

# An exploration of the offset hypothesis using disaggregate data: The case of airbags and antilock brakes

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**Abstract** The offset hypothesis predicts consumers adapt to innovations that improve safety by becoming less vigilant about safety. Previous tests have used aggregate data that may confound the effect of a safety policy with those consumers who are most affected by it. We test the hypothesis using disaggregate data to analyze the effects of airbags and antilock brakes on automobile safety. We find that safety-conscious drivers are more likely than other drivers to acquire airbags and antilock brakes but these safety devices do not have a significant effect on collisions or injuries, suggesting drivers trade off enhanced safety for speedier trips.

**Keywords** Offsetting behavior · Automobile safety · Airbags

**JEL Classification** L5 · R4

The offset hypothesis predicts that consumers will adapt to innovations that improve safety by becoming less vigilant about safety. They will, for example, drive faster in cars that are equipped with extra protection features, ride on dangerous off-road trails when wearing a bicycle helmet, leave hard-to-open (childproof) bottle caps off medicine containers, pay less attention to infants in bath seats that are intended to prevent drowning, and even take fewer precautions to prevent children from having access to cigarette lighters that have a safety device (Viscusi and Carvallo, 1994). The hypothesis was first offered by Lave and Weber (1970) and rigorously applied by Peltzman (1975) to analyze the effects of the 1960s automobile safety regulations. Since then, engineers, scientists, safety advocates, and policymakers have had to come to terms with the offset hypothesis when evaluating the

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effectiveness of a safety-enhancing technology. Some have acknowledged its importance while others have dismissed it.<sup>1</sup> Economists have been primarily responsible for testing its validity.

Most empirical tests have been a byproduct of assessments of automobile safety policies such as regulations requiring occupant safety devices, speed limits, and mandatory safety-belt laws. The majority of these tests have found evidence of offsetting behavior. But they have been conducted using aggregate data at either the national (Peltzman, 1975; Crandall et al., 1986; Chirinko and Harper, Jr., 1993; Yun, 2002), state (Calkins and Zlatoper, 2001; Cohen and Einav, 2003), county (Keeler, 1994), or city (Dee, 1998; McCarthy, 1999) level. A few researchers have used less aggregated data derived from state police accident reports (Traynor, 1993; Peterson, Hoffer, and Millner, 1995; Harless and Hoffer, 2003).<sup>2</sup>

In our view, a test of the offset hypothesis calls for an analysis of two empirical questions that require the use of disaggregate data: (1) What types of consumers are likely to switch to products with new safety devices? (2) Compared with consumers who do not switch, will consumers who do switch to products with new safety devices be more, less, or equally likely to suffer an accident after their switch?

In the automobile context, empirical studies based on aggregate data include variables that control for motorists' socioeconomic characteristics. But they cannot identify which drivers acquire vehicles with mandated safety equipment and the particular characteristics of these drivers; thus, they cannot unambiguously determine how the safety equipment affects motorists' safety. In other words, aggregate studies may confound the actual effect of an automobile safety regulation with the type of drivers who acquire vehicles that have mandated safety equipment. For example, if safe drivers who enter the vehicle market are more likely than dangerous drivers to acquire new cars with protection features, then a safety regulation may be erroneously credited with preventing serious injuries because safe drivers are less likely than dangerous drivers to be involved in accidents that cause serious injuries regardless of their vehicles' safety features.

This paper represents the first attempt (to our knowledge) to test the offset hypothesis using disaggregate data. We assemble a sample of drivers in Washington State and explore the effect of airbags and antilock brakes on automobile safety. Airbags started to gain market acceptance several years before the government required their installation in new cars beginning with the 1998 model year (Mannering and Winston, 1995). Thus consumers have been free to purchase a car with an airbag and adjust their driving behavior accordingly, enabling researchers to assess the effect of these decisions on the frequency and severity of drivers' accidents during the early to mid-1990s. Similarly, antilock brakes were gradually introduced as an option in new automobiles beginning in the 1970s.

It has been widely reported in the popular press that airbags have saved some 3,000 lives, but this claim assumes that each potential victim would have been in an accident or would not have taken measures to reduce an accident's impact if their vehicle were not equipped with an airbag.<sup>3</sup> Laboratory tests of antilock brakes conclude that they should reduce the likelihood of collisions and the severity of injuries, but their effectiveness in actual driving conditions has been questioned because drivers may not apply them properly. We find that

<sup>1</sup> Smiley (2000) discusses how the offset hypothesis is an important consideration in human factors research on the effectiveness of automobile safety devices. O'Neill and Williams (1998) claim the hypothesis has been repeatedly refuted by empirical studies and commands little credence.

<sup>2</sup> Sen (2001) tested the hypothesis using data from Canadian provinces.

<sup>3</sup> It has also been claimed that more than 100 small adults and children have been killed by airbags because they could not withstand the force released by an airbag during a low-speed crash.

safety-conscious drivers are more likely than other drivers to purchase a car with an airbag or antilock brakes. But we also find that airbags and antilock brakes do not have a statistically significant effect on the probability of an accident or its level of severity, suggesting that drivers trade off enhanced safety for speedier trips.

### 1. Analytical framework

The framework for analyzing offsetting behavior was developed by Peltzman (1975) and extended by Viscusi (1984). In our context, individuals are assumed to maximize utility from driving by trading off driving intensity (speeding, following short distances behind other vehicles, taking risks at intersections, and so on) and safety, where vehicle occupant safety may be enhanced by airbags and antilock brakes. In what follows, we develop the theoretical basis for an empirical test of the efficacy of air bags on driver safety and then extend the framework to include antilock brakes.

Figure 1 shows how the introduction of airbags into the automobile market could affect the tradeoff between driving intensity and safety. The severity of an accident ranges from only minor vehicle damage to death. We measure safety here by the probability of avoiding injury from an accident; that is, we focus on accidents classified at the “injury” severity level. (In our empirical work, we will estimate the effect of air bags and antilock brakes on accidents classified at alternative severity levels.) The marginal rate of transformation (MRT) between safety  $S$  and driving intensity  $s$  is shown by the slope  $S_s$  (linearity is assumed for simplicity). Given this MRT, the driver maximizes utility at equilibrium  $A$  (reflecting the tangency of an

