AN ALTERNATIVE TO THE HIGH-RISK-DRIVER THEORY: ADVERSE SELECTION INDUCED BY PER-CAR PREMIUMS

August 7, 2004

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Long Version of Paper presented August 9 at the
2004 Annual Meeting of the American Risk & Insurance Association in Chicago

INTRODUCTION

This is the puzzle: automobile insurers experience the most liability, collision, and uninsured motorist (UM) claims per 100 insured cars—and therefore charge the highest premiums—for cars from the low-income zip codes of both rural and urban areas. But this fact seems to contradict general insurance theory which says that people with minimum insurance should be more careful, not less.

To address the puzzle, this paper: 1) Sets out the facts of high annual risk and high premiums; 2) Considers problems with the accepted high-risk-driver theory used to explain these facts; 3) Proposes as an alternative theory that the pools of cars averaging high-annual-risk result from adverse selection induced by dollars-per-car premiums; and 4) Specifies the free-market cents-per-mile remedy that the alternative theory indicates, and identifies the reason for insurer resistance to it.

Previous Work

Smith and Wright (1992) call attention to the four-fold range across urban areas nationwide in the premiums charged by the same national companies.[1] Using the premiums of major companies, however, overlooks similarly large ranges represented by the premiums of all companies (national and regional) within single areas, both urban and rural. These ranges are apparent in insurance department buyer's guides but have not received much scholarly attention. Jaffee and Russell (2001, page 200) reproduce the buyer's guide for Berkeley California, but do not discuss the large range in premiums it shows, Figure 1: the highest premium listed is four times the lowest.[2]

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[1] For a given profile, the annual premium average for two national companies and an industry publication ranged from $516 in Milwaukee to $1925 in Los Angeles.

[2] In the California buyer's guide for Berkeley currently posted on the Internet (February 2004), Infinity no longer shows the highest premium, nor Wawanesa the lowest, but the highest premium is still about four times the lowest.

748-4807

Figure 1. *Auto Insurance Buyer's Guide.* Source: Jaffee and Russell, 2001.

1999 Automobile
Insurance Survey

California Department of Insurance

RESULTS

Based on the information you entered, the following profile and results most closely resemble your situation. Please contact a company representative for an actual quote. Please note: THIS IS NOT A PREMIUM QUOTE.

Standard Coverage Married Couple (no children driving), Husband & Wife have no violations or accidents, Berkeley

Company Name	Annual Premium	Company Name	Annual Premium
21st Century:	1,846	Hartford:	2,252
AAA:	2,464	Infinity:	6,996
Allstate:	2,248	Liberty Mutual:	3,395
California Capital:	2,686	Mercury:	2,672
Civil Service Employee:	2,100	Millers Ins:	3,813
Clarendon:	6,132	National General:	3,338
CNA Personal:	2,839	Nationwide:	2,324
Coast National:	2,494	Pacific Specialty:	N/A
Colonial Penn:	2,314	Progressive:	2,243
CSAA:	2,496	Safeco:	1,893
Explorer:	3,264	State Farm:	3,048
Farmers:	6,407	Sterling Casualty:	N/A
Financial Indemnity:	5,004	Superior Ins:	3,033
Fireman's Fund:	3,052	Travcal:	2,846
Galway:	4,039	USAA:	1,941
GEICO:	3,684	Viking of Wisconsin:	6,994
Generali US Branch:	4,032	Wawanesa:	1,663

Profile (32A)

Harrington and Niehaus (1998) report that, relative to the other urban area zip codes in Missouri, those that contain higher black (and concurrently lower-income) populations average 36 percent more liability claims and 48 percent more collision claims per 100 covered cars[3]. They conclude that (p. 441): "percent minority population is correlated with omitted variables that increase

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[3] In agreement with these findings, Solberg et al. (1979) describe the findings of a 1978 MIT doctoral thesis. "In Massachusetts, the correlation between territorial rate relativities and median income is –0.978; between such relativities and percent black, 0.532; both sets of figures are stunningly high."

claim costs." Although Harrington and Niehaus do not suggest possible omitted variables,[4] other scholars are apparently following the insurance industry's lead in labeling as established fact the theory that those paying high premiums are high-risk drivers.[5]

The basis for an alternative to the high-risk-driver theory was given in 1968 by the co-winner of the 1996 Nobel Prize in Economics (for other studies), William Vickrey. He called attention to some of the economic harms caused by charging for insurance as a fixed cost of owning a car rather than as a cost of operating it, and included these two harms (page 471): “The premium structure thus has the general effect of promoting excessive use of a given stock of cars and undue stinting on the ownership of cars.” Although Vickrey noted the resulting economic harm to carmakers, neither he nor any other economist since has pointed to any feedback effect on premiums that stinting on ownership and excessive use of a given stock of cars produces.[6]

The first description of the theoretical adverse selection effect on premiums that results from the insurance incentive to stint on ownership and pile more miles on fewer cars was published in a report to the Texas Legislature by Butler (2000).[7] Drivers who need to economize on auto insurance buy less of it. Since the unit of purchase is a car year (divisible into car days), they take less-driven cars out of insurance pools and share the cars kept insured. But these two actions constitute adverse selection against the pools by taking more premium than miles out of the pools and by adding miles without premium to them.

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4 As discussed below, this paper proposes that the omitted variable is not one of the usual categorical variables (used to define categories of cars such as by the owner’s residence zip code, driver age, and even unenforceable discount categories for “low estimated future annual mileage” such as less than 7500 miles) for obtaining the average annual risk for groups of cars. Rather it is the odometer distance as the continuous variable that for each car measures its actual miles of exposure on the road to accident risk. A later section discusses the fundamental difference in assessing driving risk between the role of categorical variables and the role of a continuous variable for measuring individual exposure.

5 For example, several papers in Cummins 2001 use the term without citation or definition, along with variants such as high cost drivers and bad drivers. The high-risk-driver theory appears to be the road traffic equivalent of the theory that a small number of accident-prone workers are responsible for most workplace accidents. However, Baker et al. 1992 state (page 131): “The concept of ‘accident proneness’ in the workplace, as in other settings, has been discredited, and it has been shown that removing workers with an excessive number of injuries would not appreciably reduce injuries in the succeeding time period.” (Since this same conclusion was reached by other studies in the early 1950s, why should auto insurers still theorize that some workers become accident prone when driving their own cars, especially since one of Baker’s co-authors, Brian O’Neill, is head of the Insurance Institute for Highway Safety which is funded and directed by insurance companies?)

6 Edlin 2003 builds on some of Vickrey’s 1968 analysis and states that per-car premiums have “largely lump-sum characteristics” (p. 53) in having little influence on day-to-day decisions about how much to drive. However, Edlin does not consider the far-from-lump-sum strong influence per-car premiums have on the major household decisions about how many cars to own that Vickrey pointed out.

7 The report was the basis for the Texas Legislature enacting the cents-per-mile choice law in 2001. As explained in the last part of this paper, the law invites insurers to offer (without changing the car’s classification) the vehicle-mile for driving coverages as the alternative *exposure unit* (insurers’ cost accounting unit) to the vehicle-year exposure unit currently used for all coverages.

Table 1. *Travis County (Austin) Texas Buyer's Guide.* Source: Texas Dept. of Insurance.

Insurance Companies (CM = County Mutual)	Ann. Premium* ($ per car)	2000 Texas-wide Total Premium (millions $)
Government Employees (Geico group)	320	70
United Services Auto. Assn, USAA, USAA CM	334	583
Southern Farm Bureau Casualty	368	229
Geico General (Geico group)	376	230
Mid-Century + Texas Farmers (Farmers group)	382	940
Allstate CM + 3 Cos. (Allstate group)	383	1,563
Progressive CM (Progressive group)	428	488
State Farm Mutual Auto.	436	2,124
Nationwide Mutual	438	211
Farmers Texas CM (Farmers group)	584	253
Colonial CM	598	125
State and CM Fire	700	333
Home State CM	714	219
Old American CM Fire (Company's average for 9 programs)	1,249	184
* Travis County. One car with minimum liability coverage (20/40/15) only and driver profile specified as "Adult male age 25-64 or female age 21-64 with **no at-fault accidents or major traffic convictions** who drives to and from work."		

This kind of adverse selection by drivers who economize undoubtedly takes place against insurance pools representing most income levels, but insurers only recognize it through some high-cost-per-car correlations, such as with owners living in low-income zip codes or having low credit scores. An analysis of where per-car premiums do and do not induce strong adverse selection requires looking at the distribution of cars by annual premium, in comparison with distributions of drivers and cars by annual risk and annual miles.

