

PREDICTION OF ACCIDENT LIKELIHOOD
USING POISSON REGRESSION

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DISCLAIMER

The conclusions and opinions expressed in this report are those of the authors and do not necessarily represent those of the State of Texas, the State Department of Highways and Public Transportation, or any political subdivision of this state or the United States government.

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ABSTRACT

Under a cooperative arrangement with the Texas State Department of Highways and Public Transportation and the Texas Department of Public Safety, the Texas Transportation Institute (TTI) conducted multivariate statistical analyses of accident and driver history data to identify categories of drivers overrepresented in traffic accidents. Data for a sample of 225,000 Texas Drivers were used in Poisson regression analyses which computed the probabilities of future accidents as a function of previous accidents, past traffic violations, age, and gender. The results substantially agreed with the findings of a comprehensive literature review.

Driver's age, along with prior accidents and traffic violations, was found to be of considerable importance in predicting future accident involvement. Drivers under 25, especially males, have more accidents. However, previous accidents and violations are the best indicators of the likelihood of future accident involvement.

The findings indicate that it may be desirable to vary the criteria for driver's license suspension for different age groups. In addition, TTI's analyses suggest that negligent accidents provide a better basis for predicting future accidents than violations and should be given more weight in license suspension. The report offers suggestions of possible methods for including consideration of accidents in license suspension procedures.

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Prologue

With his native Basque mistrust for things mechanical, Pierre limited his gear options to reverse and low, in which he drove with the throttle wide open, using all the road and both verges. Such sheep, cows, men, and wobbly Solex mopeds as suddenly appeared before his bumper he managed to avoid by twisting the wheel sharply, then seeking the road again by feel. He abjured the effete practice of using the foot brake, and even the emergency brake he viewed as a device only for parking. As he always stopped without depressing the clutch, he avoided the nuisance of having to turn off the engine, which always bucked and died as he reached his destination and hauled back on the brake lever. Fortunately for the peasants and villagers between the château and Tardets, the sound of the Volvo's loosened body clattering and clanking and the roar of its engine at full speed in low gear preceded Pierre by half a kilometer, and there was usually time to scurry behind trees or jump over stone walls. Pierre felt a justified pride in his driving skills, for he had never been involved in an accident.

(Trevanian, Shibumi)

INTRODUCTION

This report discusses the findings of a project which began development of an integrated traffic records system in Texas. The major purpose of this records system is to assist the Traffic Safety Section (TSS) of the Texas State Department of Highways and Public Transportation (SDHPT) in the identification of traffic safety problems and the development of the Texas Highway Safety Plan.

Project Objectives

This multi-year project had two principal objectives during Fiscal Year 1980:

- to initiate development of a true data base linking traffic record data files and
- to conduct multivariate analyses of accident and driver history data and identify categories of drivers overrepresented in traffic accidents.

The SDHPT and the Department of Public Safety (DPS) maintain extensive automated data files relevant to highway safety problems. These files consist of accident, driver history, driver license, and vehicle registration data, and detailed data describing highways in Texas. Because the files currently exist as separate, unlinked data sets, their structures do not permit easy or efficient linking of variables from different files.

TSS is currently limited to the analysis of accident data. Additional files containing variables relevant to highway safety are the driver history and vehicle registration files. Before countermeasures addressing highway safety problems can be developed, key subpopulations of drivers,

vehicles, and environmental (highway) conditions overrepresented in accidents must be identified. Defining these subpopulations is dependent on identifying and linking key variables from several data files, a process which begins establishment of an integrated data management system.

File Merging

During Fiscal Year 1980 accident, driver history, and license data were merged into a single data base permitting easy access to the data. The driver history file contains accident, citation, and conviction records, most of which are retained for a five-year period. The driver license file contains driver biographical data and information concerning type of license.

More than 750,000 driver license records and 2.2 million transactions in the driver history file were requested from the DPS and manipulated by the Data Processing and Analysis Group of TTI prior to final merging.

Two data sets were created for statistical analyses:

- (1) driver history, license, and accident data for all drivers involved in 1978 accidents;
- (2) driver history and license data for a random sample of 225,000 drivers and detailed accident data for the accidents in which these drivers were involved during the five-year period.

A detailed description of the merging of the accident, history and license data as well as descriptions of these three files is provided in a companion TTI report (Bowles, Sparks, & Cook, September 1980).

Data Analyses

Data for the sample of 225,000 Texas drivers were used in Poisson

regression analyses which computed the probabilities of future accidents as a function of past accidents, convictions, and other variables.

It is assumed that accident data follow a Poisson distribution within homogeneous groups (a conditional distribution). The Poisson regression is a weighted least-squares technique which adjusts for the assumption of a Poisson distribution. This technique provides estimates of the probability of future accidents for different categories of drivers. These categories were defined by number of prior convictions and number of prior accidents and by age and sex groupings.

Conclusions

The major goal of this project was to merge several data files in order to examine relationships among variables associated with accidents. The analyses conducted during Fiscal Year 1980 were principally concerned with the driver and driving history. An extensive review of the literature on statistical studies of driver-related variables and the effect of prior accidents and convictions on accident rate was conducted. This review, in conjunction with the regression analyses, was the basis for several conclusions and suggestions, which are briefly summarized below.

Driver's age was found to be of considerable importance in predicting future accident involvement. Drivers under the age of 25, especially males, have more accidents, a finding which agrees with previous studies. These results indicate the need for varying the criteria for license suspension for different age groups. Since the accident rate for the younger driver does not level off until the age of 25, extending the provisional-license administrative hearing to drivers between the ages of 18-25 may be desirable.

The best indicators of the likelihood of future accident involvement were found to be prior violations and accidents. For males, prior accidents, especially negligent accidents, provide the best single means of predicting future accidents. Prior convictions are not as good a predictor. Even male drivers whose accidents were classified as non-negligent have a higher likelihood of future accident involvement than drivers with no previous accidents. For females, prior accidents and prior convictions contribute approximately equally to the probability of future accidents.

Prior accidents are apparently only rarely used in conjunction with prior convictions in scheduling administrative hearings for license suspension. Our analyses suggest that negligent accidents provide a better basis for predicting future accidents than violations and should be given more weight in license suspension. Possible methods for including consideration of accidents in conjunction with convictions are discussed in the final chapter of this report.

The following chapter comprises a review of the literature on prediction of accidents from driver records and driver-related variables. Following this review is a chapter presenting the results of the Poisson analyses. Conclusions and suggestions are offered in the final chapter. Detailed discussions of the statistical techniques used in the analyses are presented in the appendices.

PREDICTION OF ACCIDENTS FROM DRIVERS' RECORDS: A REVIEW OF THE LITERATURE

Although some drivers have more accidents than others, drivers with multiple accidents represent only a small percentage of the drivers who have accidents. Nevertheless to be able to identify and either retrain or remove the high-risk driver from the general driving population would have obvious benefits for traffic safety. These high-risk drivers are generally defined in one of two ways. Peck, McBride, and Coppin (1970) suggest that a high-risk driver shows either accident proneness or accident liability. Accident liability is an actuarial designation for the risk of having an accident and, as such, is used by insurance companies to set their rates. For example, a person who drives more than average increases the chance of having an accident. Similarly, a person who drives in high-risk locations, such as roads with high levels of traffic density, or at high-risk times, such as late at night, also increases the chance of an accident. Thus accident liability in this sense implies nothing about driver characteristics that may contribute to collisions.

Accident proneness, on the other hand, refers to different frequencies of accident involvement for individuals whose accident liabilities are equal. If two persons drive the same amount, in the same locations, and at the same times, and one has many more accidents, that person would be classified as accident prone. In this case, a higher accident rate would be interpreted as indicating a tendency toward accidents, presumably related to an underlying complex of relatively stable psychological variables, such as personality traits, attitudes, perceptual and/or motor skills, emotional state, and intelligence.

The concept of accident proneness is very controversial, since most people who have automobile accidents have not had one before (Stewart and

Campbell, 1972; Burg, 1970). Moreover, a person who has several accidents in one time period rarely has several accidents in another time period (Forbes, 1939; Stewart and Campbell, 1972). Nevertheless, it is possible to demonstrate proneness with certain groups of drivers.

The strongest evidence of accident proneness comes from studies of professional drivers. Hakkinen, as cited in Peck et al. (1970), showed a correlation of 0.64 for predicting accidents from five psychomotor characteristics of Finnish tram drivers. Shaw and Sichel (1971) used projective personality tests to achieve a 77% accuracy rate for predicting high-risk drivers ($r = 0.66$ between test scores and the number of "driving days" between accidents).

The Shaw and Sichel studies investigated bus drivers who worked for PUTCO, the Public Utility Transport Corporation, of South Africa. The accident rate for these drivers was very high, 2.43 accidents per 10,000 miles driven. Eighty-four percent of the drivers had two or more accidents, with 32% accounting for 73% of the accidents. Part of the explanation for this extremely high rate of accidents relates to the authors' definition of accidents: any collision, even one that resulted in no damage, was counted. This is in contrast to the policies of law enforcement agencies in the United States, which establish damage or injury thresholds (in Texas, damage in excess of \$250 to any individual involved) to determine which accidents will be recorded.

After discovering that screening potential drivers by means of psychomotor tests resulted not only in better performance in the company's driver training school, but, paradoxically, also in higher accident rates, they examined personality traits of drivers and concluded that the high-accident group was more dishonest and careless, and, in general, had poorer disciplinary records. Using the TAT (Thematic Apperception Test), a

projective test of personality that uses ambiguous pictures as stimuli for stories which the examinee writes, and their own PUTCO Social Relations Test, which uses a comic strip technique to elicit the stories, they were able to predict high-risk drivers. They report that in the eight years after driver screening based on these tests was begun the accident rate decreased by 38%. They interpret this finding as evidence for accident proneness due to certain personality traits.

