban compared with rural locations (see Baker, O'Neill, Ginsburg, and Li, 1992). Patterns of such fatalities have changed substantially since the end of World War II with suburbanization, increased vehicle usage, etc. Moreover, there should be some measure of changing pedestrian exposure over time. Estimating pedestrian exposure is an interesting research challenge.

Decomposing the occupant fatality rate into accident and vulnerability rate equations is an important step, although incompletely realized by the authors because they don't build models for pedestrian fatalities or crashes, rather just reuse the occupant fatality model. Looking at crashes and vulnerability separately is in keeping with the standards implemented between 1968 and 1974 that may have had a differential effect on crash and vulnerability rates. A careful look at these standards shows many of them were invisible to the driver (hydraulic brakes, hoses and fluids; tires; and hood latch systems), others were visible (transmission shift lever sequence, lighting and mirrors) although probably not associated by drivers with crash avoidance. Most crash protection and survivability standards, (e.g., head restraints, interior padding, glazing, locks, occupant restraints, etc.) provide no feedback to drivers. It has been argued that improvements that feed back direct and immediate information to drivers, such as improved brakes, may change the driving task and may lead to different driving behavior including more risk taking (Lund and O'Neill, 1986). But there is no evidence that drivers operate their vehicles differently when the vehicles are equipped with features that provide no feedback.

This raises the issue about driver learning and driver perceptions of crash risks and losses. An important contribution in Chirinko and Harper is the recognition of the role of perception and in particular some of the findings of prospect theory (for example, see Slovic, Fischoff and Lichtenstein, 1982). They observe that if perceptions of the effect of a safety regulation are zero, then drivers may not react and offset. Furthermore, evidence from the prospect theory literature suggests that individuals underestimate and may even ignore many low probability fatality risks (Camerer and Kunreuther, 1989) or risks due to their own actions (Svenson, 1981). All these factors are likely to attenuate any relationship between safety regulations and increased driver risk taking.

A key precursor to offsetting behavior is regulation that made safety equipment mandatory. However, many of the standards simply mandated what was already in place, thus it seems unlikely to expect driver behavioral adaptation at the time of the regulation.[12] Another reason why offsetting behavior might not be found is that drivers may have been able to avoid regulations. An example of this was FMVSS 208 mandating shoulder belts. Lap belts had been standard equipment since the mid-1960s. Repeated surveys of lap belt use at the time showed 25-35 percent of front seat occupants used lap belts (Fhaner and Hane, 1973). Shoulder belt use was probably much less. It would make more sense for a driver who has enough safety without a seat belt to refuse to wear the belt rather than to find some type of offset.

Chirinko and Harper suggest that publicity surrounding the introduction of safety devices may actually lead to greater risk taking. However, it may be possible instead that drivers may become more aware of their vulnerability. As a result, they may revise their personal safety goals to higher levels (Slovic and Bischoff, 1982). Prospect theory implies that drivers might be reluctant to sacrifice the new levels of protection (this is the "status quo effect," in Camerer and Kunreuther, 1989 and McDaniels, 1992). Publicity surrounding safety regulations may also make drivers more safety conscious so that they take fewer risks. This is consistent with our findings that safety regulation of the mid-1960s is associated with a reduction in pedestrian fatality rates, although this relationship needs confirmation with more reliable data and a better fitting model. The larger issue is whether motor vehicle safety regulations or changes in economic conditions produced the substantial decreases in pedestrian and occupant fatality rates that occurred after World War II. The relationship between fatality rates and economic conditions rests on correlations, assumptions made in formulating models, and data that are not always as clean as they should be. In contrast, the relationship between occupant fatalities and seat belts, energy-absorbing steering columns, head restraints, high penetration-resistant windshields, and other improvements is obvious. When a drunk driver is coming directly at you, you are better off with an air bag than with news that the price of repairs had just inched upward.