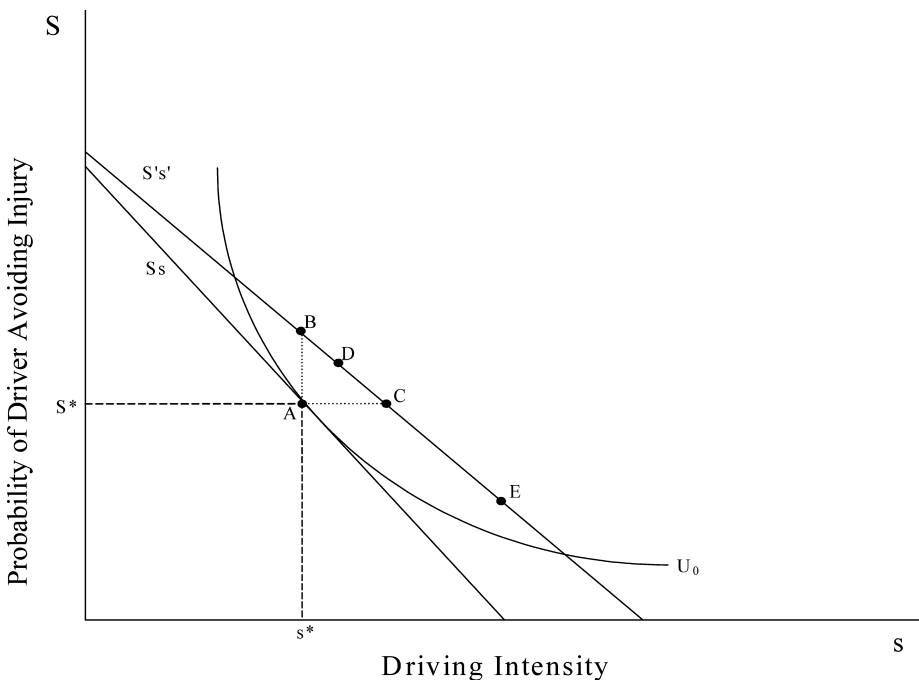


Fig. 1 The effect of airbags on safety and driving intensity

indifference curve  $U_0$ ), with  $S^*$  and  $s^*$  chosen as the optimal levels of safety and driving intensity.

The benefit provided by an airbag is that driving intensity becomes “cheaper,” because the cost of safety borne by the driver for a given level of driving intensity is lower (i.e., the probability of avoiding injury is greater) for all values of  $s$ . The MRT reflects this change by shifting from  $Ss$  to  $S's'$ .<sup>4</sup> Drivers must decide whether the value of the additional utility from expanding their safety-intensity consumption set exceeds the cost of an airbag. Assuming that driving intensity is a normal good, optimal consumption cannot be to the left of  $B$ . But a driver’s preferences could range from consuming only additional safety ( $B$ ) to increasing driving intensity with no change in safety ( $C$ ) or consuming some combination of greater safety and intensity ( $D$ ). It is even possible that a driver could choose a level of safety that is below the pre-airbag level ( $E$ ).<sup>5</sup>

Although theory suggests that some drivers will maximize utility by purchasing airbags to expand their safety-intensity possibilities, it cannot predict whether their safety will improve; this issue must be determined empirically. Our analysis starts with the choices that drivers make to maximize expected utility. Let *airbag* represent a dummy variable defined as 1 if a consumer’s vehicle is equipped with an airbag, 0 otherwise,  $p_a$  is the price of an airbag,  $s$  measures driving speed (other components of driving intensity are ignored for simplicity), and  $\Pr(\text{accident}|\text{airbag}, s)$  is the probability of a driver being in an accident resulting in an injury. Although driving faster increases the probability of an accident, it is assumed that driving speed also generates utility denoted  $V(s)$ . By assuming a value of travel time savings,  $V(s)$  can be expressed in dollars. Finally, let  $L(\text{airbag}, s)$  represent the cost of an injury from an accident.

To simplify the exposition, we assume motorists are risk neutral and specify simple linear functional forms for utility. (The resulting empirical approach is also appropriate if motorists are risk averse.) There are two possible states for a given driver with income  $Y$ . First, in the event that no accident occurs, utility is  $Y + V(s) - p_a \text{airbag}$ . If an accident occurs, utility is  $Y + V(s) - L(\text{airbag}, s) - p_a \text{airbag}$ . Expected utility is thus:

$$E(U) = Y + V(s) - \Pr(\text{accident} | \text{airbag}, s) \cdot L(\text{airbag}, s) - p_a \text{airbag}. \tag{1}$$

The driver is assumed to select the driving speed,  $s$ , and airbag option (purchase/do not purchase), *airbag*, that maximize expected utility.<sup>6</sup> These optimal choices determine the driver’s probability of getting into an accident resulting in an injury and its cost.

Accordingly, a plausible simultaneous equations model of the probability of an accident of severity level  $i$ , driver behavior, and airbag choice is given by:

$$\begin{aligned} \Pr[\text{accident}_i] &= \beta_1 \text{airbag} + \beta_2 s + \delta Z_1 + u_1 \\ s &= \beta_3 \text{airbag} + \Gamma Z_1 + u_2 \\ \Pr[\text{airbag}] &= \beta_4 s + \pi Z_2 + u_3, \end{aligned} \tag{2}$$

<sup>4</sup> The shift in the MRT reflects the notion that airbags provide safety benefits to drivers at high levels of driving intensity (where a potentially serious accident may occur), but fewer benefits at low levels of driving intensity.

<sup>5</sup> It is straightforward to use comparative statics to show formally the ambiguous effect of airbags on automobile safety.

<sup>6</sup> Optimal values of speed and airbag option will equate marginal benefits and costs of these choices.

where  $Z_1$  and  $Z_2$  denote vectors of exogenous influences (as discussed later, exogenous influences on airbag choice and accident probabilities may, in theory, be different);  $\beta$ ,  $\delta$ ,  $\Gamma$ , and  $\pi$  denote estimable parameters; and  $u$  is an error term.

The adoption of an airbag has two possible effects on the probability of an accident of a given level of severity. The first, captured in  $\beta_1$ , is the airbag’s technological impact on the severity of an accident holding driving speed constant. Engineering estimates by the National Highway Traffic Safety Administration in the late 1970s and early 1980s indicated that first generation airbags would reduce the probability of an injury twenty percent and the probability of a fatality up to forty percent. An airbag could also affect driver behavior—that is, driving speed. If an individual drives faster in a car with an airbag,  $\beta_3$  is positive, and if these higher speeds increase the likelihood of an accident of a given level of severity, then the technological effectiveness of airbags may be partially or completely offset.

Heretofore we have characterized driver behavior simply in terms of driving speed when, in fact, it encompasses several other potentially dangerous actions such as tailgating, running red lights, driving while intoxicated, driving fast in inclement weather, and so on. Unfortunately, it is difficult to obtain information on drivers’ speeds for their trips and the extent to which they engage in dangerous practices. Indeed, these decisions are endogenous and likely to vary across an individual’s automobile trips. Some researchers have used the number of (moving) traffic violations that a driver has received as a proxy for driving behavior. But traffic enforcement may be inconsistent and many aggressive drivers try to avoid these violations by using radar-detection devices and going to court to prevent a traffic citation from standing up.