However, this type of screening may exclude many more potentially successful drivers than potential high-risk individuals. This policy, while it may be justifiable for a business, is too stringent to be applied to the public. It would be impractical to deny licenses to the majority of drivers who would score unacceptably on the projective tests but would remain accident-free in order to eliminate the minority who would have accidents.

In contrast to the PUTCO study, the California Driver Record Study, which analyzed the driving records of 148,006 Californians, found much lower accident rates, only 0.09 accidents per 10,000 miles driven. Moreover, only 2.8% of this sample were accident repeaters with two or more accidents. This study found prior violations to be a more stable predictor of accidents than past accidents, perhaps because of the low rate of accident involvement. The small percentage of drivers involved in multiple accidents suggests that the concept of accident proneness may have limited usefulness for this population. As Shaw and Sichel (1971) note, however, these 2.8% of California drivers did account for 30% of the accidents in the three-year study period (Shaw & Sichel, 1971, p. 343).

The differences between studies of professional drivers and studies of the general American driving population are probably due to inherent differences in the driving circumstances of the two groups. The professional

drivers had very high exposure rates and frequently drove in situations of high traffic density. Such drivers are more likely to be involved in accidents. As a result, individual differences among drivers would be more likely to contribute to differential accident rates than in circumstances where the overall risk of accident is less.

Although most accidents in the U.S. involve drivers with no previous accidents and although drivers' exposure rates are rarely known, it is possible to identify some groups of drivers who are more likely to have accidents from information available in driver records. Several problems can hinder attempts to isolate factors that predict accident liability, however. For one thing, the driver population is constantly changing: drivers who had accidents in one time period may move, die, or simply stop driving because of suspended licenses before the second time period. These changes could create artificially low rates on accident repeaters. Also, many variables that relate to driving abilities are correlated with other variables, so that the effect of any one driver characteristic may be confounded by the effects of other characteristics. For example, the use of alcohol while driving correlates with age, sex, marital status, social status, and personality factors. Finally, as Zylman (1972) concluded, the chance of having a violation or collision recorded on one's record varies widely from one location to another. Consequently, the likelihood of a poor driver record may depend more on local policies, practices, and attitudes of law enforcement agencies than on actual driving behavior.

In spite of these and other difficulties, several studies have successfully identified some of the driver characteristics that correlate with higher levels of accidents. These characteristics include the age, sex, and marital status of the driver as well as the number and kinds of prior violations and accidents. In addition, without addressing the question of

accident proneness, some investigators have attempted to specify underlying causes for a particular group's higher risk rate.

Age

There is a strong relationship between the age of the driver and involvement in traffic accidents, with younger drivers and older drivers having a higher collision rate (accidents per unit exposure) than drivers in the middle age range. This U-shaped distribution of accidents by age groups has been identified by several investigators. For example, Solomon (1964) in a study of the main rural highways in eleven states found higher than average accident rates for persons under 20 or over 60 years of age. Perchonock (1977) identified the same increased rate of involvement for drivers under 25 or over 65 from state police reports of accidents in western New York.

These two studies do include measures of exposure rate which control for the potentially confounding factor of number of miles driven. As stated previously, exposure rate relates to the potential for occurrence of accidents. All things being equal, someone who drives more, and thus has a higher exposure rate, can expect to be involved in more accidents. In this instance, one age group might have more accidents simply because they drive more than other age groups. Another age group may be under-represented in total accidents because of decreased exposure but still have higher accident rates.

Several studies (Solomon, 1964; Peck, McBride, & Coppin, 1970) have shown that younger drivers have a higher accident rate when drivers' exposure times are equated. Similarly, the Solomon and Perchonock studies indicate an increased accident rate for drivers over 60 when exposure rate is considered. A driver in this age range drives much less frequently than others but is the culpable driver in more than his/her share of accidents. In two studies of California drivers (Ferdun, Peck, & Coppin, 1967; Peck, McBride & Coppin,

1970), exposure time was calculated from drivers' responses to a questionnaire about how often and under what circumstances they drove. The studies found increases in the accident rate both for older drivers (over 60) as well as for younger, teenaged drivers. Ferdun, Peck and Coppin (1967) found that exposure time was more important than age in determining accident rates of teenage drivers. The number of accidents of sixteen-year-olds did not differ significantly from that of 19-year-olds. However, since the 16-year-olds drove less, equating exposure times gave them a higher accident rate.

Although it is relatively easy to establish that drivers within certain age groups have higher accident rates, finding the reasons for these higher accident rates is considerably more difficult. Many variables correlate with the age of the driver. For one thing, different age groups drive at different times during the day. Perhaps predictably, the younger group had a higher percentage of night driving than the older groups. Approximately 31% of the driving by males under 20 occurs at night, compared to 23% for males 30 to 34 and only 8% for males over 65 (Solomon, 1964). Younger drivers also have a greater proportion of accidents on weekends than older drivers (Campbell, 1966). Thus, such factors as poorer visibility at night or greater traffic density during weekends may contribute to their high accident rate.

Various personality factors have also been suggested as possible contributors to the accidents of young drivers. Sobel and Underhill (1976) used structured psychiatric interview techniques to measure social stress and family dysfunction of 496 randomly selected teenage drivers in New Hampshire. They found that such factors as rebelliousness and pathologic family life were associated with traffic accidents for teenage males, but not for females. Other investigators have associated traffic accidents for teenage males with impulsiveness, lack of self confidence, and selfishness (Beamish and Malfetti, 1962) as well as with psychopathic deviance and

hypomania as revealed through their scores on the Minnesota Multiphasic Personality Inventory (Rommel, 1959).

Such psychological correlates of accident involvement are not limited to the young driver, however. Shaffer, Schmidt, Fisher, and Zlotowitz (1974) report that family and friends of fatally injured male drivers, regardless of age, rated the dead driver more belligerent, negative, withdrawn and hyperactive on the Katz Adjustment Scales than the normative means for these scales. Similarly, Harano, Peck, and McBride (1975) found that drivers of any age who reported being dissatisfied with life and driving to "blow off steam" or to think about problems had more accidents, as did drivers who sought a high degree of danger in their recreational activities or who had more non-vehicle accidents. It is unlikely, though, that personality factors alone can account for the high rate of accidents among young drivers.

Few of the factors suggested to explain the high accident rate of the young driver have also been proposed to account for the increased accident rate of the elderly driver. One characteristic that they share, however, is driving older vehicles (Solomon, 1964). Perchonock (1977) examined the hypothesis that vehicle age contributes to the high accident rate of both groups. His data show, however, that with the age of the automobile held constant, younger drivers are still significantly more likely to be the culpable drivers in accidents. That is, when the vehicles involved are the same age, the younger driver is more likely to have caused the collision. The data were insufficient to allow a similar analysis with older drivers, although there was a trend in that direction. These results indicate that vehicle age does not determine the high accident rate of old and young drivers.

One surprising similarity between these two sets of drivers concerns perceptual style. Both groups are more field dependent than drivers in the middle range (Panek, Barrett, Sterns, & Alexander, 1978, p. 411). Field

dependence refers to difficulty in disregarding irrelevant or confusing stimuli to focus on the task at hand. It is usually measured by one of two methods: (1) the Rod and Frame Test, in which the person must orient a luminous rod to true vertical while it is suspended within a frame tilted at an angle, or (2) the Body Adjustment Test, which measures the individual's ability to orient himself to true vertical while the room tilts away from upright.

A correlation has been established between field dependence and automobile accidents. Harano (1970) compared 28 drivers with accidents to 27 persons with no accidents, and found a significant difference in their field dependence scores. Those who were more field dependent had more accidents. Another study, conducted by Mihal and Barrett (1976) found that commercial drivers who were field dependent had worse accident records. Field dependent drivers in this study made more errors on tests of selective perception, indicating difficulties in selecting crucial information from an array of complex, irrelevant stimuli.

Any visual distraction decreases the driving efficiency of field dependent drivers, who take longer to process visual information and have less effective patterns of visual search while driving (Shinar, Zaidel, & Pearlberg, 1977). In a test of driving skills conducted in a simulator, field dependent persons had significantly slower reaction times and deceleration rates and were more likely to hit a pedestrian who emerged from a shed onto the road (Barrett and Thornton, 1968). These data suggest that higher instances of field dependence in young and old drivers may contribute to their higher accident rate.

Any countermeasure that simplifies the driving environment should benefit these drivers. For example, Rackoff and Mourant (1979) suggest that field dependent drivers could be aided by larger (and fewer) traffic signs as well

as by simplified design of automobile controls and dashboards. Johnson and Cole (1976) recommend decreasing the amount of roadside advertising because the high content of attention-getting but irrelevant information distracts drivers, particularly those who are field dependent.

Certainly, for the older driver a likely explanation for higher accident rates centers around a decline in both sensory and perceptual abilities. People over 60 generally have poorer visual acuity, especially night vision (McFarland, Tune, & Welford, 1964). Perceptual-motor reaction times and selective attention skills also begin to decline as early as the late forties (Panek et al., 1978), as does the ability to discriminate information that is important to safe driving from irrelevant information (McFarland et al., 1964).

Reflecting the loss of these particular abilities, the accidents of the older driver are likely to result from information failure, pulling out in front of another vehicle, or turning improperly. Accidents of younger drivers are more likely to result from failure to maintain control (Perchonock, 1977) or from speeding, which is the most frequent violation of drivers up to middle age (Harrington & McBride, 1970). For example, the older driver frequently fails to obey signs (Harrington & McBride, 1970). A study by the Indiana University Institute for Research in Public Safety found that drivers over 65 were twice as likely to have accidents due to improper lookout as other drivers (Treat, Tumbas, McDonald, Shinar, Hume, Mayer, Stansifer, & Castellon, 1977). Zaidel, Pearlberg, and Shinar (1978) found that improper lookout was a causal factor in 50% of the negligent accidents for males over 65. They interpret this finding as indicating a decline in perceptual abilities rather than sensory processes such as visual acuity.