[12]For example, the standard for lamps (108) was already an ICC regulation and GSA and SAE standards. Glazing Materials (205) was a Federal Standard based on existing codes. Standards for defrosting and defogging (103), hydraulic brake hoses (106) and Seat Anchorages (207) were SAE Standards or SAE practices. See Blomquist (1988, page 14).

APPENDIX

The Quality of the National Safety Council Data

Until 1975 there was a single source for annual total traffic fatalities, namely that from the National Center for Health Statistics. The National Safety Council (NSC) disaggregated these totals into occupant, pedestrian, and other fatality categories using state level data and various formulas to allocate totals to categories. The estimated totals by categories were published in the annual series, *Accident Facts*. In 1975 a second source became available from the National Highway Traffic Safety Administration with the Fatal Accident Reporting System (FARS). This latter source of data resulted from investigation of every reported, fatal crash on public roads in the United States and contained direct counts of occupant, pedestrian, nonoccupant, and other types of fatalities relevant to this paper.[13] Although FARS is preferable data because it uses direct counts rather than estimates for categories, Chirinko and Harper could not use FARS for this present research because it does not go back to the period before the 1966 Traffic and Motor Vehicle Safety Act. The resulting question is how much accuracy is lost with the NSC data in estimating the pedestrian fatality equation.[14]

Our examination of both NSC and FARS data suggest that from 1975 forward, when both data systems are available, FARS direct counts of occupant and pedestrian fatalities and NSC estimates of these quantities are fairly close. However, the NSC data are rounded, and the resulting error is not negligible. The size of the error is also related to the number of fatalities, becoming more pronounced as fatalities decrease in recent years. This introduces a time pattern into the residuals in the pedestrian fatality model.

The purpose of this Appendix is to provide both theoretical and empirical support for the claim about the relationship between the regression residuals and time. Before addressing that issue, the occupant and pedestrian fatalities in the two data sources are compared.

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[13]The term "pedestrian" as used in the appendix really means nonoccupants in keeping with terminology in the body of the paper and in the authors' pedestrian fatality equation. When it is important to distinguish between pedestrian and pedalcyclist fatalities, the text will use the terms separately.

[14] We are less able to address the quality of the crash data used in the AR equation. Without acknowledging the source of the data Chirinko and Harper readily acknowledge it to be of lower quality. They claim that the problems are unsystematic and merely inflate the error. Reasonable quality data that could be used to estimate the total number of crashes become available during the early 1980's in NHTSA's NASS/GES system. Even so, these data are based on police reports and it is well known that a large number of motor vehicle crashes are unreported.

Comparability of the Data

Figure A.1 presents a plot of occupant fatalities and Figure A.2 plots pedestrian fatalities over the period 1975-93, where the heavy line represents FARS data and the lighter line uses data from the NSC. Both lines seem to follow the same trend, with occupant fatalities extremely close, pedestrians not so close. The correlation between the occupant fatalities in either dataset is 0.96 ($p < 0.001$), while for pedestrian fatalities it is lower at 0.93 ($p < 0.001$). One would expect not expect exact agreement between the two data sources because they use different definitions of motor vehicle deaths. It is reasonable that NSC estimates should exceed FARS counts because the NSC defines a motor vehicle death as occurring within a year of the crash, while FARS limits the period to 30 days.

This agreement between the data is only suggestive of the quality of the NSC data before 1975. It may be that NSC estimates were modified to conform with FARS, but this seems unlikely.[15] Changes in the NSC procedure should show up in the annual time series presented in the body of this paper. But