FACTS ABOUT HIGH PREMIUMS AND ANNUAL RISK

Cars Distributed By Premiums

When viewing auto insurance buyer's guides like the California guide shown in Figure 1, questions naturally come to mind as to who is paying the highest premiums and how they are made to do it. Both questions were answered through analysis of Texas legislative testimony with reference to zip codes in Travis County, Austin, Texas.[8]

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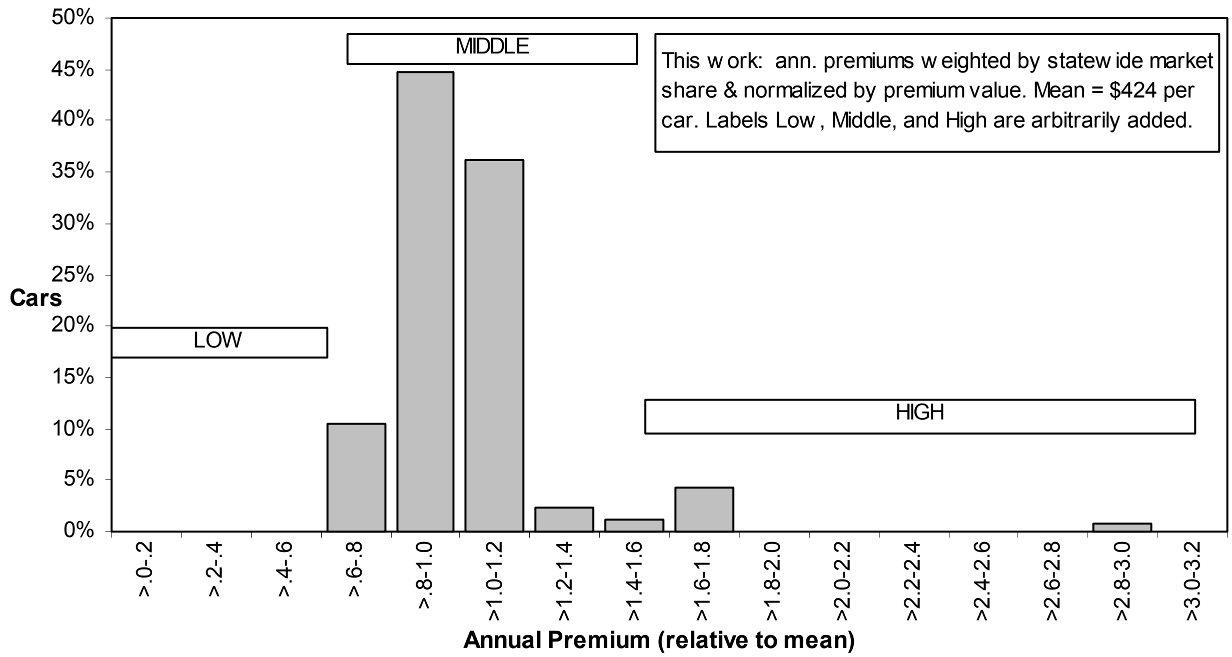
[8] Butler (2000) reports on and analyzes unplanned testimony by a former, very profitable State Farm agent (presenting testimony about forms regulation) under questioning by legislators about her reason for refusing the company's standard premiums to customers from low income zip codes. The higher number of claims per 100
(Footnote continued on next page.)

Figure 2. *Distribution of Cars by Premium Amount.* Source: Table 1.



To assess how many households pay the high premiums, Table 1 shows the premiums from the Travis county buyer's guide along with the statewide market share of each company whose premium is listed. These data are used in the histogram, Figure 2, to get an estimate of the car population in each premium bin for this locality. It shows a spread of about four times for an identical classification profile from the lowest annual premium to the highest that cannot be ascribed to differences in driver risk as supposedly identified by claim or driving records. According to the profile specified in Table 1, the car's drivers had "no at-fault accidents or major traffic convictions."[9]

Drivers Distributed By Annual Risk

Butler et al. 1988 have previously shown that the broad positively skewed distributions of drivers and cars by annual miles resemble the distributions of drivers by annual accident risk which a number of authors have derived from large samples of multi-year driver records and fitted to positively skewed gamma curves. Lemaire (1985, 1995) references many of these and describes the assumptions and fitting process. The histogram in Figure 3 comes from one of the first and largest studies (Spetzler et al., 1976), which used 9 years of California records for more than 50,000 drivers over a fourteen-year period. Significant proportions of drivers are at the extremes of the range in annual risk from less than 0.01 to 0.20 and more. Therefore, compared with the

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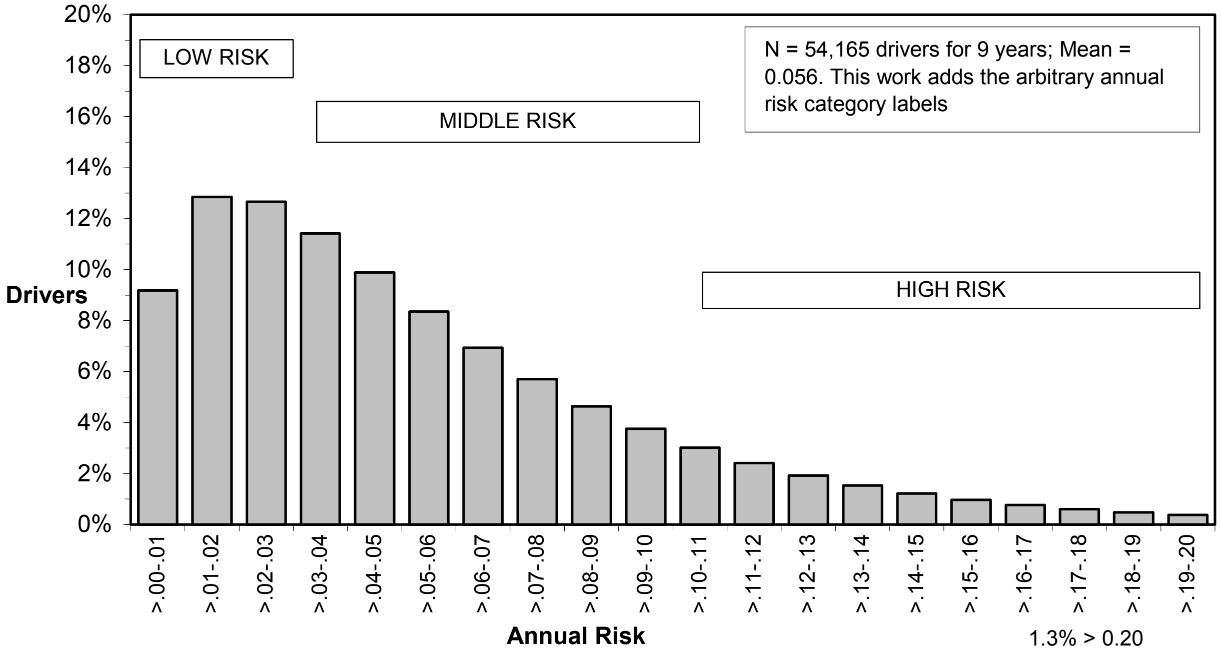
car-years in these zip codes would translate into a higher loss ratio (claim costs divided by premiums) for the agent, which in turn would result in lowered profit-sharing commissions and other sanctions by the company.

9 Note well: This stipulation about driving and claim records is not intended to validate their use for adjusting premiums. The basis for insurers' use of such records is discussed in a subsequent section.

Figure 3. *Distribution of Drivers by Annual Risk.* Source: Stanford Research Institute, 1976.



broad risk distribution based on accident involvements, what appears at first in Figure 2 to be a large range in annual premiums now seems to be truncated at the low premium end, under-populated at the high premium end, and too sharply peaked in the middle.