While the older driver relies on his years of driving experience to compensate to some extent for the loss of these abilities, the younger

driver's mistakes may be traceable to the difficulties inherent in mastering any new skill. It has been suggested that the high accident rate for teenagers relates directly to inexperience. In a study designed to assess the desirability of raising the licensing age in California, Ferdun, Peck, and Coppin (1967) found that for teenage females the total number of miles driven in life was significantly related to accidents. As experience increased, accidents decreased. However, this experience effect was not found for male drivers. The higher accident rate for younger teenage males was a function of age alone, not driving experience. Pelz and Schuman (1971) also found that accidents and violations for males were related to age effects, not to experience. Their accident rate peaked at age 18-19, regardless of how much experience the driver had before this age. For males it appears that immaturity and not inexperience per se relates to bad driving habits.

Since inexperience does at least contribute to accidents for young females, one obvious countermeasure would appear to be drivers' education. However, evidence for a beneficial effect of drivers' education is scant. Ferdun et al. (1967) found no differences in accident rates for young drivers who had taken drivers' education and those who had not. It should be noted that all of their drivers had had at least one year of driving experience, and there is some evidence that during the first year of driving both male and female drivers with drivers' training have fewer accidents (Goldstein, 1972; Crosley, 1976), but that this advantage later disappears (Harrington, 1971, cited in Goldstein, 1972). In a survey of the literature on drivers' education, Kaestner (1968) concludes that, in general, driver improvement procedures do reduce violations but not accidents.

Sex

The age of the driver interacts with the sex of the driver in determining accident rates. Young males have worse driving records than young females. Peck,

Coppin, and Marsh (1967) found that males had three times as many citations and twice as many accidents as females, but that these differences decreased with age. For the elderly driver the accident rate is reversed, with females over seventy having a higher accident rate than males (Solomon, 1964).

There is no clear evidence that one sex drives more safely than the other. Males have more accidents, but they not only drive more than females, they also tend to drive at more hazardous times than females. Campbell (1966) found that males drive more on weekends, when there is greater traffic density, and younger males drive more at night, when visibility is reduced. Solomon's study (1964) of rural roads found that 93% of the nighttime drivers were male.

With driving exposure time equated, Weber (1975) found no differences in accident involvement for males and females. This finding was corroborated by Perchonock's discovery (1977) of nearly equal culpability rates for the two sexes. Given that they had been in a accident males and females were equally likely to be the negligent party. There are, nevertheless, detectable differences in driving style for the two sexes. Using a driving simulator, Hagen (1975) found that males drive closer to the center line, drive faster, and were less consistent in operating the accelerator, all of which might be expected to contribute to accidents.

Marital status also interacts with the sex of the driver in determining accident rate. The Peck, Coppin, and Marcs study (1967) showed that married females have better driving records than single females. In general, this relation holds for males also, with the exception that married males in the youngest age group considered (under 20) had worse records than their single counterparts. This relationship perhaps indicates the existence of a set of demographic and personality variables which relate both to early marriage and to involvement in accidents.

The issue of the relationship of these sorts of variables to accidents is very complex. Sobel and Underhill (1976) correlated a number of demographic, attitudinal, social, and personality factors obtained from interviews conducted with a random sample of New Hampshire drivers, aged 16 to 19, and their parents. The only important predictor of female involvement in an accident was exposure: those who drove more had more accidents. For males, however, accidents correlated with rebelliousness, sexual activity, alcohol and cigarette use, and a pathologic or disorganized family life. Females from pathological family backgrounds showed more depression than aggression, the reverse of the male pattern, which may account for the different pattern of factors related to accidents.

Alcohol

The influence of alcohol use on driving is perhaps more difficult to isolate than the influence of any other driver characteristic available from drivers' records. Estimates of alcohol involvement in fatal accidents range from 25% to 80 or 90% (Young, Valentine, & Williams, 1977), with a conservative estimate of 36% (Zylman, 1974) being a probable figure. While alcohol use obviously adversely influences driving skills in a number of ways, it also interacts with several other factors.

For example, most drinking drivers are male. In a study by the University of Michigan Highway Safety Research Institute in which drivers were randomly stopped and asked to take an alcohol breath test, 12% of male drivers had blood alcohol concentrations (BAC) of 0.05% or higher compared to 4% of female drivers (Carlson, Clark, Compton, Douglass, & Filkins, 1971). Both Clay (1974), using Michigan drivers' records for that state's alcohol countermeasures program, and Whitehead (1975), in a Canadian study, found that drinking drivers were more likely to be male. More dramatically, a Minnesota study revealed that 93% of all driver fatalities with alcohol involved

were male (Goldstein, 1972).

The age of the driver is also correlated with driving after drinking. Whitehead found that 84% of his DWI offenders were between 20-54 years of age, which duplicated the finding of Research Triangle Institute (1971). Thus, the two high-risk age groups, drivers under 20 or over 55, drive less after drinking than the middle age range. The fact that the legal age for purchasing alcohol at the time of this study was 21 in most states may account for the relative infrequency of driving after drinking in the younger age range. The post-55 driver is characterized by greater cautiousness, driving at slower speeds, and avoiding heavily travelled roads, which may account for fewer instances of driving while intoxicated in this older age group.

Other variables that Whitehead found to correlate with driving while intoxicated were social class, with more working-class drivers drinking, and marital status, with more single, separated, or divorced drivers drinking. As Whitehead noted, however, there is a strong possibility of bias in the sample since the survey was conducted in a working-class area where drunken driving was known to occur.

Drinking drivers are also more likely to commit certain kinds of traffic violations. Speeding, especially, increases with the use of alcohol (Waller and Goo, 1969; Research Triangle Institute, 1971). The Research Triangle Institute study examined data from accidents in North Carolina for 1966, 1968, and the first half of 1969 with regard to alcohol involvement, sex and age of driver, vehicle type and condition, and speed. They found that males, particularly in the 25-54 year age range, were much more likely to have been drinking if they were speeding at the time of the accident. For drivers who were travelling at 50-59 miles per hour, approximately 20% had been drinking at the time of the accident, and approximately 75% of drivers in the 70 mph or greater category were judged to have been drinking.

The study by Waller and Goo used California police reports of driving

errors and citations to examine the performance of persons diagnosed as alcoholics and of the medically or "psychosocially" impaired. Their results also indicate that alcoholics had more accidents which involved excessive speed than drivers in control groups. In addition, alcoholics were found to make more passing errors and drive on the wrong side of the road more frequently than drivers in the control group. Related to this pattern of driving errors is the finding that the accidents of drinking drivers result more often from failure to maintain control of the vehicle than from information failures, which account for most of the accidents of non-drinking drivers (Perchonock, 1977).

Personality characteristics also appear to interact with types of convictions for drinking drivers. Pelz (1973) found a link between hostility, drinking, and high accident rates. Similarly, drivers in Michigan's alcohol countermeasures program committed significantly more "high-risk" violations, even when not drinking, than a control group of other Michigan drivers (Clay, 1974). Their pattern of violation involved actions described as impulsive, aggressive and irresponsible. Clay suggests that the relationship between drinking and automobile accidents may be mediated by these personality traits. That is, an impulsive, aggressive, irresponsible person is more likely not only to be involved in an accident but also to drive while drinking.

Even drivers' training experience interacts with alcohol use and driving practices. Wuerdeman (1976) found that for drivers under 25 who had a BAC of 0.15% or higher, those who had not taken drivers' training were nearly twice as likely to be in an accident as those who had, perhaps because the latter learned something in the course which helped them to avoid accidents after drinking. On the other hand, it might simply indicate that more cautious persons take drivers' training as well as drive more prudently after drinking. As is the case for most benefits of drivers' training, this effect disappears after age 30.

Certainly, some drivers who have been drinking apparently try to compensate for their state by their driving behavior. For one thing, they try to avoid busy roads. Carlson (1971) found that 27% of the after-midnight drivers on less travelled roads had BAC's of 0.05% or greater, while only 15% of drivers on the high volume roads met this criterion. The drinking driver apparently assumes that he can decrease the chance of accidents or arrests by choosing the low volume, less-policed, roads. That this strategy generally succeeds, with regard to arrests at any rate, is attested to by Whitehead's finding (1975) that 75% of those arrested for DWI had no previous arrest for it.

As a result of this finding, Whitehead suggests that the most effective program for decreasing driving under the influence of alcohol would be directed at the large group of drivers who drink but have not been caught. He advocates well-publicized, random breath testing, coupled with lower blood alcohol standards and vigorous enforcement. Such an approach could hardly be less successful than previous countermeasures directed at the drinking driver. Most have failed to reduce drunken driving (See Hales, Williams, & Young, 1977, for a survey of alcohol countermeasures). The most successful strategy to date seems to be simply suspending or revoking the driver's license (Hagen, 1977; Hagen, Williams, & McConnell, 1979).

Prior Convictions and Accidents

Researchers have found that type of traffic violation varies with age and sex categories of drivers. In addition, an association between accidents and prior convictions for traffic violations has been identified. Men are more likely to be convicted of speeding, equipment, passing, and major violations than women, while women have a higher rate for sign and right of way violations (Harrington & McBride, 1970). Related to sex differences and type of violation is the issue of sex differences and the prediction of future

accidents based on number of violations. O'Neill (1968) correlated prior violations with accidents, using the population of drivers in Washington, D.C. She found a statistically significant difference between males and females regarding the probability of accident involvement as citations increased. As the number of their violations increased, males were more likely to be in an accident than females with the same number of violations. Thus, the number of previous traffic violations is a better predictor of accident involvement for males than for females.