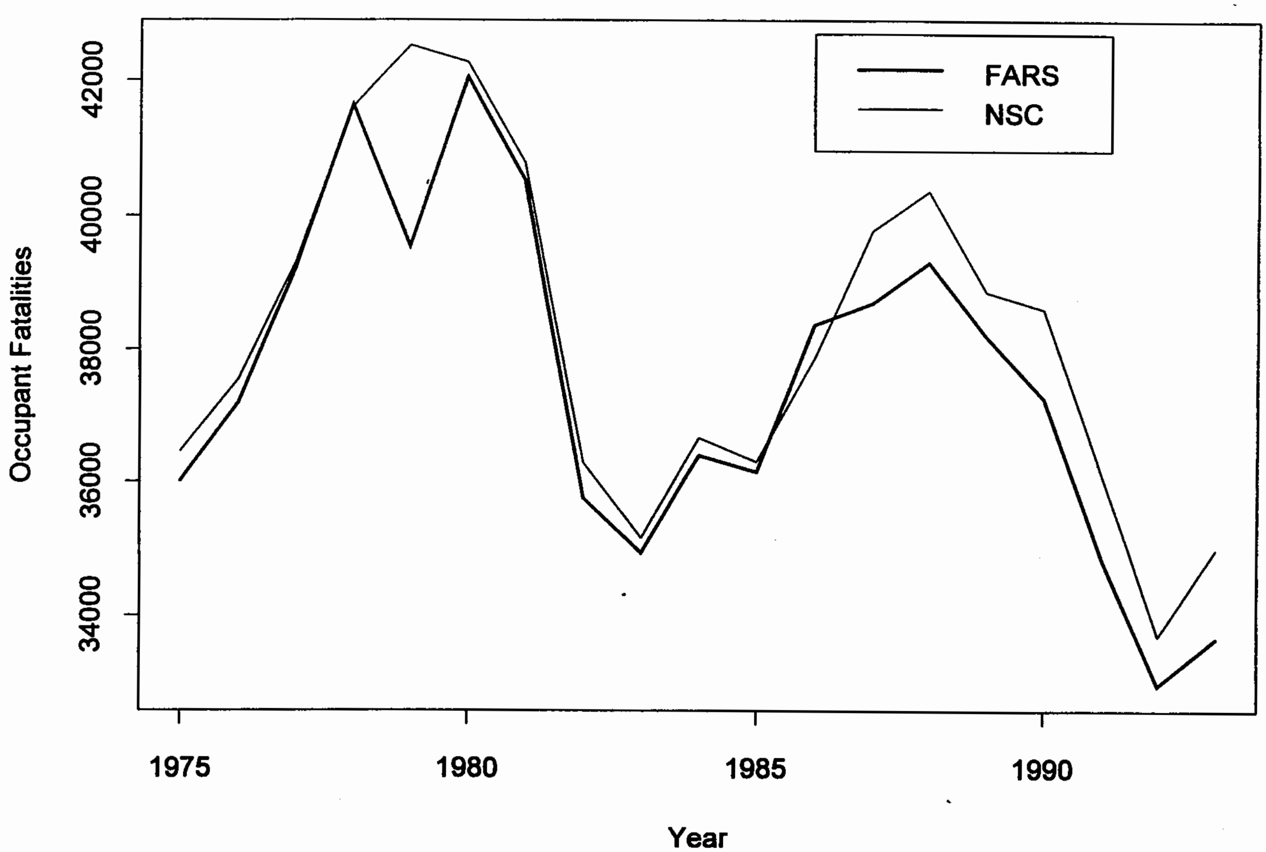

Figure A.1: Comparison of Occupant Fatalities in NSC and FARS Data

[15] The NSC usually indicates in *Accident Facts* when estimation procedures change. There are no indications of that for 1975.