Given these empirical limitations, we formulate the model as:

$$\begin{aligned} \Pr [accident_i] &= \gamma \text{airbag} + \delta Z_1 + u_1 \\ \Pr [airbag] &= \pi Z_2 + u_2. \end{aligned} \tag{3}$$

Because driver behavior is no longer held constant and most of the variables that are used to “instrument” airbags would influence driver behavior, the airbag coefficient  $\gamma$  captures the net effect of safety technology and drivers’ behavioral adaptation to this technology.

Other automobile safety technologies may also affect accident probabilities. The most important of these during the past two decades has been the introduction of antilock brakes, *abs*, which maintain steering control and shorten stopping distance by preventing skidding. As noted, laboratory tests have suggested that proper application of antilock brakes should reduce the number and severity of accidents. However, drivers may adjust their behavior in ways that offset the safety cushion provided by improved braking. Specifying this choice yields our estimable model:

$$\begin{aligned} \Pr [accident_i] &= \gamma \text{airbag} + \lambda \cdot \text{abs} + \delta Z_1 + u_1 \\ \Pr [airbag] &= \pi Z_2 + u_2 \\ \Pr [abs] &= \theta Z_2 + u_3. \end{aligned} \tag{4}$$

## 2. Data

Our empirical analysis is based on the behavior of drivers in Washington State from 1992 through 1996.<sup>7</sup> Washington state government agencies collect and maintain accurate information about drivers and their reported accidents. We hired an automobile marketing consulting firm, Alison-Fisher, Inc., to conduct a survey of licensed drivers obtained from the Washington State Department of Licensing. To ensure that our sample contained some drivers who were in accidents, we used a screener to identify drivers who had been in at least one accident during the 1992–96 period. We then randomly sampled roughly an equal share of drivers who had and had not been involved in an accident. Survey respondents provided socioeconomic data, basic commuting information, and the make, model, and vintage of the vehicles they owned (also indicating whether these vehicles contained an airbag and antilock brakes).<sup>8</sup> The percentage of vehicles in the sample equipped with airbags rose from 12 percent to 32 percent and the percentage of vehicles equipped with antilock brakes rose from 23 to 42 percent during this period, which is consistent with state and national figures.

Each driver's accident frequency for a given year was obtained from Washington State Department of Transportation databases. All vehicle accidents reported to the police are included in this database, accounting for virtually all accidents resulting in possible injury to drivers, passengers, bicyclists, and pedestrians and excluding only accidents that resulted in very minor property damage.<sup>9</sup> A few people in our sample died at some time during the sample period. A surviving family member provided data for these individuals. The final sample consisted of 1307 drivers contributing 6,234 observations on their annual accident frequencies.<sup>10</sup> Of these drivers, 271 switched from a vehicle without an airbag to a vehicle with an airbag at some point during our sample period and 270 switched from a vehicle without antilock brakes to a vehicle with antilock brakes.

Data on the severity of reported accidents for drivers, passengers, pedestrians, and bicyclists involved were also obtained from Washington State Department of Transportation databases. Following standard Federal Highway Administration classifications, accident severities were reported as property damage only, possible injury, evident injury, disabling injury, or fatality. Each sampled driver experienced at most one reported accident per year, although some drivers experienced more than one accident during the sample period.

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<sup>7</sup> Washington State safety policies have not changed during almost all of our sample period. Mandatory seat belt laws were introduced in 1986. The national 55 mph speed limit was repealed by Congress in 1995. However, Washington State increased their speed limits to only 60 mph (70 on rural interstates), and did not reinstate these limits until March 1996.

<sup>8</sup> The response rate for the sample was roughly one-third, which is somewhat greater than the cooperation that Alison-Fisher receives when it surveys people who are not members of an established consumer panel. The demographic characteristics of drivers in our sample were aligned with demographic characteristics of residents of Washington State where appropriate and diverged where appropriate. For example, in our sample the percentage of male drivers, drivers over the age of 70, and households with children were very similar to population percentages. On the other hand, in our sample the percentage of drivers who are married is higher than the percentage of residents in Washington State who are married because our sample is restricted to people who are old enough to drive legally.

<sup>9</sup> The National Highway Administration (2001) reports that accidents not reported to the police almost exclusively involve only minor property damage. Only a small share of accidents in our sample involved pedestrians and bicyclists.

<sup>10</sup> Some drivers did not contribute observations for each of the five years because they either purchased their first car or died midway through the sample period.

Compared with population figures, our sampling procedure—which as noted selected an equal share of drivers who had and had not been in an accident during 1992–96—led us to slightly over-sample drivers who had been involved in accidents with property damage only and to slightly under-sample drivers who had been involved in accidents with greater severity. To obtain consistent parameter estimates, we computed appropriate sample weights based on accidents in Washington State for each level of severity from 1992–96.<sup>11</sup> By using the weights, the distribution of accident severities in the sample was consistent with the distribution of accident severities in the population.

Our original sample contained 614 accidents classified as property damage only, 16 as possible injury, and another 16 as evident injury or worse. The weights decreased the share of accidents classified as property damage 6 percent, and increased the share of accidents classified as possible injury and the share classified as evident injury or worse roughly 3 percent.

### 3. Estimation procedure

The dependent variables in our model are the probability of a particular driver being involved in an accident with outcome  $i$ , the probability that the driver has selected a vehicle with an airbag, and the probability that the driver has selected a vehicle with antilock brakes. Preliminary estimations indicated that it was difficult to obtain plausible coefficient estimates using the five accident severity classifications because of their narrow spacing. Thus, the accident outcomes we included are no accident, an accident resulting in property damage only or possible injury (collision), or an accident resulting in at least evident injury.

Accounting for the contemporaneous correlation of the error terms and the endogeneity of the discrete airbag and antilock brake choices that may influence the accident outcome probabilities calls for the estimation of a simultaneous discrete choice model. Consistent parameter estimates of the model can be obtained by maximum likelihood estimation.

Our likelihood function contains three dependent variables, each taking discrete values. We code the multinomial accident outcome variable into three binary variables  $\tilde{Y}_i = 1$  if outcome  $i$  occurs, 0 otherwise. For accidents that result in evident injuries, it must be the case that a collision occurred. Hence, the collision and evident injury dependent variables are both equal to one in this situation.