O'Neill obtained similar results for drivers under the age of thirty compared with those over thirty. The number of citations was a better predictor of those drivers under age 30. Drivers over the age of 30 with multiple citations somehow manage to avoid accidents more successfully. Based on these different relationships between prior convictions and accident involvement for the different groups of drivers she recommends the adoption of different standards for the deployment of countermeasures. For example, a 16-year-old male might receive a warning letter only after one citation, while a 40-year-old female might not receive the letter until her third citation.

Several investigators have examined the predictive relationship between prior convictions and future accidents. Peck, McBride, and Coppin (1970) found that accidents increased as a driver's violations increased, regardless of the type of violation. While speeding had the highest absolute correlation with accidents, the best predictor was still the total number of one-count convictions.

Shuster's study (1966) of youthful drivers revealed that moving violations in the previous three years were a better predictor of accident involvement than any of the biographical or attitudinal variables he considered. Similarly, Harano (1975) found that for repeat traffic violations the number of previous convictions predicted accidents better than such

psychological variables as responsibility, emotional stability, and cautiousness as measured by the Gordon Personal Profile.

When drivers are categorized on the basis of having had several accidents or having been the culpable driver in a serious accident and compared to other drivers who are either accident-free or not legally culpable, the association between prior convictions and accident involvement becomes even greater. Harano, Peck, and McBride (1975) selected two groups of male drivers, one group which had been involved in three or more accidents in a three-year period and another group which was free of accidents during that time. Of the 337 variables they considered, 140 significantly differentiated the two groups. After a cluster analysis and a regression analysis were performed to reduce the number of variables, six variables or "cluster domains" remained, including citation frequency. Drivers with three or more accidents had more convictions on their driving record than drivers who had no accidents.

A similar study by Banks, Shaffer, Masemore, and Fisher (1977) paired 82 drivers who had been in fatal accidents. Forty-one of the male drivers had been judged legally innocent in regard to the accident, while the other 41 with whom they were matched were legally culpable for the same accident. The culpable drivers had three times as many prior violations as the innocent drivers.

In comparing the predictive value of past convictions vs. past accidents, most investigations have found past convictions to be a more stable indicator of future accidents than past accidents (Burg, 1970; Peck, McBride, and Coppin, 1970; Harano, 1975). Burg suggests that the greater number of citations relative to accidents makes them less a function of chance and thus improves their predictive value.

While acknowledging the relationship between prior convictions and

accident involvement, some researchers maintain that past accidents also predict future accident involvement. For example, Kwong, Kuan, and Peck (1976) found that both past accidents and violations discriminated between drivers who had an accident during a certain time period from those who did not. Stewart and Campbell (1972) contend that if the proportion of drivers with accidents or violations in a two-year before period who had accidents in the two-year after period is used as the measure, then prior accidents becomes the better predictor. For example, for prior violations, the proportion never rises above 0.30 regardless of how many violations the driver had, but for a driver with seven or more prior accidents the proportion who had accidents in the after period rises to 0.70. When the data are examined in this manner it appears that past accidents may be able to predict future accident involvement better than past convictions. However, the small number of drivers in this extreme category limits the usefulness of this approach. For example, there were only six drivers in the seven-or-more-accident category, of whom two had no accidents in the after period, two had one, and two had two collisions.

The finding that past traffic convictions and/or accidents correlate with future accidents does not mean that accident rates could be dramatically reduced by removing drivers with several violations or accidents from the road. Most American accidents involve drivers who were previously accident-free. Using California drivers, Burg (1970) found that approximately 70% who were involved in an accident during a three-year period had been free of accidents in the previous three years.

These findings agreed with Forbes' early discovery (1939, 1972) that 80% of the drivers who had an accident had not been in an accident in the previous three years. Most drivers who have accidents have never had one before.

Neither would the revocation of the licenses for drivers with extremely deviant violation records reduce the accident rate significantly. In a study of North Carolina drivers, Stewart and Campbell (1972) found the same proportions as Burg: of drivers who had four violations in a two-year period 30% had an accident in the next two years, but 70% had none.

Similarly, Robertson and Baker (1975) looked at the violation records of drivers involved in fatal crashes in Maryland during 1970-1971. They found that drivers with four or more convictions were nine times as likely to be involved in fatal accidents as drivers with no prior convictions. However, only five percent of the drivers in fatal accidents had four or more convictions and 52% of the drivers had no prior convictions at all.

These studies show that while it is possible to predict that drivers with high accident and/or conviction rates will be more likely to be involved in future accidents, these drivers will nevertheless account for only a small percentage of total accidents. Countermeasures directed at this group of drivers will not greatly reduce the overall accident rate. As several studies indicate, countermeasures need to be directed at large numbers of the "normal" driving population to be effective (Burg, 1970; Peck, McBride, and Coppin, 1970; Robertson and Baker, 1975). For example, Peck et al. (1970) suggest a program of driver re-training directed at the general driver population. Alternatively, a large variety of countermeasures might be tailored to specific high-risk drivers who have had no previous accidents or violations, such as teenage drivers, the elderly, or drunken drivers, as well as the habitual offender. The need for nontraditional approaches to driver improvement is revealed in the failure of the usual lecture-oriented programs to reduce accidents (Peck et al., 1979). Targeting specific groups with materials designed for their particular deficiencies, and employing active, skill-oriented techniques for learning, rather than passive, instructor-

centered ones, might be more effective in improving driving skills and reducing the potential for accidents.

DATA ANALYSES

The purpose of the analyses described in this report is to compute the probability of having a future accident as a function of past accidents, convictions, and other variables. Regression analyses are commonly performed using accidents as a predictor variable when the error term is assumed to be normally distributed with mean 0 and constant variance. A more legitimate assumption is that accidents follow a negative binomial distribution. It is assumed that accident data follow a Poisson distribution with a large portion of drivers having either zero or one accident. In many instances, a Poisson distribution provides an adequate fit to the data and has the added advantage that tests of inferences are easier to perform.

The validity of the assumption that the accidents follow a Poisson distribution was tested by Weber (1970). Weber divided a sample of 148,000 individuals, taken from the 1964 California Driver Record Study, into 2880 groups according to sex, marital status, age, area of residence, conviction history, and accident history. Accident distributions were obtained for the 193 groups which contained at least 100 or more individuals. Weber found that for 86.5% of the groups the hypothesis of a Poisson distribution was acceptable at the 0.05 level.

Estimates for the parameters of the regression equation

$$y = B_0 + B_1x_1 + B_2x_2 + \dots + B_kx_k$$

are obtained using an iterative re-weighted least squares procedure outlined in Appendix A. Here y represents the number of accidents in the two-year after period and x_i ($i=1, \dots, k$) are the explanatory variables such

as prior accidents or convictions. An explanation as to how the estimates might be obtained using an ordinary least squares procedure is provided in Appendix B.

Males and females were analyzed separately as they represent two distinct populations with regard to the likelihood of having an accident. The data set was divided into a 3-year before period and a 2-year after period. The purpose of the analyses is to identify those variables which contribute to the likelihood of having a future accident. The variables considered for entry into the Poisson regression are listed in Table 1.

TABLE 1
VARIABLES

IAGE	1/AGE (females)
CAGE	$1/(\text{AGE})^3$ (males)
DRIV-EDU (driver education)	$\begin{cases} 0 & \text{no} \\ 1 & \text{yes} \end{cases}$
LISC-CO (commercial license)	$\begin{cases} 0 & \text{no} \\ 1 & \text{yes} \end{cases}$
LISC-CH (chauffer's license)	$\begin{cases} 0 & \text{no} \\ 1 & \text{yes} \end{cases}$
LISC-MO (motorcycle license)	$\begin{cases} 0 & \text{no} \\ 1 & \text{yes} \end{cases}$
NBSPEED (speeding violations)	
NBRSFYRW (failure to yield right of way)	
MISC (all other violations)	
NBMVA (negligent multi-vehicle accidents)	
NNBMVA (non-negligent multi-vehicle accidents)	
NBSVA (negligent single vehicle accidents)	
NNBSVA (non-negligent single vehicle accidents)	

The same variables were considered for entry into the model for both males and females with the exception of the age variable. For females the age function was decided to be of the form $\frac{1}{AGE}$. From a plot of mean number of after accidents as a function of before accidents a mildly down-sloping curve is observed which can be adequately modelled by a function of the form $\frac{1}{AGE}$. Accidents in the after period peak with the youngest group considered, the 20-year-olds, and then decline to age 35 at which point they level off. See Figure 1 for a plot of mean after accident rates versus age for females.

Although the curve is similar in shape for males, it decreases much more sharply. The 20-year-old males have a much higher accident rate than the 20-year-old females. This rate declines precipitously up to about age 30 and then levels off. For the males a function of the form $\frac{1}{(AGE)^3}$ provided a better fit. A plot of mean after accident rates versus age for males is shown in Figure 2.

Although the plot of mean accident rates versus the number of before accidents shown in Figure 3 might imply a nonlinear relationship, the relationship is basically linear when accidents are broken down by categories. As the number of accidents in the before period increases so does the accident rate in the after period. As shown in Figure 4, similar results were obtained for mean after accident rates versus number of before convictions. Greater numbers of convictions in the before period were related to a greater likelihood of accidents in the after period.

Only the results of model fitting will be discussed here. Refer to Appendix B for further details.