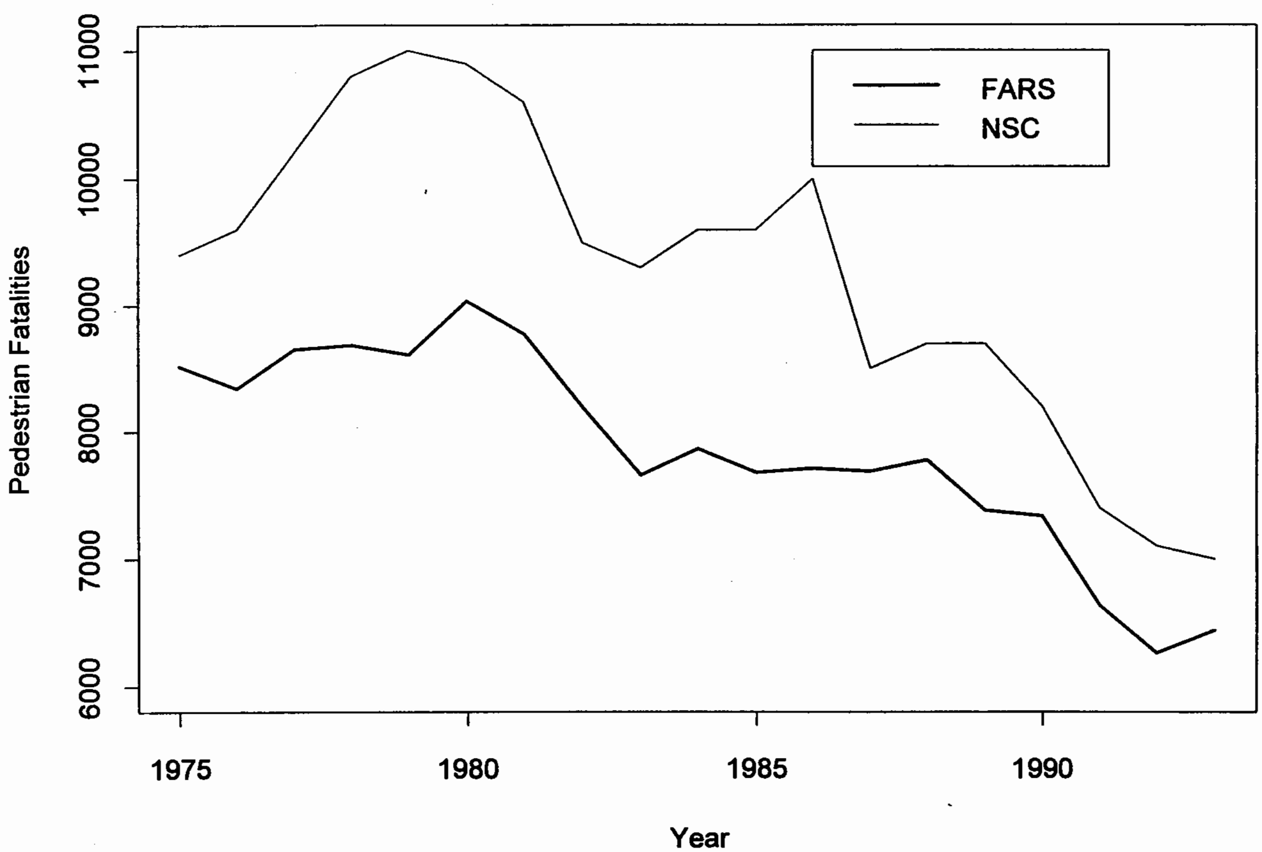

Figure A.2: Comparison of Pedestrian Fatalities in NSC and FARS Data

there does not seem to be any. Inspection of Figure 1a shows that aside from the large drop in pedestrian fatalities in the 1974-73 difference, there was about the same amount of fluctuation in the period 1975-80 (where adjustments would be expected) as in 1965-75. Therefore, although it would have been preferable to have a pre-1975 time series of actual pedestrian and pedalcycle fatality counts, there seems to be little reason to distrust the NSC pedestrian fatality data.

Roundoff Error

As mentioned above, both pedestrian and pedalcycle fatality components are rounded in the NSC data. Rounding of pedestrian fatalities is to the nearest 100, while pedalcyclist fatalities are rounded to the nearest 10 until 1971, when the number of fatalities was 800, then the nearest 100 thereafter as the number of fatalities increased to 1000. Rounding is analogous to adding a uniform random number to the actual value before rounding. The associated uniform random variable has a range of -50 to 50 and a variance of 2500/3 when rounding to the nearest 100, and a variance of 25/3 when rounding to the nearest 10. The impact on the error is examined in the following.