Each  $\tilde{Y}_i$  is expressed as a function of independent variables, including the endogenous airbag and antilock brake choices, and an error term:

$$\tilde{Y}_i = \tilde{X}'_i \tilde{\beta}_i + \tilde{\varepsilon}_i; \quad i = 1..3, \quad (5)$$

where the errors are distributed as normal random variables  $\tilde{\varepsilon}_i \sim N(0, \tilde{\sigma}_i^2)$ . (To interpret the coefficients,  $\tilde{\beta}_i$ , for evident-injury accidents, we must take the sum of the coefficients in both the collision equation and the evident accident equation, because the dependent variable is equal to one in both equations.) We can unambiguously determine how the explanatory variables influence each accident outcome by invoking the plausible restriction that the accident outcome equations must contain the same vector of independent variables,  $\tilde{X}_i$ . We omit the “no accident” outcome and interpret all estimated effects relative to it (as the base

<sup>11</sup> These data were from the Washington Department of Transportation (1997).

case). Thus, the probability of accident outcome  $i$  can be expressed as:

$$\Pr[i] = \Pr[\tilde{X}'_i \tilde{\beta}_i > \tilde{\varepsilon}_i]. \tag{6}$$

Along with the two other binary dependent variables (the choices of airbags and antilock brakes) we can construct a system of four binary variables that can be expressed as a function of independent variables  $X'_i$  (which may vary by equation  $i$ , except in the accident outcome equations) and an error term:

$$Y_i = X'_i \beta_i + \varepsilon_i; \quad i = 1 \dots 4, \tag{7}$$

where the errors are distributed as standard normal random variables  $\varepsilon_i \sim N(0, 1)$ .

If the errors are uncorrelated across the equations, then each dependent variable takes the distribution:

$$f_{Y_i}(y) = \Phi(X'_i \beta_i)^y \cdot (1 - \Phi(X'_i \beta_i))^{1-y},$$

where  $\Phi$  is the cumulative standard normal density function. However, the error terms are likely to be correlated, and we define  $\rho_{ij}$  to be the correlation between  $\varepsilon_i$  and  $\varepsilon_j$  for all  $i \neq j$ .

To derive the joint probability density of the four dependent variables, we first denote  $q_i = 2y_i - 1$ , which creates a variable equal to 1 or  $-1$  depending on the value of the dependent variable  $y_i$ . Then we define  $w_i = q_i X'_i \beta_i$ , and the modified correlation  $\tilde{\rho}_{ij} = q_i q_j \rho_{ij}$  for all  $i, j = 1 \dots 4; i \neq j$ . It follows that the modified covariance matrix  $\tilde{\Sigma}$  has elements  $\tilde{\Sigma}_{i,j} = \tilde{\rho}_{ij}$ , where the diagonal elements are all equal to 1. (Note that all error terms have a variance of 1, so the covariance matrix is equivalent to the correlation matrix.) The joint probability density function for the dependent variables can now be written as:

$$f_{Y_1, \dots, Y_4}(y_1, \dots, y_4) = \Phi_4(w_1, \dots, w_4; \tilde{\Sigma}), \tag{8}$$

where  $\Phi_4$  is the cumulative four-variate normal density function.

Our likelihood function, which is the product of the joint density taken over all observations  $k = 1..N$ , is given by:

$$L(\beta_1, \dots, \beta_4, \Sigma) = \prod_{k=1}^N \Phi_4(w_{1k}, \dots, w_{4k}; \tilde{\Sigma}). \tag{9}$$

As noted, we use weights to ensure that the incidence of accidents of varying levels of severity in our sample is consistent with the incidence of these accidents in the population. The weights,  $\omega_k$ , are defined as the proportion of accidents of a given level of severity in the population divided by the proportion of accidents of a given level of severity in the sample. Taking the natural logarithm of the likelihood function and accounting for the sample weights yields:

$$\log(L(\beta_1, \dots, \beta_4, \Sigma)) = \sum_{k=1}^N \omega_k \cdot \log(\Phi_4(w_{1k}, \dots, w_{4k}; \tilde{\Sigma})). \tag{10}$$



Maximization of this log-likelihood function with respect to the coefficient vectors,  $\beta$ , and the modified covariance matrix is achieved by using the Geweke–Hajivassiliou–Keane (GHK) simulator for multivariate normal probabilities. Boersch-Supan and Hajivassiliou (1990) discuss its properties; details of the simulation procedure are provided in the appendix.

#### 4. Specification, identification, and additional econometric issues

We have developed a model that jointly estimates the determinants of automobile accident outcomes and the driver's choice of whether to acquire a vehicle with airbags and/or antilock brakes. Accident outcomes are assumed to be influenced by vehicle safety attributes, driving exposure, and driver characteristics. We include both airbags and antilock brakes in our accident equations. Assuming their technologies perform as expected, airbags should reduce evident injuries and antilock brakes should reduce collisions and evident injuries unless drivers offset the enhanced safety by driving more aggressively. Airbags could increase collisions by encouraging aggressive driving. The variables we use to measure drivers' exposure to other vehicles are the distance they commute to work and a dummy variable indicating whether they reside in an urban area and drive more than 20,000 miles per year. The drivers' characteristics we include are their age, gender, family size, and education to indicate the care with which they are likely to operate a vehicle.

Drivers' choices of whether to obtain a vehicle with an airbag or antilock brakes are assumed to be influenced by the availability of discounts offered by some insurance companies during the sample period for equipping a vehicle with these safety devices, drivers' experiences with these safety devices in other vehicles that they have owned, and drivers' characteristics that capture preferences for expanding the safety-intensity consumption set.

Because two endogenous variables are included in the specification of the accident outcomes, those equations are identified only if our model specifies exogenous variables that influence the probabilities of acquiring a vehicle with an airbag and antilock brakes but that do not influence the probability of an accident outcome. As noted, the choices of airbags and antilock brakes are likely to be influenced *a priori* by economic considerations (i.e., insurance discounts) and drivers' previous experience with vehicles equipped with these safety devices. On the other hand, it is difficult to justify including these considerations in the accident outcome equations, thus enabling those equations to be identified without theoretically implausible exclusion restrictions.

We explored some additional econometric issues that were raised by our data and analysis. Accident outcomes were recorded by the police officer that arrived at the scene of the accident. However, it is possible that some accidents could be incorrectly recorded or assessed. For example, an accident may be classified as collision damage only when it resulted in an injury. Formally, any reporting error causes the dependent variable to be misclassified, which yields biased parameter estimates. We therefore applied the procedure developed by Hausman et al. (1998) to explore the extent of the problem here by adding misclassification parameters to the likelihood function that we maximize. We found that the misclassification parameters were statistically insignificant, which suggests that our data are not subject to systematic misclassification of accident severities.