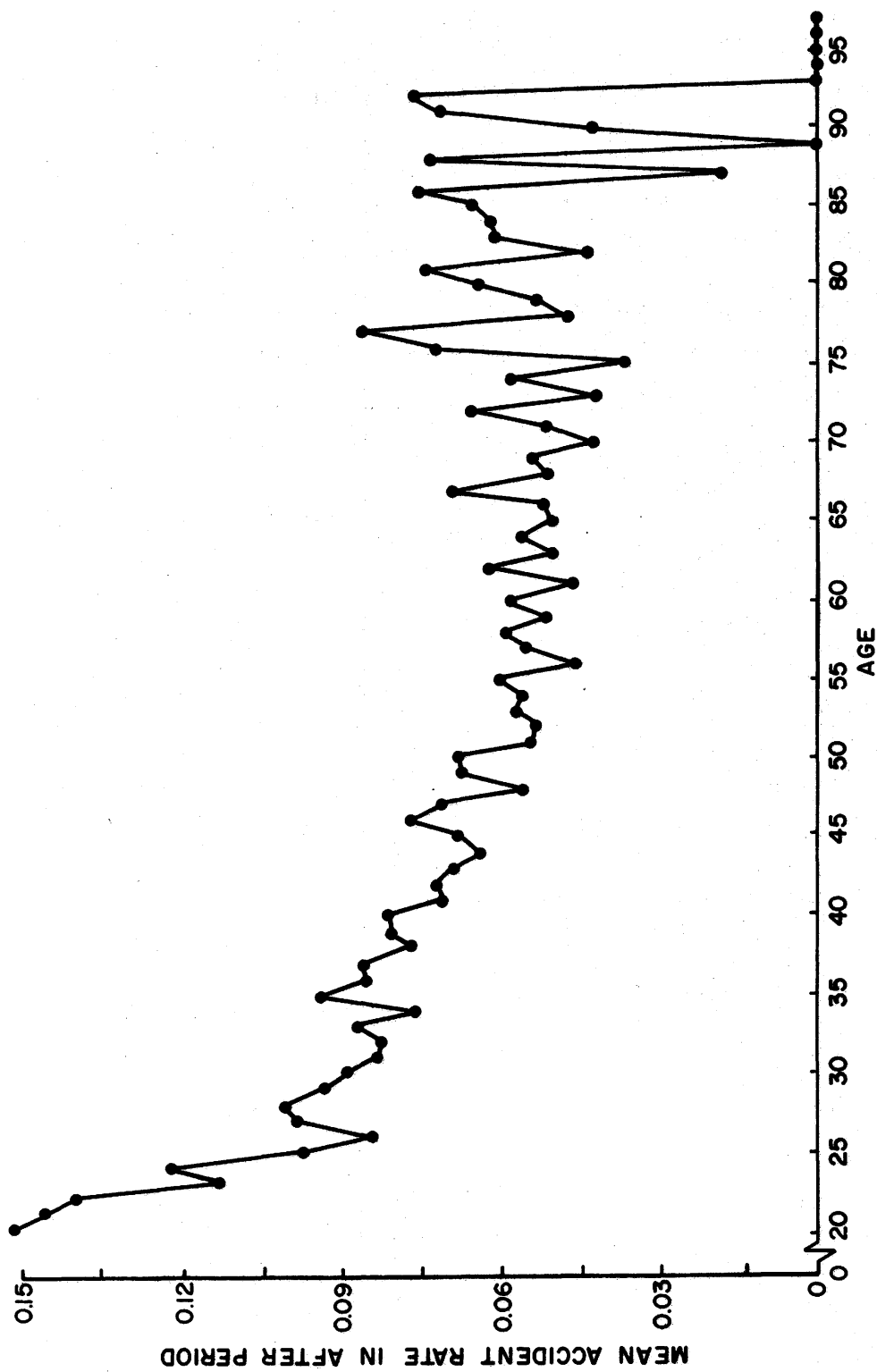


Figure 1. PLOT OF MEAN ACCIDENT RATE IN AFTER PERIOD BY AGE: FEMALE DRIVERS.

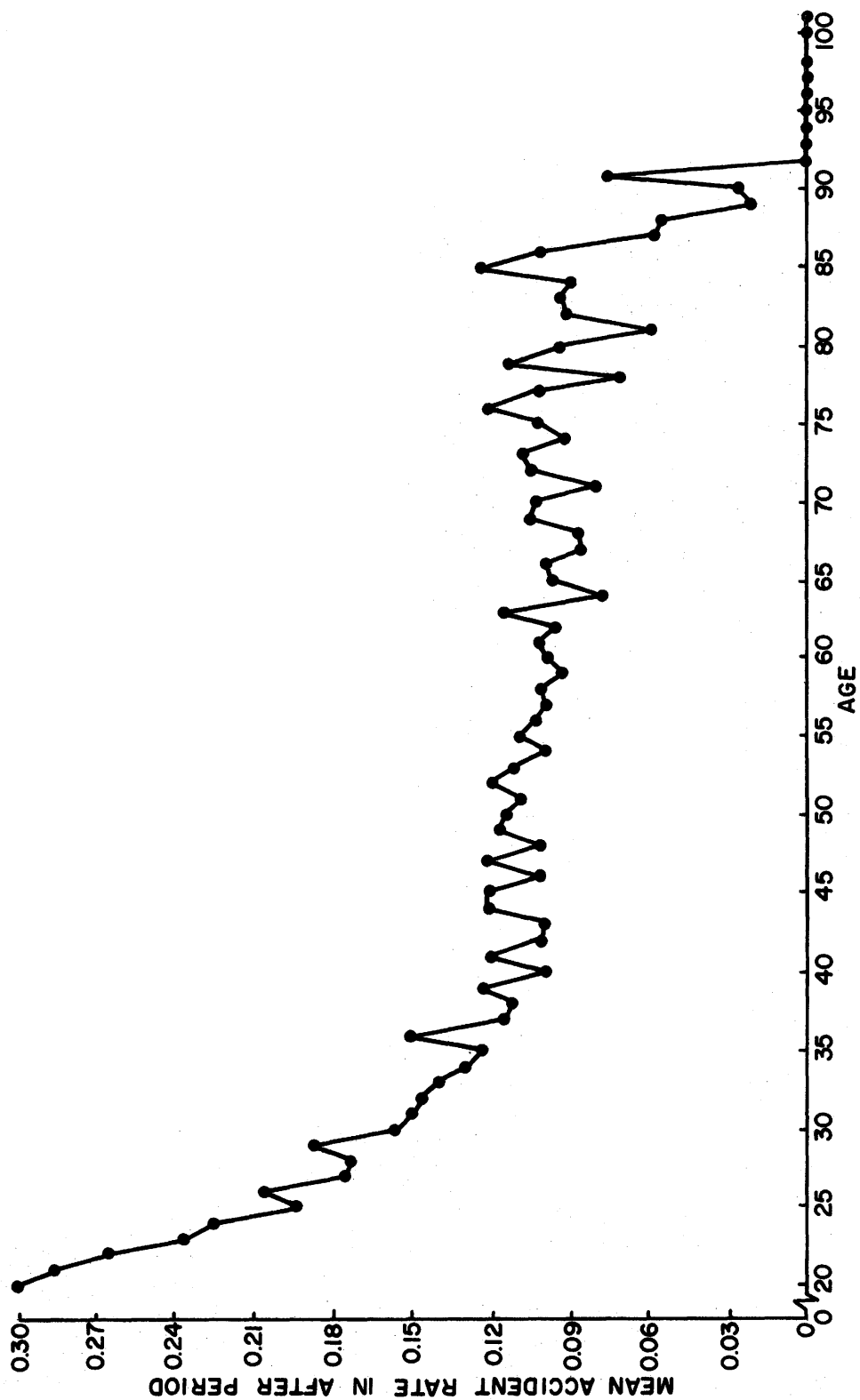


Figure 2. PLOT OF MEAN ACCIDENT RATE IN AFTER PERIOD BY AGE: MALE DRIVERS.