The pedestrian fatality equation as used in the paper in differenced logs form is given below:

$$= \log(\tilde{y}_t) - \log(\tilde{y}_{t-1}) + v_t - v_{t-1} + \log\left(1 + \frac{u_t}{\tilde{y}_t e^{v_t}}\right) - \log\left(1 + \frac{u_{t-1}}{\tilde{y}_{t-1} e^{v_{t-1}}}\right)$$

$$\log(y_t) - \log(y_{t-1}) = \log(\Pi x_{it}^{b_i} e^{v_t} + u_t) - \log(\Pi x_{it-1}^{b_i} e^{v_{t-1}} + u_{t-1})$$

In the equation, the subscripts i and t represent the variable index and time respectively, x_{it} represents a typical exogenous variable, b_i is a slope coefficients, v_t is a normal random variable with mean 0 and variance s^2 that would have resulted from the regression in the absence of roundoff, y_t is the response variable, u_t is the roundoff that enters additively, and $\tilde{y}_t$ is the predicted value that would be obtained in the absence of roundoff. Although the roundoff in u_t contains roundoff from both pedestrian and pedalcycle fatalities, the pedalcycle roundoff is only important from 1971 forward when it is rounded to the nearest 100.

The important quantity is the two last terms because they contain the roundoff u_t. To determine the importance of those terms, we can concentrate on one of them and later double the result. We can expand one of the terms as a Taylor series ignoring higher order polynomials as

$$\log\left(1 + \frac{u_t}{\tilde{y}_t e^{v_t}}\right) = \frac{u_t}{\tilde{y}_t e^{v_t}} - \frac{1}{2}\left(\frac{u_t}{\tilde{y}_t e^{v_t}}\right)^2 + O\left(\frac{u_t}{\tilde{y}_t e^{v_t}}\right)^3$$

Ignoring the higher order terms is safe because the denominator is approximately two to three orders of magnitude larger than the numerator. (For example, a typical value of the roundoff quantity u_t would be -50 and 50, while the denominator, estimated pedestrian fatalities would be around 9000). Thus, the quadratic term is on the order of 10^{-5} or 10^{-6}. Recall that the denominator is pedestrian fatalities (or fatalities per VMT) and the numerator is roundoff fatalities (or roundoff fatalities per VMT).

This last equation shows that error resulting from the roundoff is a decreasing function of the size of the predicted or actual value of fatalities. As the predicted values decrease over time, one might expect the residuals in the pedestrian fatality equation would increase over time. Figure A.3 confirms this. In particular, regressing the residuals on time, and omitting the outlier year of 1974 produces a value of R^2 of .1996 (b_1 = .0014, t=2.954, p = .0056.).