The panel structure of our data suggests that identification could be improved by adding fixed or random effects. Specifying fixed effects in a probit model may lead to biased

parameter estimates (Greene, 2003) and the nature of automobile accidents suggests that driver heterogeneity would best be captured in the error term by specifying random effects. However, we found that we could reject the hypothesis that random effects played a role in motorists' accidents.<sup>12</sup> Driver heterogeneity could also be captured by random parameters for the safety attributes in the accident equations. Thus, we estimated random parameter probit models for the accident outcome probabilities, but the standard deviations of the random parameters were statistically insignificant. This finding indicates that fixed parameters are an appropriate specification of our model. Finally, we specified year dummies to capture unobserved influences over time on drivers' accident outcomes and airbag and antilock brakes choices, but the dummies were insignificant and their exclusion had no material effect on the other coefficients.

## 5. Estimation results

Using the method of multivariate simulation, we obtain maximum likelihood parameter estimates of our simultaneous equations model of Washington state drivers' annual airbag and antilock brake choices and their accident outcomes for 1992–96. Table 1 presents the estimated coefficients, along with the estimated covariance matrix. Note that the coefficient estimates in the column for the evident-injury outcome reflect the sum of the estimates (and their covariance) in the collision and evident injury equations because both dependent variables are equal to one for accidents that result in evident injuries. (The standard errors for these estimates also take this relationship into account.) A likelihood ratio test of the null hypothesis that the error correlations simultaneously equal zero yields a chi-squared test statistic of 583.9 with six degrees of freedom, which suggests that we are likely to obtain biased estimates of airbags and antilock brakes if we treat them as exogenous in the accident outcome equations.

The coefficients in the airbag and antilock brake equations are, in general, statistically significant and of plausible sign. The identifying variables, capturing insurance discounts and previous safety option ownership history, increase the likelihood that drivers will purchase a vehicle with an airbag and antilock brakes.<sup>13</sup> On the other hand, drivers with older vehicles are less likely to choose either feature because automakers were only gradually making these options available during the time period covered by our sample.

The estimates of socioeconomic characteristics capture certain drivers' preferences for the additional safety that airbags and antilock brakes can provide.<sup>14</sup> Male drivers tend to purchase these safety options more than their female counterparts, perhaps because they are less discouraged than females by the potentially harmful effects that (first generation) airbags may have on smaller drivers and are more inclined to explore the new technology represented by antilock brakes. Compared with other drivers, those who are married are more likely to purchase airbags and antilock brakes, and those with children are more likely to acquire antilock brakes but less likely to acquire airbags, most likely because of their

<sup>12</sup> We rejected this hypothesis using single equation random effects probit models.

<sup>13</sup> We estimated a model where we interacted the insurance discount dummies with the driver's income, but the inclusion of income did not improve the statistical fit.

<sup>14</sup> In addition to the variables reported in the table, we also estimated models that included the exposure variables, commute distance and vehicle-miles traveled, and a driver's age, income, occupation, and residential location (urban versus rural) but found them to be statistically insignificant and to have little effect on the other coefficients.

**Table 1** Estimation results<sup>a</sup>

Variable	Dependent Variables			
	Probability of airbag in vehicle	Probability of ABS in vehicle	Probability of collision	Probability of evident injury in accident
<b>Vehicle attributes</b>				
Airbag dummy (1 if vehicle has an airbag)	Dependent variable	–	–0.340 (0.277)	–0.471 (0.530)
ABS dummy (1 if vehicle is equipped with ABS)	–	Dependent variable	0.088 (0.271)	–0.180 (0.489)
Age of Vehicle (years)	–0.061 (0.012)	–0.034 (0.006)	–	–
<b>Ownership history and discounts</b>				
Airbag history dummy (1 if driver owned another vehicle with airbags)	0.445 (0.048)	–	–	–
Airbag discount dummy (1 if driver received an insurance discount for airbags)	0.074 (0.019)	–	–	–
ABS history dummy (1 if driver owned another vehicle with ABS)	–	0.545 (0.039)	–	–
ABS discount dummy (1 if driver received an insurance discount for ABS)	–	0.067 (0.017)	–	–
<b>Driver characteristics</b>				
Male driver dummy (1 if driver is a male)	0.123 (0.038)	0.140 (0.034)	–	–
Male driver dummy multiplied by 1/VMT in thousands	–	–	–0.005 (0.008)	–0.091 (–0.032)
Elderly dummy (1 if driver is over 70) multiplied by 1/VMT in thousands	–	–	–0.002 (0.0003)	–0.003 (0.001)
Married driver dummy (1 if driver is married)	0.330 (0.102)	0.144 (0.090)	–	–
Children dummy (1 if driver has children under 14)	–0.104 (0.040)	0.095 (0.036)	–	–
Age of driver in households of four or more persons	–	–	–0.001 (0.003)	–0.083 (0.026)
College dummy (1 if driver has some college education)	0.152 (0.041)	0.028 (0.037)	0.027 (0.074)	–0.355 (0.198)
<b>Driving exposure</b>				
Long-distance commuter dummy (1 if driver's one-way commute exceeds 15 miles)	–	–	0.265 (0.076)	0.148 (0.245)

(Continued on next page)

potentially harmful effects on smaller occupants. Finally, drivers with some college education are more likely than other drivers to acquire airbags but not more likely to acquire antilock brakes, possibly because of concerns about the effectiveness of antilock brakes in certain situations.

**Table 1** (Continued)

Variable	Dependent Variables			
	Probability of airbag in vehicle	Probability of ABS in vehicle	Probability of collision	Probability of evident injury in accident
Urban extensive driver dummy (I if driver resides in Census defined urban area and drives at least 20,000 miles per year)	–	–	0.190 (0.098)	0.667 (0.251)
Constant	–0.964 (0.130)	–0.606 (0.106)	–2.022 (0.092)	–4.507 (0.602)
Log likelihood at convergence	–6854.42			
Number of observations	6234			
$\rho_{\text{evident,collision}} =$	0.902 (0.037)	$\rho_{\text{evident,ABS}} =$	0.137 (0.127)	$\rho_{\text{evident,airbag}} =$ 0.063 (0.089)
$\rho_{\text{airbag,ABS}} =$	0.569 (0.026)	$\rho_{\text{collision,ABS}} =$	–0.006 (0.136)	$\rho_{\text{collision,airbag}} =$ 0.167 (0.141)