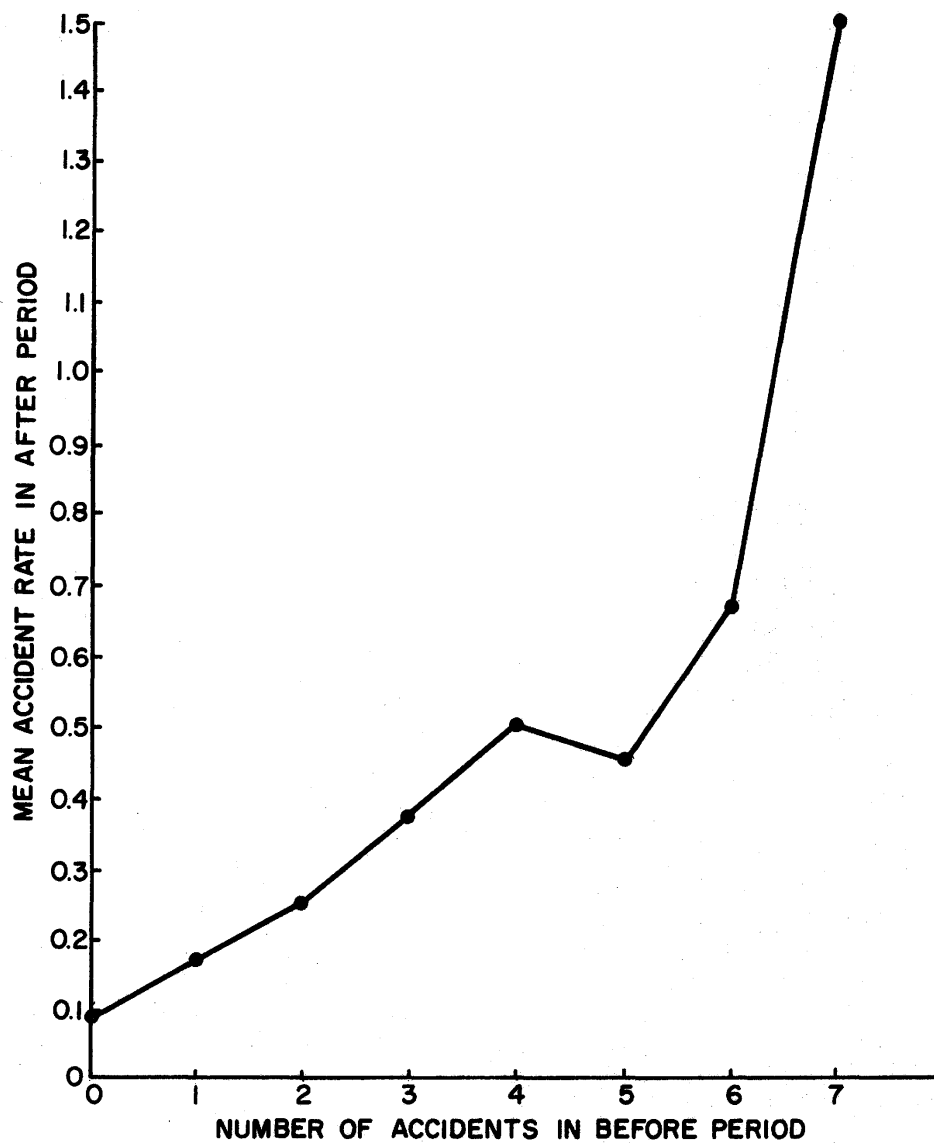


Figure 3. PLOT OF MEAN ACCIDENT RATE IN AFTER PERIOD BY NUMBER OF TOTAL ACCIDENTS IN BEFORE PERIOD.

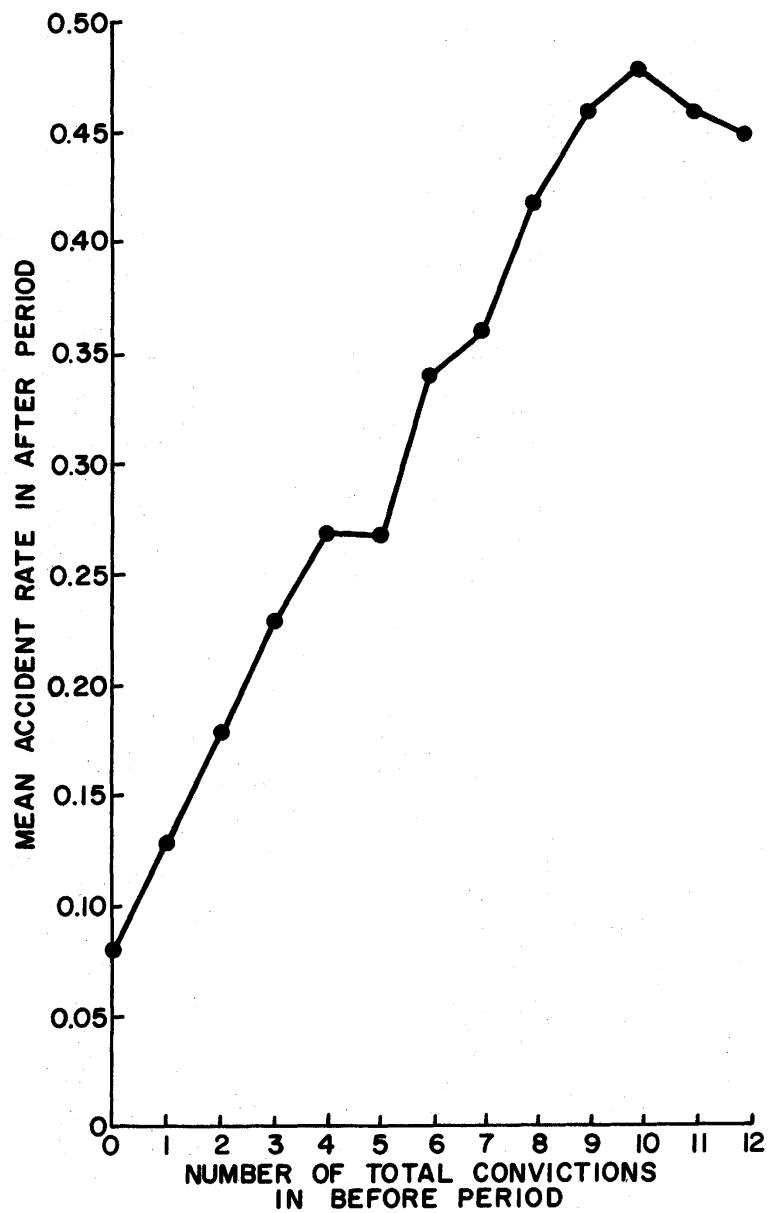


Figure 4. PLOT OF MEAN ACCIDENT RATE IN AFTER PERIOD BY NUMBER OF TOTAL CONVICTIONS IN BEFORE PERIOD

Analysis of Males

Preliminary analyses using ordinary least squares (OLS) indicated that DRIV-EDU and LISC-M0 were not even marginally significant. They were therefore not included in the Poisson regression. The final model selected is given as

$$\begin{aligned} y = & 0.05798 + 1034.81\text{CAGE} + 0.02678\text{LISC-CO} \\ & + 0.05414\text{LISC-CH} + 0.02598\text{NBSPEED} + \\ & 0.04520\text{NBRSFYRW} + 0.05263\text{MISC} + 0.07078\text{NBMVA} \\ & + 0.04525\text{NNBMVA} + 0.08165\text{NBSVA} + 0.06737\text{NNBSVA}. \end{aligned}$$

All parameters in the final model were significant at $\alpha < 0.01$.

Considerable emphasis has been placed on the young driver as a high accident risk. Using the above equation, it is possible to estimate the effect of age relative to other variables such as prior convictions or prior accidents. Consider a 20-year-old, for instance, with no prior violations or accidents. Such an individual has an expected accident rate of 0.1874, while a 30-year-old who also has a perfect record for the past three years would have an expected accident rate of 0.0963. In other words, the 20-year-old will be twice as likely to have an accident during the next two years. The decline in expected accident rate is less dramatic after age 30.

In addition to age, past accident record should be taken into account. It is clear from the regression equation that prior accidents are more important in determining the likelihood of a future accident than prior violations. For example, consider a 30-year-old with one negligent single-vehicle accident in the previous three years but with no violations. His expected accident rate is 0.1779, which is almost as high as that of a relatively inexperienced 20-year-old with a clean record.

Although violations are of less importance in predicting the likelihood of a future accident than prior accidents, as few as two prior violations can move the 30-year-old driver into the same risk category as a 20-year-old driver. Consider a 30-year-old driver with two violations for failure to yield right-of-way but no prior accidents. His accident rate would be 0.1867, which is nearly the same as that of a 20-year-old with a clean record. For further examples of potential accident rates for different age groups, refer to Figure 5.

Although age is important in determining the likelihood of a future accident, particularly for the driver under 30, youth in and of itself is insufficient to put an individual in the same category with chronic violators. Both prior accidents and violations are better predictors of future accidents than age.

Analysis of Females

Preliminary analyses using ordinary least squares indicated that DRIV-EDU, LISC-MO, and NNBSVA were not even marginally significant and they were therefore dropped from the regression equation. After fitting a Poisson regression model to the data, it was discovered that LISC-CO was not significant with $X^2 = 1.26$ and 1 degree of freedom. LISC-CO was then deleted and the Poisson regression was rerun. The following equation was obtained:

$$\begin{aligned} y = & 0.02188 + 1.49707\text{IAGE} + 0.04223\text{LISC-CH} \\ & + 0.03119\text{NBSPEED} + 0.03676\text{NBRSFYRW} + \\ & 0.04663\text{MISC} + 0.04726\text{NBMV} + 0.02519\text{NNBMVA} \\ & + 0.04980\text{NBSVA}. \end{aligned}$$

Significance tests using the chi-square distribution indicate that all parameters included in the final model are significant at $\alpha < 0.01$.