Authors who use the Gamma model distribution of drivers by annual risk caution that there is nothing in probability theory that supports use of such a distribution. In fact other models comprising just two or three mixes of low, middle, and high annual risk can provide reasonable matches to observed accident record experiences of large samples of drivers.[10] The fact that a mixed Poisson process with a Gamma distribution turns out to be the negative binomial function seems to be an accidental consequence of having two adjustable shape parameters and without probabilistic significance.[11]

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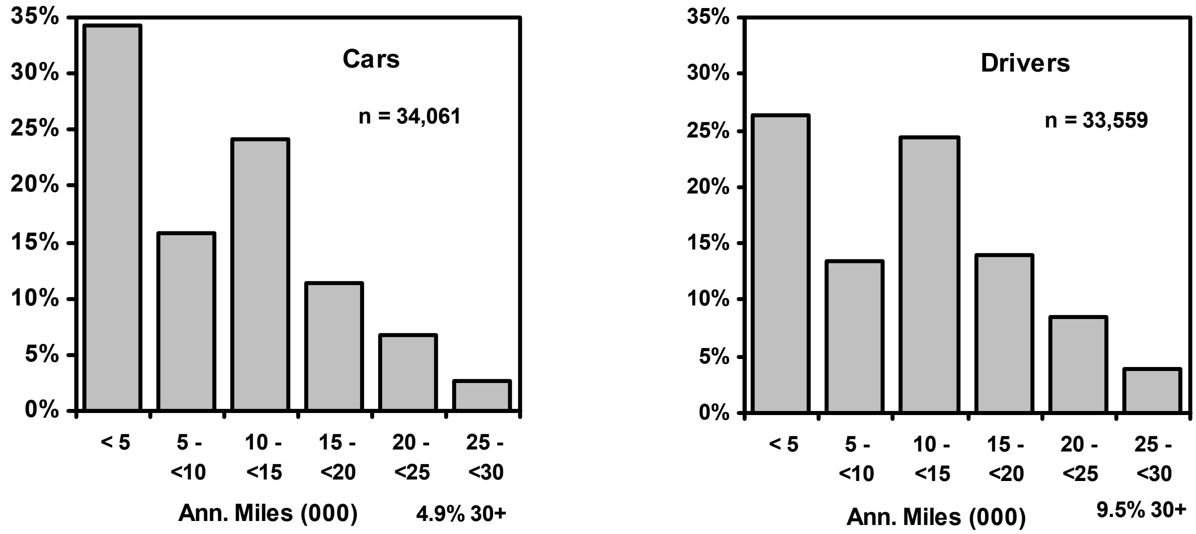
10 For example, Lemaire 1995 (page 39) illustrates this with a model Poisson parameter distribution consisting of about 91% 0.08 annual claim risk and 9% 0.36 annual claim risk. (At a risk rate of 10 claims per million miles, these annual risks translate into 8K and 36K annual miles.)

11 As a probability function, the negative binomial uses a single average failure (accident) rate per trial to give the distribution of the number of trials before a given (integral) number of failures occurs. In contrast, in the Poisson application each value for the Gamma distribution represents a different (continuous) average annual accident rate from zero to 0.30 and beyond.

Figure 4. *Cars and Drivers Distributed by Driver-Estimated Miles*. Source: National Household Transportation Survey, 2001.



Drivers And Cars Distributed By Estimated Miles

The 2001 National Household Travel Survey asked drivers to estimate how many miles they drove and how many miles each household car was driven in the last 12 months. Both distributions shown in Figure 4 are broad and positively skewed. The most drivers and cars are in the less-than-5K miles bins. The fact that more than one-third of cars are in the low-annual-miles bin compared with one-quarter of drivers suggests that the excess of low-miles cars are from households with more cars than drivers. The 2001 survey estimates that U.S. households overall average nearly 9% more vehicles than drivers.

The occurrence of the second mode at the 10K to <15K miles bin may be partially due to an edge effect where many people rounded their estimates up to 10K miles and so an excess of drivers and cars are included in the higher bin. This second mode has been consistent from past surveys as well. Because of possible bias in estimates of miles driven, beginning in 1995, the surveys have also been asking respondents for actual odometer readings.

Cars Distributed By Odometer Miles

What does resemble the positively skewed model distribution of drivers by annual risk (Figure 3) is the distribution of cars by annual miles from odometer readings. The histogram in Figure 5 comes from the 1995 federal survey of household transportation in which respondents were telephoned twice at least two months apart and asked to get their odometer readings, while the interviewer waited when possible. The odometer differences for each vehicle were extrapolated to an annual miles value and appropriately weighted, which collectively are the data shown.[12]

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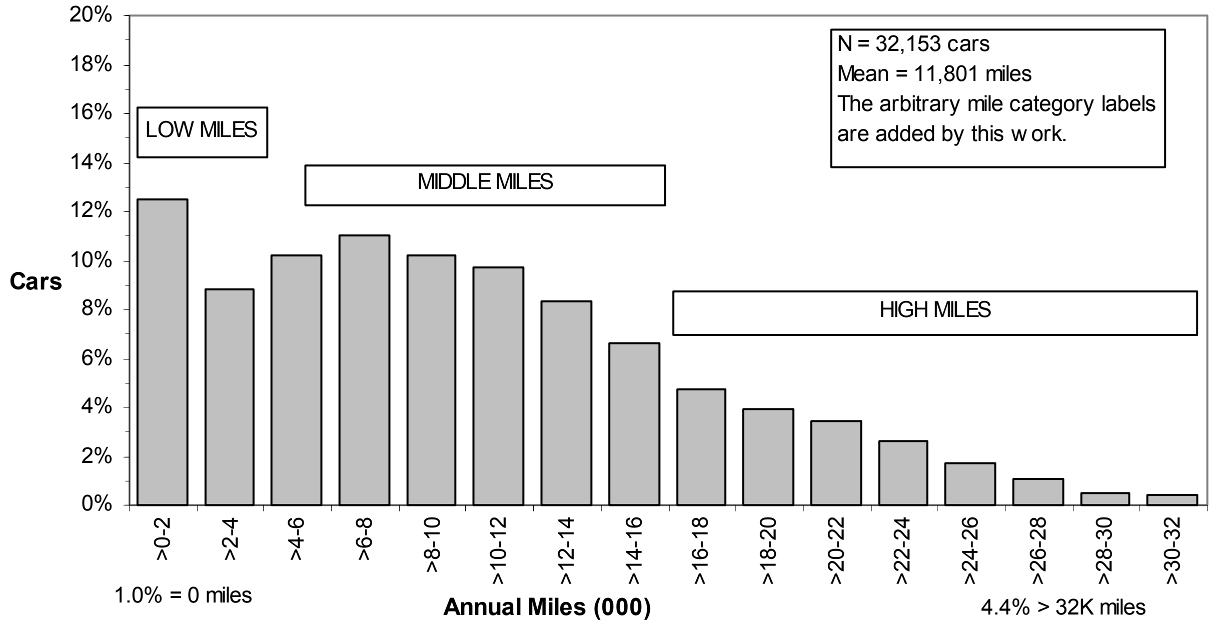
[12] Pickrell and Schimek 1999 point out significant problems with the odometer method and therefore include the owner estimates along with the odometer values in their study.

Figure 5. *Cars Distributed by Odometer Miles.* Source: Nationwide Personal Transportation Survey, 1995.



Unlike the Gamma model distribution of drivers by annual risk (Figure 3), the odometer miles distribution of cars is distinctly bimodal. The stronger mode is at the lowest annual miles bin for cars that are driven at all. Furthermore, 1% of cars were not driven at all, and, if insured, transferred no risk to the insurer.[13]

The general skewed shape of the driver-estimated distribution of cars by annual miles, Figure 4, is similar to the odometer miles distribution of cars, particularly if the difference in bin widths is accounted for, 2K versus 5K miles wide. Reduction of the 34% cars for the <5K miles bin by 2.5 gives an average of about 14% for each 2K miles sub-bin in the 0-<5K interval. This compares reasonably well with an average of nearly 11% over the <5K miles interval of the odometer reading bins with the 1% cars not driven at all included.

Problems With the High-Risk-Driver Theory

"High Risk Drivers" Are Cars, Not Drivers

The high-risk drivers used to explain cost correlations are not drivers at all. Instead, the correlations refer to cars because the car-year is the auto insurance unit of cost accounting. In deciding at what premium level (low, middle, or high) to accept customers, insurers use correlations with categories of cars defined by data such as owner's residence zip code, credit score, prior or no prior insurance, home owning or not, military rank, occupation, single payment

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[13] States with mandatory insurance require that if cars are licensed, whether driven or not, they must be insured. The premiums paid for driving coverages of idle cars, less administrative expense, represent pure profit for their insurers.

or installment plan, driver record, marital status, and, very selectively, driver sex. Insurers theorize that the correlations distinguish cars with high-risk and low-risk drivers. But, in fact, these indisputably strong correlations with claims per 100 car-years do not evaluate driver groups at all on a statistically valid driver-mile basis. Instead they are much more likely to be the result of various groupings of cars that—on average only—are driven more miles or fewer miles annually.

Claims Can't Separate High- from Low-Annual-Risk Cars

Although claim records act like a number of other category variables that proxy for average annual miles, they are special in both factual and subjective ways. First, since accidents are random, using these records to assign cars to premium categories is assigning them at random. The question to be answered is why the results are systematic, which seems to support the high-risk-driver theory. Second, expert witnesses in legislative hearings fall back on presumed claims by drivers designated as high risk to explain the high costs correlated with cars from low-income zip codes. But this explanation disregards the fact that the large majority of the drivers living there, as elsewhere, have produced no recent claims.