<sup>a</sup>Huber-White standard errors are in parentheses

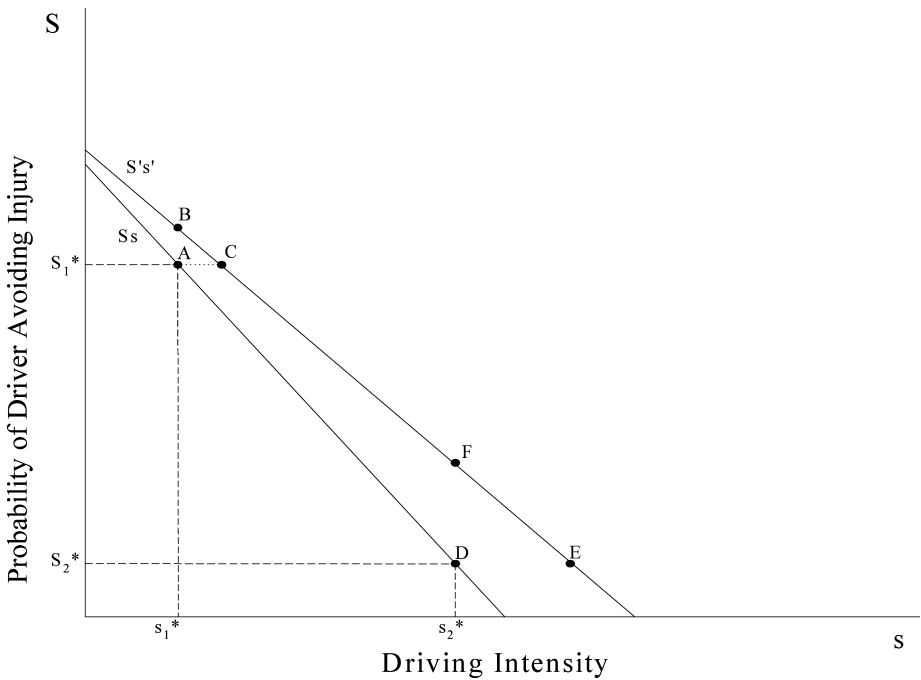
In sum, these findings appear to broadly reflect the preferences of motorists who are safety conscious. To be sure, there is no generally accepted set of variables that characterize a safety-conscious driver. On the other hand, automobile insurance companies tend to identify drivers who are less safety conscious as having a poor driving record, males between the ages of 16 and 25, and possibly low income. We investigated the possibility but found no evidence that drivers who would be expected to be less safety-conscious than other drivers, based on their driving violations, age, sex, and income, were more likely to purchase airbags and antilock brakes. Levitt and Porter (2001) report a similar finding. Such drivers may experience the greatest reductions in the probability of being involved in an automobile accident that leads to injury; however, it appears that safety-conscious drivers are more attracted than other drivers to automobile safety options.

As noted, the effect that airbags and antilock brakes have on the accident outcome probabilities depends on the extent to which drivers adjust their behavior in response to the improvement in automobile safety provided by these devices. Indeed, independent evidence suggests that drivers who have acquired airbags and antilock brakes are likely to drive more aggressively. Peterson, Hoffer, and Millner (1995) found that injury claims increased on vehicles following the adoption of an airbag system.<sup>15</sup> Smiley (2000) reports that the average insurance claims of models with antilock brakes are somewhat higher than the average claims of models without antilock brakes and that taxi drivers whose vehicles were equipped with antilock brakes reduced the headways that they allowed for the vehicles in front of them.

The parameter estimates in Table 1 indicate that airbags and antilock brakes have statistically insignificant effects on collisions and evident injuries.<sup>16</sup> Recall that the coefficients

<sup>15</sup> Harless and Hoffer (2003) question whether the authors obtained that finding because they included vehicles that are used for daily rental service.

<sup>16</sup> We also found that airbags and antilock brakes had statistically insignificant effects when we treated them as exogenous and estimated a single equation model for accident outcomes. Collinearity between airbags and antilock brakes does not appear to be a factor in our findings because their correlation was only 0.4. Other vehicle attributes, such as weight and acceleration, may change when consumers acquire a car with airbags. Thus, we estimated a model that controlled for automobile class (coupe, sedan, light truck, etc.), but found that



**Fig. 2** The effect of airbags on the safety and driving intensity of safety-conscious and less safety-conscious drivers

reflect the net impact of airbags’ and antilock brakes’ technological effect on safety and drivers’ adaptation to this technology. Thus, the findings suggest that offset behavior is occurring and that it is sufficient to counter the modest technological benefits of airbags and antilock brakes.<sup>17</sup>

We stress that our findings of offsetting behavior occur in an environment where it appears that safety-conscious drivers are more likely than other drivers to acquire airbags and antilock brakes. These drivers will benefit least—in terms of expanding their safety possibilities—from the safety options and can offset their safety benefits without an extraordinary increase in their consumption of intensity. Figure 2 illustrates this possibility by contrasting the utility maximizing choices of a safety-conscious driver 1 and a less safety-conscious driver 2. The safety-conscious driver’s optimal consumption of safety,  $S_1^*$ , and intensity,  $s_1^*$ , is at

these distinctions had statistically insignificant effects that did not alter other parameter estimates. Finally, our findings were unchanged when we restricted our sample to drivers who during our sample period switched from vehicles without one or more of the safety options, to vehicles with one or more of the safety options (others may have switched before the sample period).

<sup>17</sup> Based on the estimated coefficients, airbags result in roughly a 20 percent decrease in the probability of an evident injury or worse with a standard error of 25 percent. Recall, that NHTSA’s predictions of the technological effectiveness of airbags were that they would reduce the probability of an evident injury or worse by as much as 40 percent, so considerable offsetting behavior is clearly occurring. Note that our estimate and NHTSA’s prediction is not conditional on seatbelt use, which in all likelihood would reduce the marginal improvement in safety attributable to airbags. Moreover, the large standard error of our estimate indicates that we cannot reject partial—or even complete—offsetting behavior with any reasonable level of statistical certainty.

equilibrium *A*. According to our findings, the introduction of, say, airbags does not increase this driver's utility by increasing his or her already high level of safety (equilibrium *B*), but increases it by allowing greater driving intensity with no reduction in safety (equilibrium *C*). Thus, the safety-conscious driver finds it beneficial to acquire an airbag because its cost,  $p_a$ , is less than the value of the utility gain from additional intensity; that is,  $(U(C) - U(A))/\lambda > p_a$ , where  $\lambda$  is the marginal utility of income.