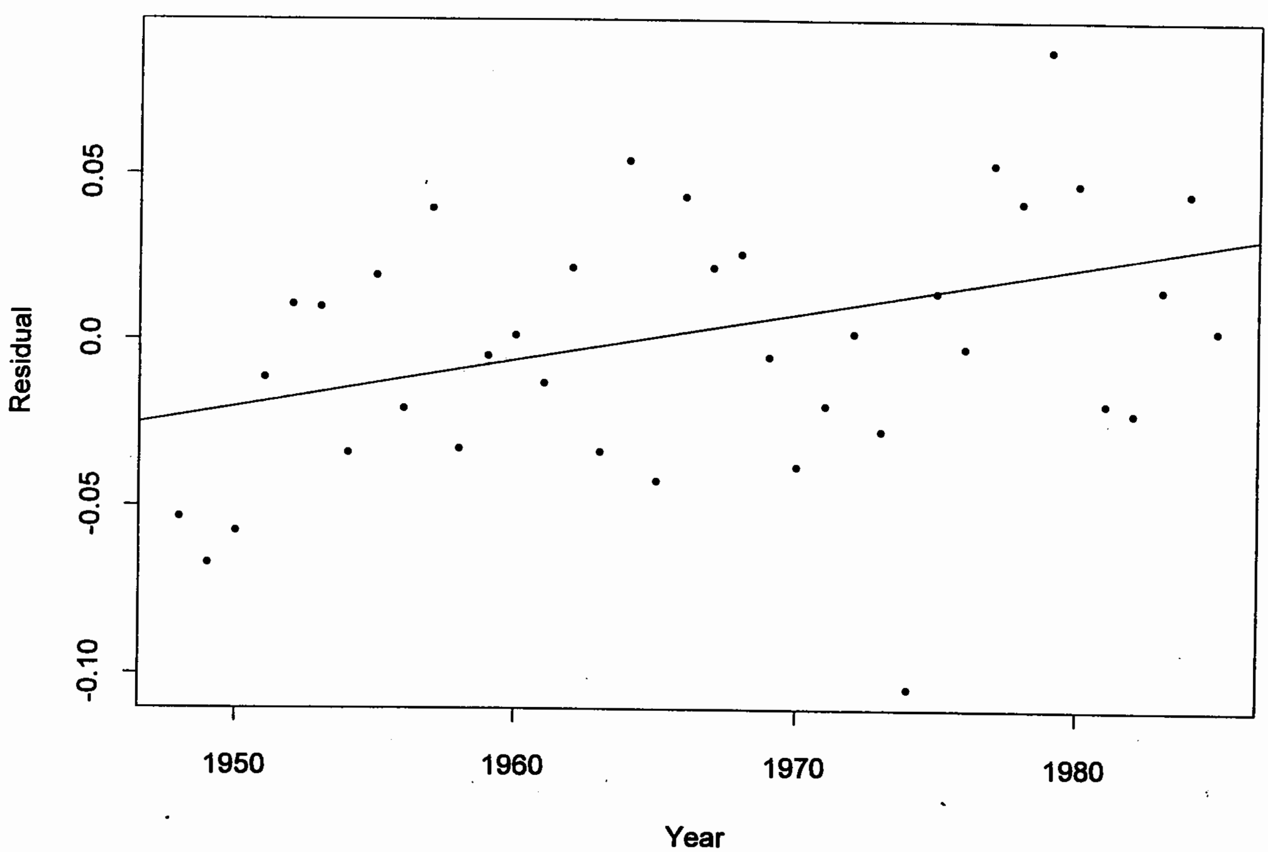

Figure A.3: Residuals and Time in the Pedestrian Fatality Regression

An approximation for the variance due to roundoff can be obtained from the estimated variance from the first term. This is

$$Var\left(\frac{u_t}{\tilde{y}_t e^{v_t}}\right) \approx \left(\frac{1}{\tilde{y}_t e^{v_t}}\right)^2 Var(u_t)$$

A reasonable numerical value for the right hand side of this equation would be $((2500/3)/9000^2)=1.0289 \times 10^{-5}$ where 9000 is about the average number of pedestrian fatalities. Because the regression equation for pedestrian fatalities requires differencing, the variance needs to be doubled. Taking the square root for the standard deviation produces 0.0045. While this may appear negligible, it is actually about 10 percent of the standard error of the estimate (0.04405) reported for that the pedestrian fatality regression in Chirinko and Harper. Adding in the pedalcyclist roundoff after 1971 would double the variance again, producing an estimated standard error of 0.0064.

Conclusion

To summarize, this Appendix has shown that the NSC data compare favorably with FARS data from 1975 to date. This does not support the accuracy of the NSC data prior to 1975 nor does it impugn that accuracy. The roundoff error in the data does represent a problem. The time trend of the error is disturbing because the magnitude of the error increases over time. Among other things, this suggests that regression coefficients for variables such as SAF that switch on later in the time period, may be subject to more error than those present through the entire series. Additionally, the amount of error is not insignificant when compared to the magnitude of the regression residuals.

REFERENCES

Baker, S.P., O'Neill, B., Ginsburg, M.J. and Li, G. 1992. The Injury Fact Book, 2nd edition. New York: Oxford University Pess.

Belsley, D.A., Kuh, E., and Welsch, R.E. 1980. Regression Diagnostics: Identifying Influential Data and Sources of ollinearity. New York: John Wiley and Sons.