Systematically, insurers find that if the cars that have had a claim in the past three years are sorted from a main pool that produces, for example, 5 claims per 100 car-years, the sub-pool of these cars produces 7.5 claims per 100 cars in the following year, a 50% increase from the original average. Also, as a consequence of such sorting, the average annual risk of the large claim-free pool decreases about 7%.[14] Analysis shows, however, that both changes are inevitable byproducts of the annual mile mixtures of cars inherent in today's insurance pools.

The occurrence of traffic accidents can be understood as a process of random sampling with replacement. In effect this is the exact basis of the mixed annual risk Poisson model which Spetzler et al. used in 1976 to estimate the annual risk distribution of California drivers shown in Figure 3 (above). For each value in the annual risk continuum, the model may be pictured as placing 100 black balls (cars) in a jar. One ball is picked at random to represent an accident involvement, and then replaced in the jar and stirred prior to picking the next ball so there is a chance of individual balls being picked more than once (having multiple accidents). Before a ball is replaced, however, its color is changed from black to white (first accident), then from white to green if picked a second time, then from green to red for a third pick of the same ball. In order to model the record produced by an annual risk of 5 accidents per 100 cars for three years, 15 picks and replacements are made. Probability theory predicts that, provided the picks are random (colorblind), about 86 of the balls will still be black (no accident), 13 white, 1 green, and 0.05 red (which if the experiment were scaled up from 100 to 10,000 balls would be 5 red balls). Note that none of the 100 balls had a risk different from any of the others of being picked (0.01 each time), whether or not it had been picked once or even several times before. Therefore

[14] Calculated from the model that follows. In actuality, "accident-free or claim-free drivers usually save at most 5%," according to the Casualty Actuarial Society. Butler and Butler (1989, p. 229).

sorting balls by color for a further experiment would not affect results. So why in actual insurance pools is the average annual risk greater (typically by 50%) for sub-pools of cars that have produced claims?

Unlike balls in a jar, cars assigned to an insurance pool differ from each other by the number of miles each is subsequently exposed on the road to being picked at random. While accidents randomly pick low annual miles cars in the pool along with middle- and high-miles cars, obviously an accident sample of the pool will not represent the mix of cars in the pool but the proportions of these cars that are on the road. Therefore, the road sample of cars in a pool will be biased to the cars driven more miles. An example illustrates the biasing process.

To approximate the positively-skewed distribution of cars by annual miles shown in Figure 5, assume a two-component insurance pool with two-thirds of cars driven 5K miles a year (low annual risk) and one third driven 20K miles a year (high annual risk). This mix produces a pool average of 10K miles per car. But the proportion of miles added to the pool by the 5K mile and 20K mile cars is just reversed from the proportion of cars in the pool—2/3 of the miles added are by the 20K mile cars and 1/3 by the 5K mile cars. In other words, the proportion of cars exposed on the road to risk of accident is just reversed from the proportion in the insurance pool. Therefore, an accurate random sample of the proportion on the road will consist of two-thirds 20K mile cars and one-third 5K mile cars. (If the sampling rate is assumed to be 5 claims per million vehicle miles, then the 5K mile and 20K mile cars have an annual accident risk of 0.025

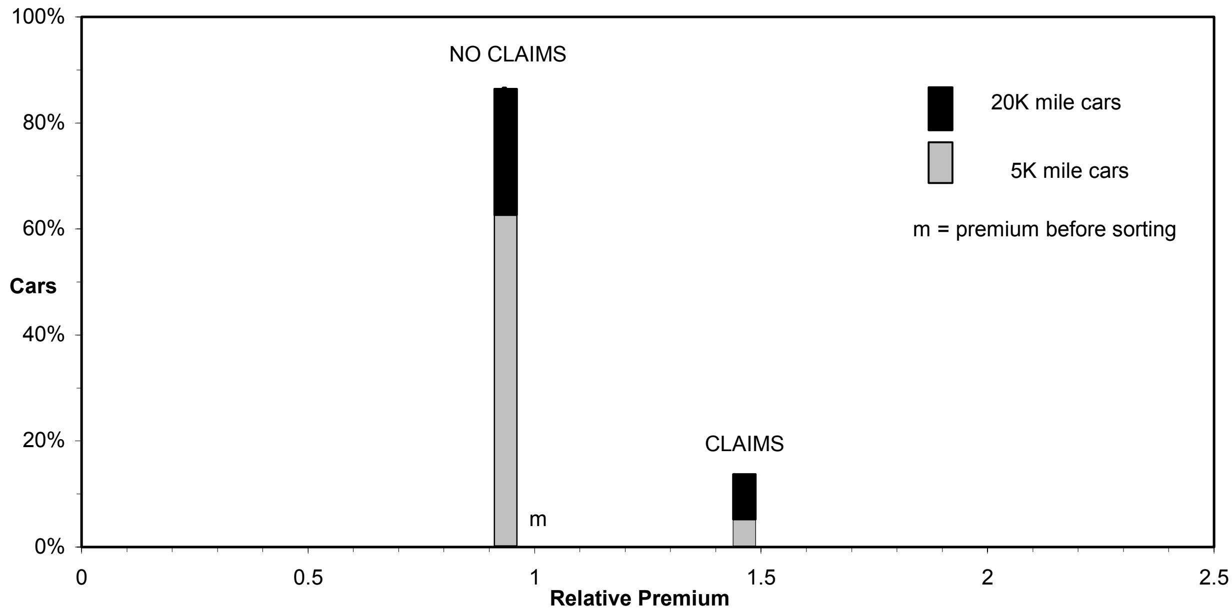
Table 2. *Redistribution of Cars by Premiums.* Source: Calculation by author.

Pool	Avg. ann. miles	Relative premium	Distribution of Cars (%)		Proportion of 5,000-mile cars in pool
			5,000 ann. miles cars (Low Risk)	20,000 ann. miles cars (High Risk)	
Unsorted pool	10,000	1.00	66.7	33.3	2/3
Redistribution by 3-year record at 5 claims per million vehicle miles					
No-claims sub-pool	9,280	0.93	61.8	24.7	~2/3
Claims sub-pool	14,630	1.46	4.8	8.6	~1/3

and 0.100 respectively, which averages 0.05 for the pool.) So randomly sampling by accident produces a sample with this proportion and an annual miles average of about 15,000 miles, a 50% increase over the 10,000 mile average for the unsorted pool. The premium distribution of cars by claim record category after random sampling for three years is given in Table 2 and is also shown in Figure 6.

The process of sorting insurance pools by claim records erroneously designates one-third of the cars with claims as high annual risk even though these cars each add only half the average miles and annual risk to the pool. This is a dilemma of false positives in testing for high annual risk (which Lemaire, 1995, reviews) that for years has confronted designers of systems for pricing by claim records: the conflict between surcharges that are too small on high annual risk cars necessarily coupled with raising the premiums at random on cars that are already adding less annual risk than average to their pool. Then there is the matter that the claim free sub-pool is

Figure 6. *Premium Distribution of Cars Sorted by Claim Records.* Source: Table 2.



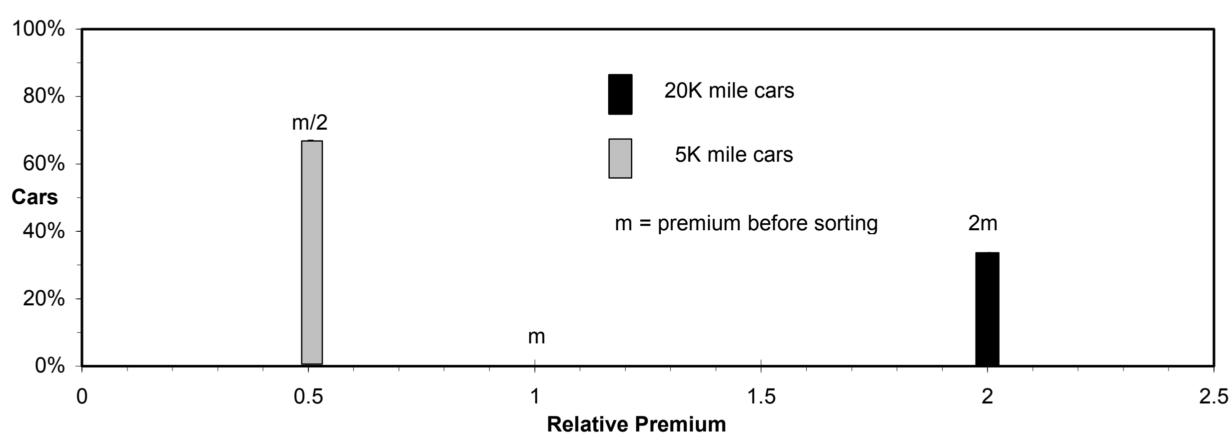
supposed to test negative for high annual risk, but a large majority of high annual risk cars are also included in the discount sub-pool. The answer to whether claim record categories sort out high-risk, high-mile cars is that a minority of these cars loses only part of their subsidy through the claim surcharges and a majority of them shares the small no-claims discount with the low-mile cars.