In contrast, consider a less safety-conscious driver, who initially maximizes utility at equilibrium *D*. This driver would benefit from additional safety (*F*), but as a riskier driver would only value airbags because they facilitate greater risk-taking behavior. On the other hand, the level of driving intensity at equilibrium *E* may be too intense and because the less-safety conscious driver finds the value of utility from additional intensity closer to equilibrium *F* is less than an airbag's cost, he or she does not acquire an airbag.

The other explanatory variables in the accident outcome equations indicate that different forces contribute to accidents that only result in vehicle damage and accidents that also lead to evident injuries. We find that the probability of experiencing a collision is largely explained by a driver's exposure to other vehicles. This is consistent with the notion that collisions are in large part random; hence, the more one drives, the greater the chance he or she will be involved in an accident that results in vehicle damage. Specifically, drivers who have a non-trivial daily commute (of more than fifteen miles each way) and those who both reside in an urbanized area and drive over 20,000 miles per year significantly increase their chance of getting in a collision by exposing themselves to more traffic and/or potentially hazardous driving conditions.<sup>18</sup>

People who are over the age of 70 tend to have a driving routine that rarely exposes them to hazardous driving situations. Thus, we find that they have a lower probability of getting into a collision than their younger counterparts who have better reflexes but tend to drive much more in hazardous conditions. As expected, this effect diminishes as elderly drivers increase their vehicle-miles-traveled (VMT). Other socioeconomic characteristics that might affect the probability of a collision such as gender, family size, and education have statistically insignificant effects, which is consistent with the view that collisions are largely random and systematically affected only by time spent on the road.

Driving exposure also contributes to accidents that result in an evident injury or worse. People who live in an urban area and drive more than 20,000 miles per year experience a large increase in the probability that they will suffer at least an evident injury in an accident. But we do not find a statistically greater likelihood of these injuries for commuters, possibly because although more driving generally results in more accidents, the familiarity and lower speed of a daily commute reduce the incidence of physical injuries when collisions occur.<sup>19</sup>

We also find evidence that drivers over the age of 70, drivers who have some college education (and presumably higher permanent income), and older drivers who have a family (households of four or more) are less likely to experience an accident causing bodily harm.<sup>20</sup>

<sup>18</sup> We also estimated a model that measured exposure with a driver's actual commute distance and vehicle-miles-traveled, but it did not fit as well as the model presented here.

<sup>19</sup> Although vehicle collisions tend to occur far more frequently during the morning (7AM–10AM) and evening (4PM–7PM) peak periods, vehicle fatalities occur in equivalent amounts in peak and off-peak periods. Thus, we would expect that the share of collisions that result in a fatality is greater in off-peak than peak periods. In fact, according to the Washington Department of Transportation (State Highway Accident Report, 1996), approximately eight of every thousand accidents occurring off peak resulted in a fatality, while three of every thousand accidents occurring in a peak period did.

<sup>20</sup> We also estimated a model that included income, but it was insignificant. Evidently, its effect is sufficiently captured by the education variable.

Drivers with these socioeconomic characteristics are more likely to avoid potentially hazardous driving conditions, such as driving late at night or in inclement weather, and more likely to drive safely because they have higher opportunity costs of (or in the case of elderly drivers are less able to withstand) an injury from an accident than drivers without these characteristics. Male drivers are also less likely to get in accidents with evident injuries or worse, perhaps because men tend to be larger than women and can withstand more impact before sustaining an injury. However, as males drive more, this effect diminishes.

In sum, certain drivers take predictable steps to reduce the likelihood that any accident that they experience will lead to a physical injury. To be sure, the rare and highly random nature of these accidents can be explained to a greater extent by factors that would be difficult to include in our specification because they are clearly endogenous. For a given set of roadway conditions, these factors include drivers' decisions whether to exceed a safe speed, drive while intoxicated, drive with defective equipment, or reduce attention to the road. Other important decisions include when a motorist decides to drive—at night, in inclement weather, and so on. Indeed, data from the Collisions and Data Analysis Branch for the Washington State Department of Transportation indicate that driver violations and adverse roadway and driving conditions contributed to the vast majority of all accidents during our sample period.

## 6. Implications of the findings

Mannering and Winston (1995) concluded that driver-side airbags achieved market acceptance because consumers were willing to pay the marginal cost of installation. Consumers' willingness-to-pay was also consistent with estimates of the technological benefits of airbags as reflected in how much they reduced the probability of an automobile fatality. Using disaggregate data, we have found that safety-conscious drivers are more likely than other drivers to acquire airbags and antilock brakes. But the implication of our central finding—airbags and antilock brakes have had a statistically insignificant effect on accident outcome probabilities—is that drivers who have purchased airbags and antilock brakes accrue their benefits through greater intensity (i.e., mobility).<sup>21</sup> As pointed out by Smiley (2000), mobility improvements such as higher speeds or quicker lane changes provide an immediate payoff: drivers reach their destinations faster. Such behavior appears to have offset the technological capability of airbags and antilock brakes to improve Washington State motorists' safety.<sup>22</sup>

Previous empirical tests of the offset hypothesis based on aggregate data have found varying degrees of offsetting behavior by motorists, but have been unable to systematically identify the types of drivers who are likely to engage in such behavior. By doing so, we have significantly added to the credibility that our findings actually reflect offsetting behavior.

Although one should exercise caution about generalizing from driver behavior in one state, there are no indications that Washington State drivers are unrepresentative of U.S. drivers. Thus, as other automobile safety technologies become available, we may also find that consumers realize their benefits by seeking greater mobility. For example, interest is

<sup>21</sup> Airbags introduced after 1997 are claimed to be less likely to hurt small drivers in low-speed crashes. It is doubtful, however, that such technological failure, which is alleged to have occurred in a small number of deployments, has played an important role in our findings on the effects of airbags.

<sup>22</sup> This conclusion is consistent with aggregate data that implies drivers are trading off safety improvements for mobility. Since 1992 (the first year of our sample), the fatality rate in both Washington State and nationally has remained fairly constant at approximately 1.4 and 1.75 fatalities per 100 million vehicle miles traveled respectively, while the share of vehicles with airbags and antilock brakes has increased dramatically. At the same time, average vehicle speeds have increased.

growing in a new generation of active safety systems, whose sophisticated collision detection and avoidance technologies enhance drivers’ safety. Vehicle manufacturers and Federal policymakers may attempt to promote these systems to the public on safety grounds, when, in fact, drivers may respond to them by traveling closer to other vehicles at higher speeds or paying less attention to their driving.

We stress that the presence of offsetting behavior does not indicate that a safety-enhancing technology has not produced social benefits. In many instances, such as airbags and antilock brakes, it may suggest that consumers benefited in ways that were not anticipated or intended by proponents of the technology. Assessments of the social desirability of safety enhancing technologies must keep this possibility in mind.