Blomquist, G. 1986. A utility maximization model of driver traffic safety behavior. *Accident Analysis and Prevention* 8:371-375.

Blomquist, G. 1988. The Regulation of Motor Vehicle and Traffic Safety. Boston: Kluwer Academic Publishers.

Camerer, C.F. and Kunreuther, H. 1989. Decision processes for low probability risks: Policy implications. *Journal of Policy Analysis and Management* 8:565-592.

Chirinko, R.S. 1994. As cars get safer, drivers ignore risks. *New York Times Magazine* (April 11, 1994).

Chirinko, R.S. and Harper, E.P. 1992. Buckle up or slow down? New estimates of offsetting behavior and their implications or automobile safety regulation. University of Chicago, Harris School of Public and Policy Studies Working Paper Series (92-7).

Chirinko, R.S. and Harper, E.P. 1993. Buckle up or slow down? New estimates of offsetting behavior and their implications for automobile safety regulation. *Journal of Policy Analysis and Management*, 12(2):270-296.

Crandall, R.W., Gruenspecht, H.K., Keeler, T.E., Lave, L.B. 1986. *Regulating the Automobile*. Washington, DC: The Brookings Institution.

Evans, L. 1986. Risk homeostasis theory and traffic accident data. *Risk Analysis*, 6, 81-94.

Evans, W. and Graham, J.D. 1991. Risk reductions or risk compensation: The case of mandatory safety belt use laws. *Journal of Risk and Uncertainty* 4:61-73.

Fhaner, G. and Hane, M. (1973). Seat Belts: Factors Influencing their Use: A Literature Survey. *Accident Analysis and Prevention* 5:27-43.

Garbacz, C. 1985. A note on Peltzman's theory of offsetting consumer behavior. *Economic Letters* 19:183-187.

Garbacz, C. 1991. The impact of the New Zealand seat belt law. *Economic Inquiry* 29(2):310-316.

Garbacz, C. 1992. The evidence on the effectiveness of seatbelt laws. *Applied Economics* 24(3):313-315.

General Accounting Office. 1976. Effectiveness, benefits, and costs of federal safety standards for protection of passenger car occupants. (CED-76-121.) Washington, DC: U.S. Dept. of Transportation.

Graham, J.D. 1983. Automobile Safety: An Investigation of Occupant Protection Policies. Ph.D. dissertation, Carnegie-Mellon University, Pittsburgh, PA.

Graham, J.D. and Garber, S. 1984. Evaluating the effects of automobile safety regulations. *Journal of Policy Analysis and Management* 3:206-224.

Keeler, T.E. 1994. Highway safety, economic behavior and driving environment. *American Economic Review* 84:684-693.

Lund, A. and O'Neill B. 1986. Perceived risks and driving behavior. *Accident Analysis and Prevention* 18:67-370.

Lund, A. K. and Zador, P., 1984. Mandatory belt use and driver risk taking. *Risk Analysis* 4:41-53.

McDaniels, T.L. 1992. Reference points, loss aversion and contingent values for auto safety. *Journal of Risk and Uncertainty* 5:187-200.

National Safety Council. 1994. *Accident Facts*. Itasca, IL.

Peltzman, S. 1975. The effects of automobile safety regulation. *Journal of Political Economy* 83:677-725.

Robertson, L.S. and Baker, S.P. 1976. Motor vehicle sizes in 1440 fatal crashes. *Accident Analysis and Prevention* 8:167-175.

Slovic, P. and Fischoff, B. 1982. Comment: Targeting risk. *Risk Analysis* 2:227-234.

Slovic, P., Fischoff, B., and Lichtenstein, S. 1982. Facts versus Fears: Understanding Perceived Risk in Kahneman, D., Slovic, P., and Tversky, A., (eds), Judgement Under Uncertainty: Heuristics and Biases. Cambridge University Press, Cambridge, MA. Pp 463-489.

Svenson, O. 1981. Are we less risky and more skillful than our fellow drivers? *Acta Psychologica* 47:143-148.

White, H. 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica* 48:817-838.