Figure 7 shows that odometer readings would precisely sort the cars into their component groups, all paying the same amount per mile and the same premium in proportion to their annual risk.

High *Annual* Risk Not the Same as High *Per-Mile* Risk

The attempts to subdivide the annual risk and annual miles continuums with low, middle, and high labels in Figures 3 and 5 shows the arbitrariness of categorizing what are clearly

Figure 7. *Premium Distribution of Cars Sorted by Miles.* Source: Table 2.



continuously varying values. Each mile a car is driven has a risk of accident and therefore transfers a statistical but real cost to the car's insurer. That cost would not exist if the mile had not been driven. (By law each mile a car is driven must be permanently recorded on its odometer, and, in most states, each mile driven must be insured.) Therefore, a proportional relationship is inescapable between the miles a car travels and the accumulated annual risk transferred to its insurer.[15]

Although auto insurance cost is currently recorded only on an annual basis, measuring individual driving risk in fact requires two variables, one for each individual car and one determined by the car's risk category.[16] Individual annual risk equals annual miles driven multiplied by a risk-per-mile rate for the category to which the car is assigned. What insurers record as high annual risk for zip-code and other categories is in fact the product of two measurable variables, the pool's average miles per car-year and its per-mile risk rate, neither of which insurers measure.

Owing to the randomness and very low per-mile incidence of traffic accidents, the proportionality constant of risk to miles—risk per mile—cannot be a property of individual drivers or cars. Per-mile insurance risk can only be the property measured by the claims experience of a large pool of cars. Full statistical credibility can only come from the number of car miles of exposure needed to produce about 1,000 claims. This number takes about 200 million car miles of driving exposure to produce for relatively high risk rate coverages like property damage liability and collision.

The monetary rate of risk transfer derives from the average cost of each kind of claim. For example, if the average cost (severity) of a property damage liability (PDL) claim is $2,000, a risk rate of 5 PDL claims per million miles translates to a cost 1.0¢ per mile transferred to the insurer for providing this coverage.

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15 Edlin 2003 considers the proportionality of insurers' cost to miles driven an unsettled issue. But the issue seems to be one of perspective rather than substance. It arises by comparing accident involvements with different annual mileage amounts on a time-period basis. This retains the vehicle-year as the statistical unit of analysis, rather than using the vehicle-mile unit. Any evidence for non-proportionality on a time basis of accidents to mileage can probably be explained as insufficient car classification, such as by driver age and car use, both well known to be correlated to average annual miles and concurrently to have a strong influence on per-mile accident involvement rates. From an insurance company standpoint setting class cents-per-mile premium rates according to annual mileage increments would make per-mile rates a function of amount of mileage a car travels during a time period and introduces logical (and consequently severe costing and pricing) problems. For example, all else made equal by classification, it cannot make any difference to an insurer's cost per mile whether 20,000 miles is driven in one or two cars, or takes one or two years to drive.

16 In the law and economics literature on accidents, these two variables are called level of activity and level of care, Shavell 1987. Despite the similarity in name, however, the amount of accident-producing activity (driving) is an individual continuous variable expressed in miles. In contrast, the level of care is a categorical variable, which is measured as the experienced accident or claim rate per mile for a large category of drivers or cars. If a category definition is modified, its risk rate per mile will change even though some members of the redefined category are the same as before.

Per-Mile Risk is a Property of Categories, Not Individuals

State accident reports are good indicators of average miles of annual exposure of different groups. Reports generally include the age and sex of each driver involved, and the insurance status of each vehicle. Each year a very large majority of licensed drivers are not involved in a reported accident. About 90% of young drivers do not have an accident during the year and this majority grows to 98% for middle aged and older drivers. But at every age the non-accident majority of women is slightly larger than the majority of men, Table 3.

At each age women and men drivers have virtually the same accident involvement rates per mile. However, in making comparisons across age groups, account must be taken of known variations in per-mile risk by driver age. This necessity is clear from the data in Table 3 on accident

Table 3. Accident involvement by driver age and sex (Texas 1999, Dept. Public Safety)

Driver age =	17	22	25	35	45	55	65	70
% Men – no involvement reported	88.1	92.6	94.1	95.6	96.5	97.1	97.5	97.2
% Women – no involvement reported	91.9	94.5	95.6	96.6	97.5	98.0	98.5	98.3
Ratio of %Men to %Women not involved in an accident	**0.96**	**0.98**	**0.98**	**0.99**	**0.99**	**0.99**	**0.99**	**0.99**
% Men – involved in an accident	11.9	7.4	5.9	4.4	3.5	2.9	2.5	2.8
% Women – involved in an accident	9.1	5.5	4.4	3.4	2.5	2.0	1.5	1.7
Ratio of %Men to %Women – involved in an accident	**1.30**	**1.35**	**1.34**	**1.28**	**1.39**	**1.45**	**1.45**	**1.63**
Involvements per million miles*	31	8	7	4	4	4	5	6
* National estimates from Williams, 1999.								

involvement reports in Texas normalized to numbers of licensed drivers in each age and sex group.[17] Teenage men and women drivers have an identical pattern of rapid decrease in involvements over a few years. Since at each age, men and women have about the same per-mile risk rates, the difference in accident involvements indicate that men average 28% to 63% more miles per driver annually in the age groups shown in Table 3.

The variation of risk rates per mile for driver categories by age and sex has been well studied with non-insurance data. By using annual miles data from the Nationwide Personal Transportation Survey combined with federal compilations of state accident involvement reports, Williams (1999) shows the lowest and predominant accident involvement rates are 4 to 5 per million miles for drivers age 30 to 65, Table 3. Against this risk rate as a standard, age groups below and above the middle age range average higher accident involvement risk per mile. Age 17 drivers start at about 31 accidents per million miles and decrease to 8 per million miles at age 22. Above age 65 involvement rates gradually increase over the next 20 years with drivers age

[17] Note that the 1000 accident credibility standard is met because at each group defined by driver age and sex, the Texas drivers were involved in 1,000 to 3,000 accidents. This statistical stability is evident in the regularity of values in Table 3, in the intermediate values not shown, and in the near constancy of values from year to year.

80 and older averaging 18 accident involvements per million miles. However, less driving on average at the young and old ends of the driver age range moderates the effect of the elevated per-mile rates on annual risk.[18]

The high-risk-driver theory of insurance cost treats drivers as having a particular annual risk as a permanent characteristic and even proposes a lifetime 50-year accident record history for evaluating each individual's personal annual risk.[19] But risk per-mile is clearly a property of age groups. All drivers age 17 must be taken as having a risk rate per mile six or seven times more than drivers in their middle years. With respect to per-mile risk rates, one would better refer to high-risk-rate *ages* rather than high-risk drivers. Every driver now at a low risk-rate age has previously been at a high risk-rate age, and faces the prospect of being in age groups that have slowly increasing per-mile risk rates. But a low risk rate per mile for a middle-aged driver multiplied by a high number of miles their car is driven during a year nonetheless transfers a high annual risk to that car's insurer.

Category Averages Can't Proxy For Individual Annual Miles of Risk

Because the annual miles of exposure of individual drivers and cars varies over the entire possible range, including zero, individual annual risk for a car or driver cannot be measured by the group's average miles. In each conceivable category, the annual premiums paid to transfer zero miles and 100,000 miles of risk to the insurer are nearly or exactly the same.

Relative to women, men are commonly labeled as high risk drivers. In their study of California driver records, Spetzler et al. 1976 report that the 30,293 men drivers averaged nearly twice the annual risk, measured by accident involvements, as that of the 23,872 women drivers.[20] The two broad distributions of men and women drivers by annual risk, however, shows that labeling one group high risk and the other low risk on the basis of a large 2:1 difference in the average annual risks is very misleading, Figure 8.