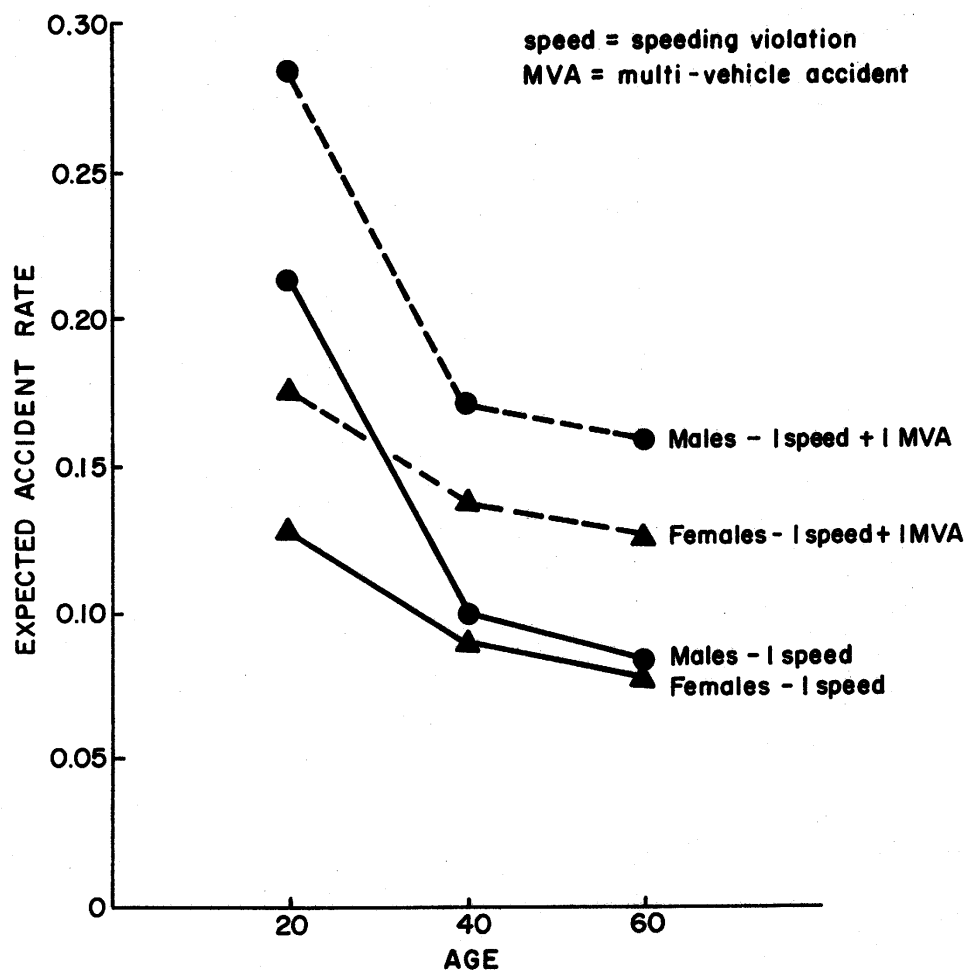


Figure 5. EXPECTED ACCIDENT RATES VERSUS AGE OF DRIVER

The most noticeable difference between the above equation for females and the one for the males is that the parameters are somewhat smaller in the above equation. Much of the difference may be attributed to differences in exposure as outlined in the previous chapter. As noted there, females drive significantly less than males.

Another major difference in the two equations is in the relative contributions of violations and prior accidents. For males, prior accidents made a much larger contribution than prior violations. For the females, prior accidents are roughly equal in importance to prior violations. Also, in the equation for females NNBSVA (non-negligent single-vehicle accidents) did not make a significant contribution towards explaining the likelihood of having a future accident and was therefore deleted. As was true for males, age in and of itself is not a sufficient reason to classify a female driver in a high-risk category.

For a comparison of potential accident rates under various driving records, the reader is referred to Figures 6 and 7 for male and female drivers respectively. Figure 8 shows the effect of accumulated violations and accidents on the accident rates of forty-year-old drivers. These figures demonstrate that as numbers of past violations and accidents increase so does the potential for future accidents. It should be emphasized that past accident record is equally important (more important in the case of males) to prior convictions in predicting the likelihood of future accidents.

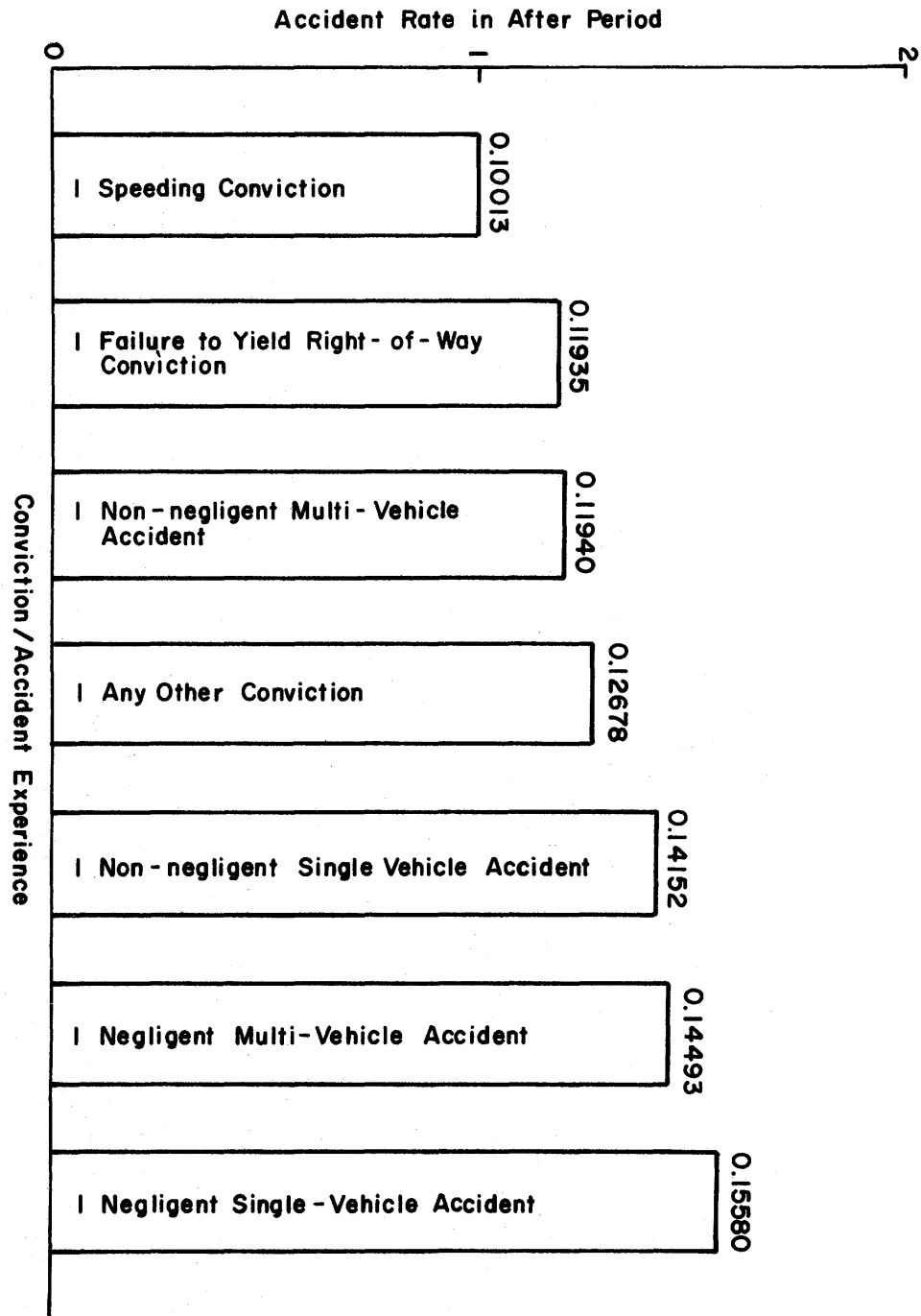
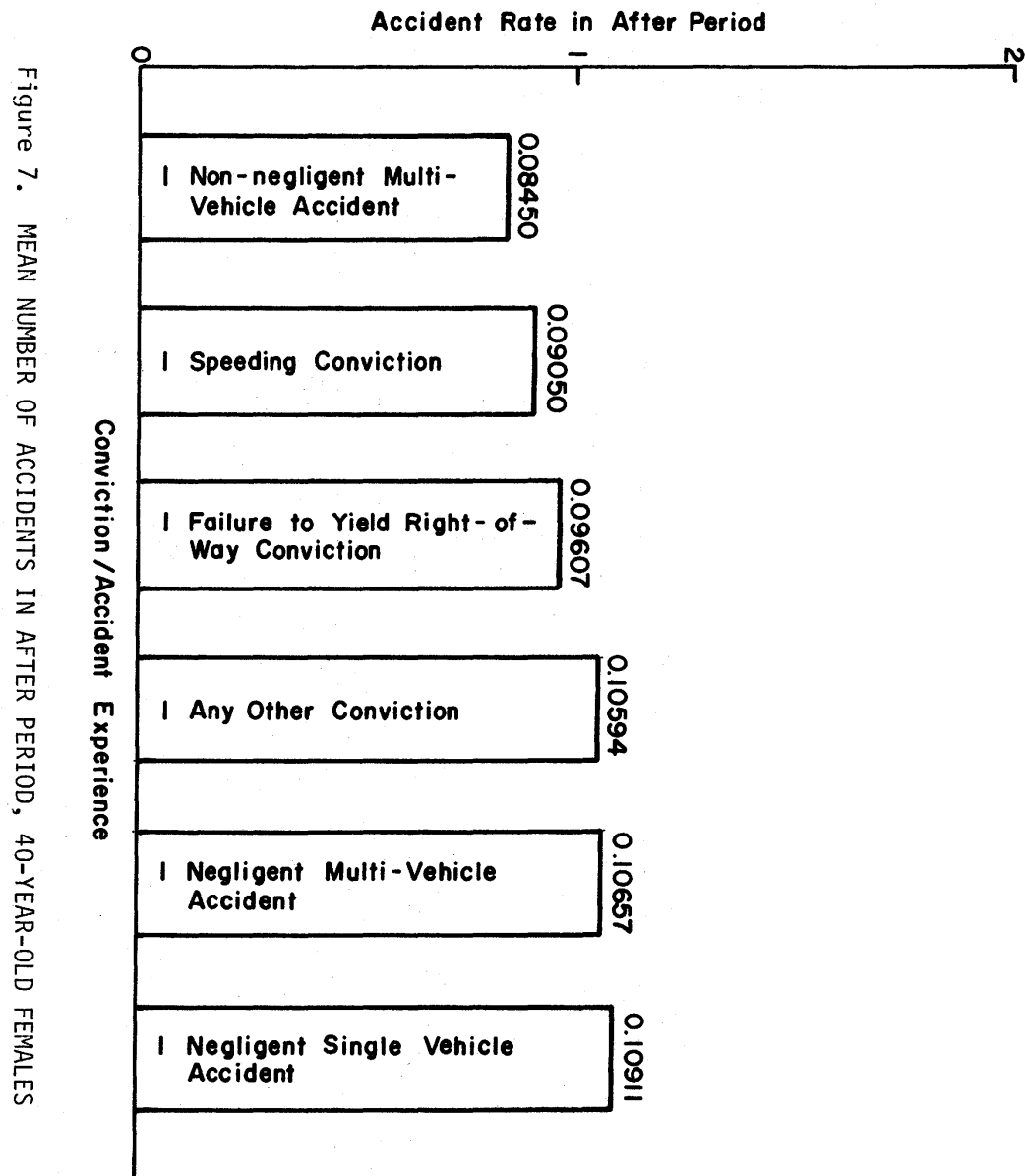
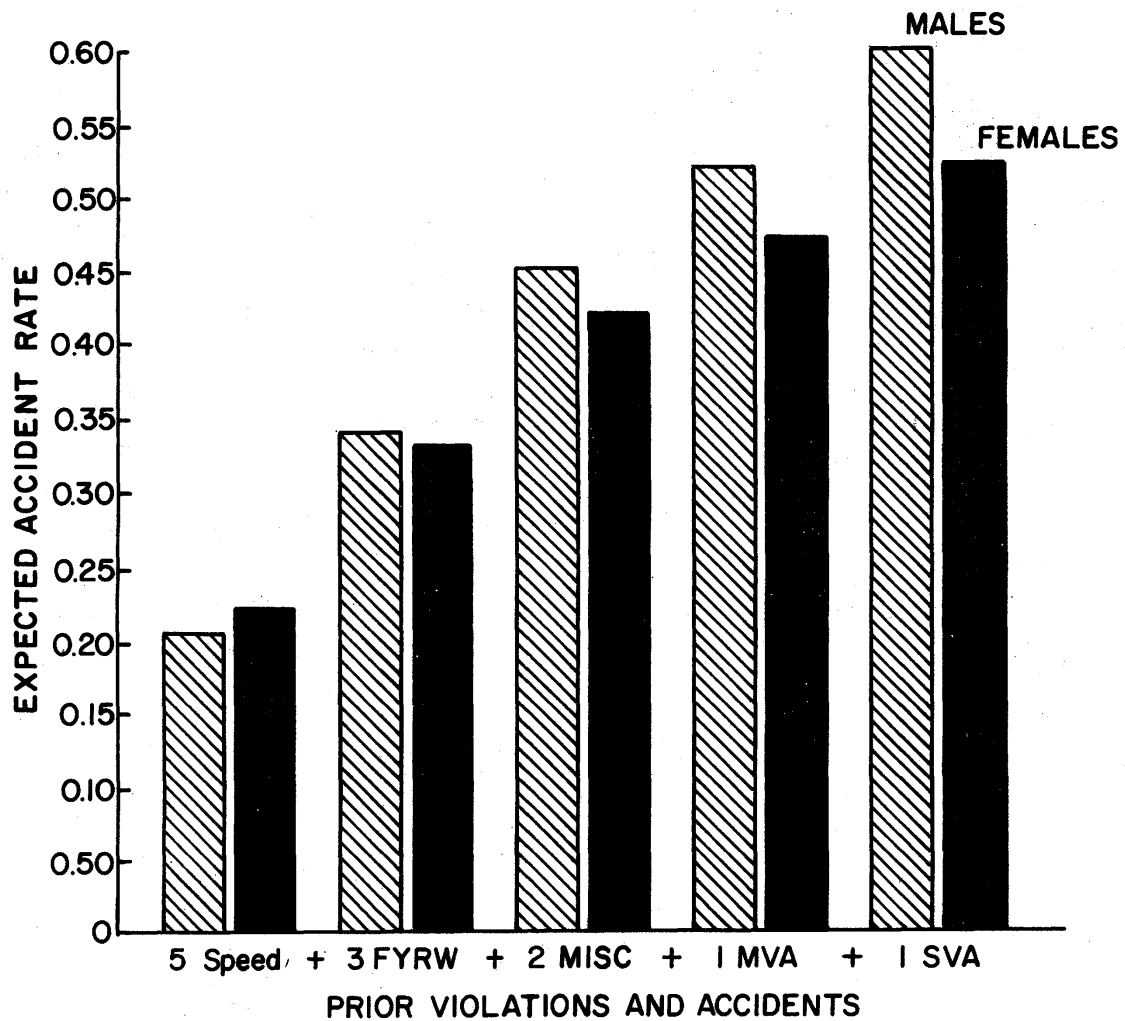