**Appendix: Evaluating the multivariate normal distribution using GHK simulation**

Maximizing the log-likelihood function in Eq. (10) is computationally difficult because it requires evaluation of the multivariate normal cumulative distribution of order  $n$ . As no closed form solution exists, we compute the multivariate normal probabilities by using the GHK smooth recursive simulator. The general idea behind this simulator is the fact that the probability a random variable  $Y$  falls in an arbitrary interval  $(a, b)$  is given by:

$$\Pr(a_1 < y_1 < b_1; \dots; a_n < y_n < b_n) \approx \frac{1}{D} \sum_{d=1}^D \prod_{k=1}^n Q_{dk},$$

where  $Q_{dk}$  are univariate normal probabilities that are easy to compute and  $D$  is the number of draws. The  $Q_{dk}$  are computed using the following recursive algorithm:

1. Factor the covariance matrix of the  $Y_i$ , namely  $\tilde{\Sigma}$ , using the Cholesky factorization  $\tilde{\Sigma} = LL'$ , where  $L$  is a lower triangular matrix with elements  $l_{ij}$ .
2. Define  $Q_{d1} = \Phi(\frac{b_1}{l_{11}}) - \Phi(\frac{a_1}{l_{11}})$ .
3. Generate a random observation  $\varepsilon_{d1}$  from the truncated standard normal distribution in the range  $A_{d1} \rightarrow B_{d1} \equiv \frac{a_1}{l_{11}} \rightarrow \frac{b_1}{l_{11}}$ .
4. For steps  $k=2..n$ , compute  $A_{dk}$  and  $B_{dk}$  using the formulas below, then repeat step 3 as appropriate:

$$A_{dk} = \frac{1}{l_{kk}} \left[ a_k - \sum_{i=1}^{k-1} l_{ki} \varepsilon_{di} \right], \quad \text{and} \quad B_{dk} = \frac{1}{l_{kk}} \left[ b_k - \sum_{i=1}^{k-1} l_{ki} \varepsilon_{di} \right].$$

5. Define  $Q_{dk} = \Phi(B_{dk}) - \Phi(A_{dk})$ .

We continue steps 1 to 5  $D$  times and then take the sample average. In the estimations reported here,  $D = 800$ . We found that the parameter estimates changed very little for values of  $D$  between 400 and 800.

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## References

- Böersch-Supan, Axel and Vassilis Hajivassiliou (1990). “Smooth Unbiased Multivariate Probability Simulators for Maximum Likelihood Estimation of Limited Dependent Variable Models,” *Journal of Econometrics* 58, 347–368.
- Calkins, Lindsay Noble and Thomas J. Zlatoper (2001). “The Effects of Mandatory Seat Belt Laws on Motor Vehicle Fatalities in the United States,” *Social Science Quarterly* 82 December, 716–732.
- Chirinko, Robert S. and Edward P. Harper, Jr. (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 (Spring), 270–296.
- Cohen, Alma and Liran Einav (2003). “The Effects of Mandatory Seat Belt Laws on Driving Behavior and Traffic Fatalities,” *Review of Economics and Statistics* 85, 828–843.
- Crandall, Robert W. et al. (1986). *Regulating the Automobile*. Washington, DC: Brookings.
- Dee, Thomas S. (1998). “Reconsidering the Effects of Seat Belt Laws and Their Enforcement Status,” *Accident Analysis and Prevention* 30, 1–10.
- Greene, William H. (2003). *Econometric Analysis*. Upper Saddle River, NJ: Prentice Hall.
- Harless, David W. and George E. Hoffer (2003). “Testing for Offsetting Behavior and Adverse Recruitment Among Drivers of Airbag-Equipped Vehicles,” *Journal of Risk and Insurance* 70, 629–650.
- Hausman, J. A., Jason Abrevaya and F. M. Scott-Morton (1998). “Misclassification of the Dependent Variable in a Discrete-Response Setting,” *Journal of Econometrics* 87, 239–269.
- Keeler, Theodore (1994). “Highway Safety, Economic Behavior, and Driving Environment,” *American Economic Review* 74, 684–693.
- Lave, Lester B. and Warren E. Weber (1970). “A Benefit-Cost Analysis of Auto Safety Features,” *Applied Economics* 2, 265–275.
- Levitt, Steven D. and Jack Porter (2001). “Sample Selection in the Estimation of Air Bag and Seat Belt Effectiveness,” *Review of Economics and Statistics* 83, 603–615.
- Manning, Fred and Clifford Winston (1995). “Automobile Air Bags in the 1990s: Market Failure or Market Efficiency?,” *Journal of Law and Economics* 38, 265–279.
- McCarthy, Patrick S. (1999). “Public Policy and Highway Safety: A City-Wide Perspective,” *Regional Science and Urban Economics* 29, 231–244.
- National Highway Traffic Safety Administration, *Traffic Safety Facts 2000*, U.S. Department of Transportation, Washington DC, December 2001.
- O’Neill, Brian and Allan Williams (1998). “Risk Homeostasis Hypothesis: A Rebuttal,” *Injury Prevention* 4, 92–93.
- Peltzman, Sam (1975). “The Effects of Automobile Safety Regulation,” *Journal of Political Economy* 83, 677–725.
- Peterson, Steven, George Hoffer, and Edward Millner (1995). “Are Drivers of Air-Bag Equipped Cars More Aggressive? A Test of the Offsetting Behavior Hypothesis,” *Journal of Law and Economics* 38, 251–264.
- Sen, Anindya (2001). “An Empirical Test of the Offset Hypothesis,” *Journal of Law and Economics* 44, 481–510.
- Smiley, Alison (2000–01). “Auto Safety and Human Adaptation,” *Issues in Science and Technology* Winter, 70–76.
- Traynor, Thomas L. (1993). “The Peltzman Hypothesis Revisited: An Isolated Evaluation Of Offsetting Driver Behavior,” *Journal of Risk and Uncertainty* 7(2), 237–247.
- Viscusi, W. Kip (1984). “The Lulling Effect: The Impact of Child-Resistant Packaging on Aspirin and Analgesic Ingestions,” *American Economic Review* 74, 324–327.
- Viscusi, W. Kip and Gerald O. Carvallo (1994). “The Effect of Product Safety Regulation on Safety Precautions,” *Risk Analysis* 14, 917–930.
- Washington Department of Transportation, *Washington State Accident Report*, Transportation Data Office, Olympia, Washington, 1997.
- Yun, John M. (2002). “Offsetting Behavior Effects of the Corporate Average Fuel Economy Standards,” *Economic Inquiry* 40, 260–270.