Each category of cars—by driver sex, for example—will show the full range of annual risk. Even though men's average annual risk is nearly twice women's, 28% of the men drivers showed an annual risk of less than women' average, and 13% of women had an annual risk greater than men's average.[21] Annual risk depends on individual annual miles of exposure that varies continuously across drivers and cars, and so also must vary continuously across each pool of cars that insurers assemble. Therefore individual annual risk cannot be measured by dividing pools of insured cars into more and more sub-pools according to zip codes and other strong correlations

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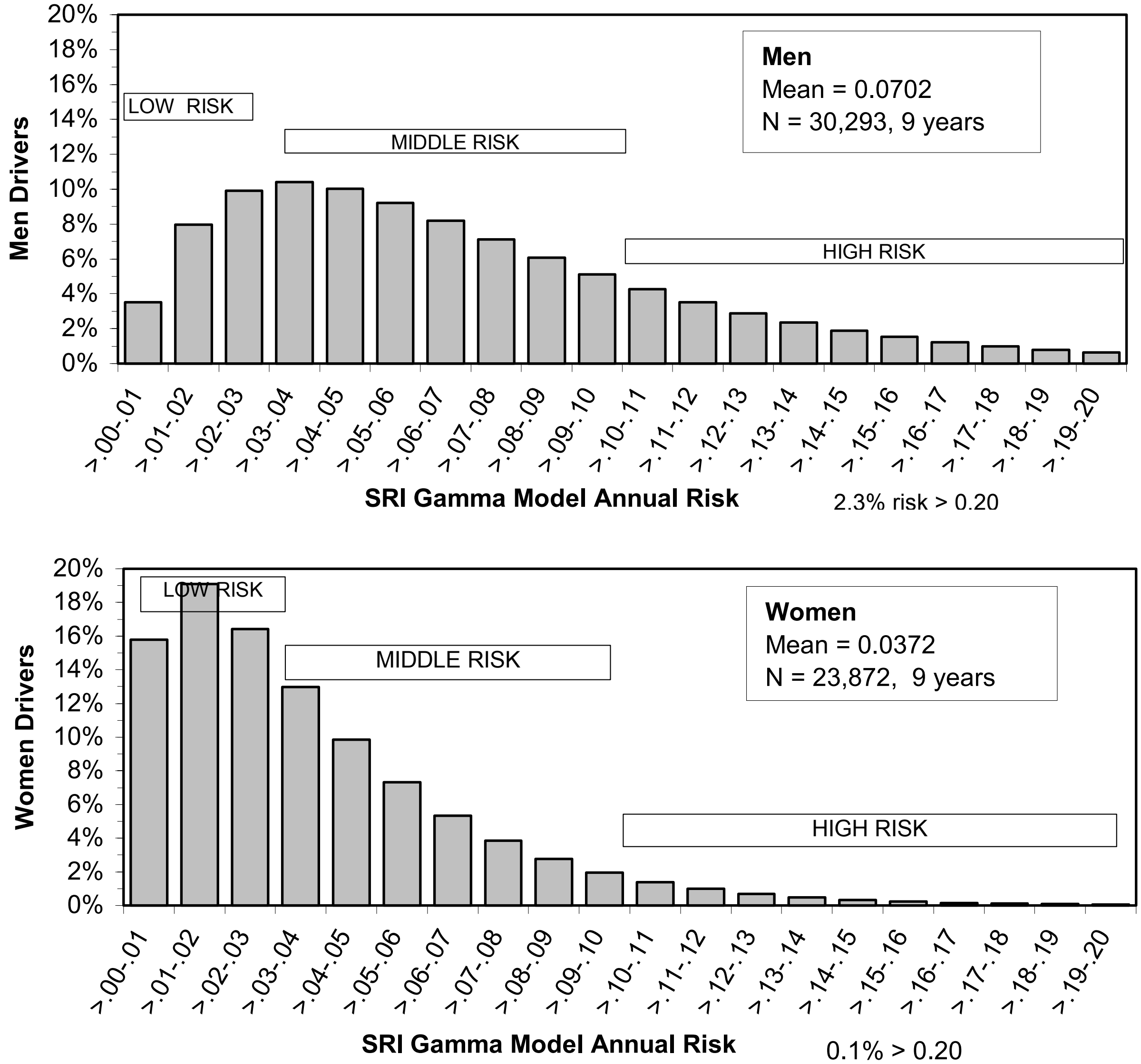
[18] At the higher 18- and 80-year-old risk rate of 16 accident involvements per million miles, driving 2K miles generates an annual risk of 0.032, whereas at a middle age risk rate of 5 per million miles, driving 20K annual miles generates three times more annual risk of 0.10.

[19] Boyer et al. 1991, page 209.

[20] Over the nine-year records, women's average annual risk was 0.0372, and men's was 0.0703, 89% more than women's.

[21] Spetzler et al. 1976.

Figure 8. *Men and Women Drivers Distributed by Annual Risk.* Source: Spetzler et al. 1976.



with average annual cost.[22] Furthermore, because drivers make large and often unforeseen changes in miles they drive an individual car—for example owing to illness, car breakdown, and job changes—each sub-pool will always contain cars driven much more and much less than the annual average for the sub-pool.

Ignored Correlations

For decades insurers have been collecting exposure and loss data on a vehicle year basis, categorizing it according to all information available on customers, and then looking for correlations of annual risk with each category. However, apparently for marketing or political

[22] Owing to low accident rates per mile, the experienced annual risk per car for small sub-pools of a few thousand cars or less is not statistically stable and may show wide year-to-year fluctuations, in contrast to much smaller year to year variation in the small sub-pool's average miles per car.

reasons they ignore some strong correlations established decades ago.[23] Because men average more miles of driving than women in every age group, men's average annual accident involvements are significantly greater than women's, as shown in Table 3 (above). Nonetheless, insurers only use the difference in annual risk by driver sex as a premium multiplier for cars with young drivers. Consequently driver sex has no effect on the premium paid for insuring more than three out of four cars.

Insurers also know that because on average older cars are driven much less than newer cars, as corroborated by each Nationwide Personal Transportation Survey, the number of bodily injury liability claims per 100 cars decreases markedly with car age. Setting annual premiums according to the correlation would mean lower premiums for older cars and higher premiums for newer cars. Nonetheless, premiums for liability coverage do not vary at all by car age. Presumably it is competition for the business of men and owners of newer cars that causes insurers to ignore the correlations of annual claims with driver sex and car age.[24]

High Uninsured Motorist (UM) Claims by Faultless Drivers

The idea that certain drivers cause most accidents and that other drivers are faultless in the accidents in which they are involved fosters the high-risk-driver theory's explanation for the correlation of more liability claims with categories such as low-income zip codes and low credit scores. However, the theory does not account for the correlation of UM claims with liability claims. The number of UM and liability claims per 100 insured cars vary up and down *together* across zip code, credit score, claim record, and other pricing categories.

The difficulty the liability-UM correlation presents for the high-risk-driver theory is that while payment of a liability claim requires the *fault* of the insured car's driver, payment of a UM claim requires the *non-fault* of the insured car's driver. But the counter-factual belief that the public and many legislators hold to is that high risk drivers cause more accidents but only have the average number of accidents caused by others. From this logic it follows that premiums for these drivers should be increased only for claims for which they are culpable, and consequently some states prohibit insurers from including UM claims along with liability and collision claims as a basis for raising premiums, even though the UM claim correlations are just as solid.

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23 In the last few decades, computers have speeded the process of looking for correlations with annual risk per car through multivariate analysis that allows checking many possible correlations simultaneously.

24 McNamara (1984, page 44) describes how insurers in the 1960s discovered the decrease in bodily injury liability claims incurred by cars as they get older and explains that insurers did not reduce premiums by car age as a consequence because "the basic justification of relativities among classes must recognize that the use of statistics should be leavened with a liberal dose of common sense."
For a recent explanation of why insurers ignore strong correlations, see Bradsher's 1998 report quoting fears by auto insurers of SUV owners' wrath expressed to legislators and talk show hosts as keeping insurers from raising the liability premiums in accord with the greater injuries on average inflicted by these vehicles on occupants of lighter cars, whose owners the report found were not making a fuss about subsidizing the liability premiums of the heavier cars.

The alternative explanation offered here is that a pool of insured cars that averages more annual miles—resulting from adverse selection by economizing drivers—will be involved annually in more accidents and will average more claims per 100 cars of all types, including uninsured motorist claims along with liability and collision claims.[25]

The high-risk-driver theory looks like a political label—a label that creates an attitude toward a group not represented in the discussion—rather than a neutral theory designed to further understanding.[26] In regard to the theoretical existence of so-called high-risk drivers, it stretches credulity to maintain that a bell-shaped or other symmetrical distribution of drivers about an average by any driver-mile measure of individual skill, care, or safety could be reconciled with the observed broad positively skewed distributions of drivers by annual risk or of cars by annual odometer miles. Furthermore, why do the supposed high-risk-driver groups appear to have low credit scores or to be concentrated in low-income zip codes, the very groups that have the greatest need to economize on fixed expenses such as car insurance?

ALTERNATIVE ADVERSE SELECTION THEORY

Self-Sorting Causes Adverse Selection

Today, a fixed premium covers all the miles a car can be driven in a year. Therefore, the only sure way to save on insurance is to own fewer cars and drive each more miles than previously. Obviously, inconvenience discourages drivers from saving this way. But where many financially stressed households have to save by piling more miles on fewer cars, the annual claims per 100 cars increases. In response, companies must raise premiums, which forces more households to economize by selling their less-used cars or illegally taking them off policies. Thus, in low-income zip codes, today's pay-per-car system backfires because it sets off an upward spiral of increasing average miles per car, higher premiums, and still more marginal cars being taken out of the pool.

In non low-income zip codes the insurance pools include more cars driven under 5,000 miles a year.[27] These low-mileage cars mean lower average miles and cost per car to companies,

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[25] The absence-of-adequate-care argument might be reintroduced by saying that even drivers found faultless may not have been sufficiently defensive, but that is usually taken into account when assessing comparative fault in discounting liability and UM claims. It is not arguable, however, that most two-car accidents would not have happened if the faultless car had not been on the road albeit in a legal and prudent manner.

[26] Since high-risk drivers seem to have only theoretical existence, they will never be represented in the discussion. Apparently almost all drivers are convinced that they are above average—in what Jaffee and Russell (1998, page 90) call the Lake Wobegon effect—and the tiny rest consider themselves to be average drivers. This unrealistic belief has a negative effect on safety according to the Insurance Institute for Highway Safety, 2002, which observed: “Driver inattention and/or failure to obey traffic laws is a factor in most fatal crashes. Yet virtually no drivers admit they’re part of the problem. They believe they’re in control behind the wheel, their own driving is better than average, and they won’t get in a crash.”

[27] The number of cars per household increases with income level. Nationwide Personal Transportation Surveys.

Table 4. *Progressive Saving by a Household and the Effect on Insurer Income.*

Need to economize	Insured Miles driven (total = 30,000)				Annual Premium (base = $500 per car-year)		
	Car 1	Car 2	Car 3	Car 4	Total*	Per mile	Excess (+)/shortfall (-)**
I. (least)	14,000	10,000	5,000	1,000	$1,440	4.8 ¢	**+$320**
II.	15,000	10,000	5,000	†	$1,120	3.7 ¢	**0**
III.	18,000	12,000	†		$800	2.7 ¢	**-$320**
IV. (greatest)	30,000	†			$500	1.7 ¢	**-$620**

* 20% low estimated future mileage discount applied to Cars 3 & 4; 20% multicar discount applied to all cars except with Need IV where Car 1 is the only car.
** Assumes that 3.7¢ per mile is the average rate the insurer needs to cover costs for this class and coverage.
† Car removed from policy by owner.

justifying lower premiums per car. It's not so much the high-annual-risk/high-annual-miles cars in a pool that makes it a high annual risk pool, but the low annual miles cars missing from it.[28]

Table 4 shows how a hypothetical household can save premium as its financial condition worsens without reducing its vehicle miles of travel. If the average for the pool is 10,000 annual miles per car, then the company needs 3.7¢ to cover costs and profits. With four cars insured, the company collects nearly 30% more than this breakeven rate for the 30,000 annual miles the household drives. But after the household has sold three of the four cars to economize, the company collects less than half (1.7¢) of the 3.7¢ cost per mile of the same risk transferred to it.

Figure 9 combines the distributions of cars by annual miles nationally and by premiums in Travis County, Texas. In zip codes where per-car premiums do not induce much adverse selection of low-annual-mile cars out of the insurance pools, the miles-per-car average is held down by low annual mile cars despite high annual mile cars in the pools. Some of the offsetting can be done within the same household, as suggested by the four-car household in Table 4.

[28] Vickrey (1968, p.471) noted the overcharging of marginal cars, especially in multi-car households: "The individual who is on the margin of decision is more likely to be one who if he decides to maintain the car will be using it substantially less than the average or, especially in the case of the second car, will be on the margin precisely because the occasions when the two cars would be in use simultaneously will be less frequent, so that the availability of the second car would add relatively little to the total mileage. To be sure, moderate discounts are often allowed by insurers for the insurance of a second car under the same ownership, but the discounts that could be offered on this basis…would still not eliminate the overcharge of the marginal car."

Table 5. *Effect on Premium Income Through Loss of a Marginal Car.*

Need to economize	Insured miles driven in year	Premium paid (base = $500 per car year)		
	1 Car	Total*	Per mile	Excess**
I.-III	3,000	$400	**13.3 ¢**	**+$289**
IV.	†	0		0

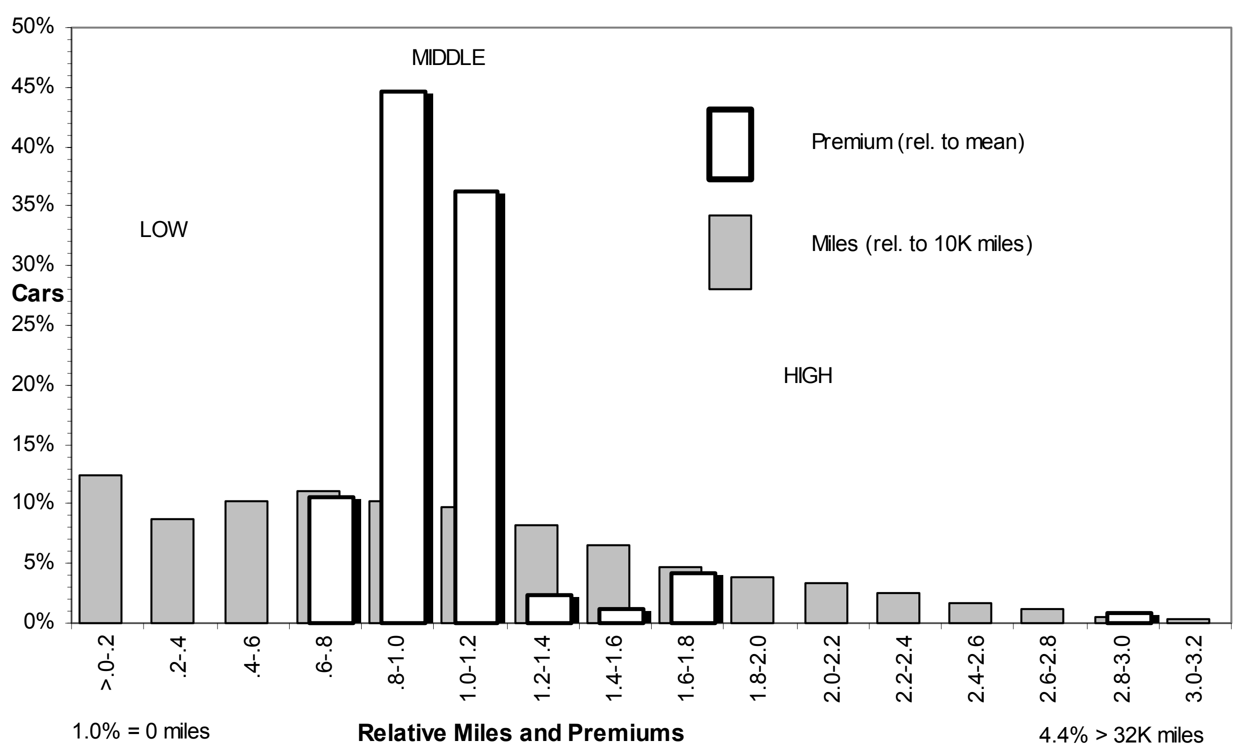
* 20% low estimated future mileage discount applied to Car
** Assumes 3.7¢ per mile meets insurer's cost.
† Policy cancelled by owner.

Table 5 shows what happens to premium income when a need to economize forces single-car households that do not need many miles of driving to give up their car: insurers lose the excess premium that helps to hold middle premiums down (Figure 9). Furthermore, if the car is sold instead of being driven uninsured, those miles that the household still needs are transferred (without premium) to the cars of neighbors and relatives, which raises the miles and cost per car of the insurance pools containing those cars.

Premium and Income Effects on the Demands for Insured Cars and Miles

The preceding explanation of why the insured cars of low income households are labeled high-risk-drivers depends on these relationships: As household income falls (or per-car premiums rise), the number of insured cars falls faster than the number of insured miles driven, which

Figure 9. *Combined Distributions of Cars by Premium and by Annual Miles.* Source: Figure 2 and Figure 4.



increases the miles and cost per car-year transferred to insurers. Conversely, as household income rises (or per-car premiums fall), the number of insured cars rises faster than the number of insured miles driven, which decreases the miles of risk per-car transferred to insurers.

This may be restated as: income and premium elasticities of demand for insuring cars have magnitudes greater than the income and premium elasticities of insured miles of driving. There is no doubt that the premium elasticity of the demand for insured miles of driving is smaller. In fact, because premiums are charged on a per-car basis, the premium elasticity of the demand for driving is zero (perfectly inelastic) except to the extent that premiums act like a tax on income. All the insured miles are free once the fixed premium is paid.

However, the premium and income elasticities for insuring cars (as distinct from insuring miles) are reported to be relatively high. Blackmon and Zeckhauser, 1992, report for Massachusetts: "The demand for insured vehicles per household was estimated as a log-linear (constant elasticity) function of income, price [premium], and household density." And "The demand for vehicles should decrease with population density because substitute transportation becomes more readily available….Our estimated coefficients were income 0.477, price –0.569, and density –0.044."[29] However they "did not have a data set to control for exogenous variables that could influence the driving decision."[30]

The effect of income on the demand for household miles of driving can be proxied by the income effect on the demand for gasoline. The demand for gasoline as a proxy for miles show a relatively low elasticity.

Changes in the number of miles of driving per car on a large scale is very important to auto insurers. The number of insurance claims paid historically varies directly with large-scale determinants of driving amount. Insurance companies point out in rate filings and elsewhere that driving and claims always decrease significantly (5% to 15%) with a sharp rise in unemployment or the price of gasoline (Butler et al., 1988).

How Enforcement Can Induce Adverse Selection

In their national study of the effect of taxes and other factors on state car registrations per capita, Pritchard and DeBoer (1995), not only confirmed the positive income and negative insurance cost effects on registrations found in the Massachusetts and California studies, but also found (as expected) that the presence of mandatory insurance in a state reduced its car registrations.

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[29] Based on California data, Jaffee and Russell 1998 (page 107) conclude that "we have confirmed the Blackmon and Zeckhauser [1991] result that the demand for registered cars is highly premium elastic."

[30] Evidently this statement agrees that the endogenous premium variable does not "influence the driving decision," only the ownership decision.

The trend in state legislatures after adopting mandatory insurance has been to steadily increase detection and punishment for violations,[31] including impoundment of uninsured cars and jail for repeated offenses. Driver reaction to the increased risk of driving an uninsured vehicle may have the effect of raising premiums in low income zip codes. Drivers will shift more miles from uninsured cars to insured cars, and would thus raise the average miles and the premium for cars in the pool. Per-car premiums unnecessarily force drivers to choose between giving up low-mile but essential cars and being criminalized for driving them without insurance.

How Credit Scores Detect Adverse Selection

Annual liability claims per car for households with the lowest credit scores are about twice what they are for cars in households with the highest credit scores.[32] Insurers theorize that this correlation indicates a causal connection between financial negligence leading to credit problems and driving negligence leading to more accidents.[33] The alternative theory proposed here is that drivers with financial problems, as a group are adversely selecting against insurance pools by insuring fewer cars and driving them more miles.

A tiebreaker between theories is that low credit scores correlate not only with more liability claims for which negligence of the insured car's driver is the condition for payment, but also with more UM claims for which the driver's non-negligence is the condition for payment of the claim. This additional correlation is inconsistent with the negligent, high risk drivers theory. However, the parallel correlations of both liability and uninsured motorist claims are consistent with the more annual miles of exposure per car theory to explain more claims per car-year of all kinds.

FREE MARKET REMEDY

To end the premium spiral set off by adverse selection in low income zip codes, Texas passed the cents-per-mile choice law in 2001 (House Bill 45). The law invites insurers to offer the vehicle-mile as the alternative exposure unit to the current car-year unit for driving coverages. The choice of exposure unit[34] between the vehicle-year unit and the vehicle-mile unit is easy for

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31 For example, Texas made insurance mandatory in 1982, then made proof of insurance a condition for registration, inspection, and driver's licensing and in 1992, and in 2004 is studying a system for comparing periodically data from auto insurers on all cars they insure with the state's file of all registered cars to detect which cars are not insured.

32 Miller and Smith (2003) report that the annual cost per car to insurers for property damage liability claims is 64% more for households with the lowest "credit-based insurance scores" than the cost per car for households with the highest scores. The study presents data on other coverages, but not on uninsured motorist claims. Note that if the pools with the highest score average 8,000 annual miles per car, the pools with the lowest score could easily average 64% more miles, about 13,000 miles per car, that would fully account for the greater annual cost insurers report without any difference between the pools in per-mile risk.

33 Hartwig and Wilkinson, 2003, theorize that the "statistical correlation between good credit and relatively low insurance losses confirms the reasonable assumption that the responsibility required to prudently manage one's finances is associated with other types of responsible and prudent behaviors, such as…safe operation of cars."

34 In an early survey paper on *exposure units* that remains on the Casualty Actuarial Society's examination syllabus, Dorweiler (1929) wrote: "The mileage exposure medium is superior to the car-year medium in yielding

(Footnote continued on next page.)

companies to set up. (Insurers have long offered the vehicle-mile as an alternative exposure unit to the vehicle-year for some commercial fleets with fluctuating levels of business volume.)

After first assigning a car as usual to a risk class (by territory, car and driver type, and car use), the company would offer the customer a choice between staying with, for example, a fixed premium of $600 a year for driving coverages (liability, collision, uninsured motorist, and personal injury protection) or paying the matching 4.0¢ a mile for the same risk class and coverage to buy miles of insurance in advance.

The miles would be added to the odometer reading and recorded on the insurance ID card. The owner buys more miles when needed. The company has the odometer read annually and when the owner changes cars or companies. Owners pay only for the miles of insurance protection used, and if the odometer limit is exceeded or if the odometer reading is tampered with, the car is uninsured. It's that simple.

Per-mile premiums would also eliminate a major enforcement problem. Today's ID card shows the policy term but not whether insurance has lapsed through non-payment of installments. Under the per-mile alternative to per-car premiums, checking the odometer reading against the ID card's odometer limit shows immediately whether prepaid insurance is actually in force.

Prospective Adverse Selection by Making Per-Mile Premiums Available

Although Texas law invites insurers to offer per-mile choice, no legislative or regulatory approval should be needed in any state. Nevertheless, to date no insurer in has announced plans to offer this option, which involves only a change in exposure unit. Having a choice between a per-car premium and a matching per-mile premium would allow car owners to decide for themselves which method to use.

But a company's resistance to this remedy can be understood in terms of the prospect of intense adverse selection against its own traditional pay-per-car risk pools that would be induced by

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an exposure that varies with the hazard, as it responds more to the actual usage of the car." (Note that Dorweiler's phrase "responds more" tends to obscure the fact that car-year exposure unit does not respond at all to actual use of the car.) Dorweiler further states that "[t]he devices and records necessary for the introduction of [the car-mile] medium make it impractical under present conditions," and that while the car-year "measures the exposure prospectively, the [car-mile] require[s] a final adjustment which would be determined retrospectively."

Allstate senior actuary Richard Woll, at the Casualty Actuarial Society's ratemaking seminar in 1988 in a discussion of the then ongoing case Pennsylvania NOW v. State Farm, Allstate, et al. (suing unsuccessfully to change the exposure unit for driving coverages from the car-year to the car-mile under the rate regulatory act and Pennsylvania Equal Rights Amendment), distinguished between car-miles as an actual odometer exposure measurement and categories of estimated future mileage as one of many possible car classification factors. He said:

"[I]t makes an awful lot of sense to think of it [mileage] as an *exposure* variable. However, when you are trying to explain classification effects, you have got to recognize that mileage is a *classification* variable today, not an exposure variable. What is explained by mileage [classification] on a prospective basis is quite different than looking backward and explaining effects through past actual mileage." Emphasis added. From the author's audio tape transcript.

competition from the new, optional, matching risk pools using the vehicle-mile exposure unit. Low-miles cars would leave existing pools for the matching per-mile pools. This would be adverse selection against today's per-car pools because it would take more premium than miles from them.

In the traditional pools in non-low-income zip codes, the annual miles and cost per car would spiral up in exactly the same way adverse selection occurs against the pools in low income zip codes today. Managing the competition from the new adverse selection may be challenging for insurers, but economically it should be preferable to the adverse selection that currently requires drivers to give up cars in order to economize on premiums.

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