Figure 6. MEAN NUMBER OF ACCIDENTS IN AFTER PERIOD, 40-YEAR-OLD MALES





Speed = speeding violation
 FYRW = failure to yield right-of-way
 MISC = miscellaneous violations
 MVA = multi-vehicle accident
 SVA = single-vehicle accident

Figure 8. EXPECTED ACCIDENT RATES FOR FORTY-YEAR-OLD DRIVERS AS A FUNCTION OF ACCUMULATED VIOLATIONS AND ACCIDENTS.

CONCLUSIONS

Driver's age was found to be of considerable importance in predicting future accident involvement. Drivers under the age of 25, especially males, have more accidents, a finding which agrees with several previous studies on accident rates for drivers of different ages (Solomon, 1964; Ferdun, Peck & Coppin, 1967; Peck, McBride & Coppin, 1970; Perchonock, 1977). As shown in Figure 5, a 20-year-old male with one speeding violation and one multivehicle accident in the three-year before period is almost twice as likely as a 40-year-old or 60-year-old male to have an accident in the after period.

These results indicate the need for varying the criteria for license suspension for different age groups. Currently, administrative hearings on license suspension are scheduled for any license holder over eighteen who has four convictions in one year or seven in two years. Drivers under eighteen who hold provisional licenses are eligible for an administrative hearing if they are convicted of two moving violations within one year. Since the accident rate for the younger driver does not level off until the age of 25 or older, extending the more rigorous standard for an administrative hearing to drivers between the ages of 18-25 may be desirable.

The present findings reveal that after 25 age ceases to be a major determinant of accident involvement (refer to Figures 1 and 2). The lack of an increased accident rate for older (60 plus) drivers is probably due to the absence of information on exposure rates for the various age groups. Other studies have shown an increased risk for the older driver only after equating age groups on amount driven.

While driver's age contributes significantly to the prediction of future accidents, the best indicators of the likelihood of future accident involvement

are prior violations and/or accidents. For males, prior accidents, especially negligent accidents, provide the best single means of predicting future accidents. Prior convictions are not as good a predictor. Even drivers whose accidents were classified as non-negligent have a higher likelihood of future accident involvement than drivers with no previous accidents. These results support the conclusions of Stewart and Campbell (1972), who suggest that prior accidents are a better predictor of future accidents than prior convictions. For females, prior accidents and prior convictions contribute approximately equally to the probability of future accidents.

While administrative hearings may be scheduled for reasons other than convictions, including habitual recklessness and responsibility for an accident resulting in serious property damage or personal injury, those categories which relate to prior accidents are apparently only rarely used. For example, only 14 hearings were scheduled for habitual recklessness in Fiscal Year 1980, compared with 24,213 for habitual violators (Texas Department of Public Safety, 1980). The habitual violator is much more likely to have his/her license suspended than the driver who is involved in repeated accidents but manages to avoid convictions.

According to the results of our analysis, negligent accidents provide a better basis for predicting future accidents than violations and should be given more weight in assigning administrative hearings for license suspension. There are a variety of ways in which accidents could be taken into consideration. The simplest system would be to have separate sets of standards for hearings based on convictions and accidents. For example, a driver might be eligible for a hearing after four convictions within one year or after three negligent accidents within one year. Another method would combine accidents and convictions so that a driver with four convictions and/or accidents within one year would be called in for a hearing.

To some extent there will be overlap with either of these techniques since negligent drivers who have accidents will probably have been convicted of one or more violations at the time of the accident. However, since these drivers are more likely to be involved in future accidents than drivers who have multiple violations but no accidents, this "double counting" is in line with accident probabilities. In addition, this technique would identify those high risk drivers who are repeatedly involved in accidents, but who somehow manage to avoid convictions.

Again, different standards for the young driver are justified. This driver may need to receive an administrative hearing after only one negligent accident, or perhaps after one accident and one violation.

Regarding the point system which some states have instituted, there appears to be little justification for weighting different types of violations differently in determining the criteria for license suspension. The present findings corroborate Peck, McBride, and Coppin's recommendations (1970) that each violation should count equally. Even though speeding violations are more highly significant than any other variable but age, this result is probably due simply to the high number of speeding convictions. In fact, in terms of predicting future accidents, a speeding conviction is less important than other types of violations. For example, TTI's analysis indicates that a single violation for failure to yield right of way actually contributes more to the likelihood of a future accident than a speeding violation.

While speeding violations contribute less to the prediction of future accidents than right of way and miscellaneous violations, they nevertheless make a significant contribution to the likelihood of accidents and should be considered. Moreover, they should not be treated as less important than other violations. For one thing, speed influences the severity of an accident: accidents which occur at excessive speeds are more likely to cause serious

injury or death. Also, costs other than safety hazards must be considered. Increased fuel consumption due to higher speeds may justify giving the same weight to speeding violations as to other types of violations.

Although LISC-CH and LISC-CO were included in the regression equation for males and LISC-CH was included for females, and even though both variables had positive coefficients, there is no indication that chauffeurs or commercial drivers tend to be poorer drivers than the rest of the population. The different rates, although statistically significant, are most likely due to differences in exposure. These groups of drivers have more accidents because they drive much more frequently than other drivers. If exposure rates were equated their accident rate would probably be equal to or less than the rate for other drivers.

A final point should be emphasized. Regression equations based upon data from driver license files tend to have very low predictive power. For the ordinary least squares equation used to obtain initial values, females had an R^2 of only 0.016, and the comparable equation for males had an R^2 of only 0.039. This means that the regression equations left 98.4% and 96.1% of the variation unexplained for females and males, respectively.

Thus, although age, prior convictions, and prior accidents make significant contributions toward predicting the likelihood of future accidents, they account for only 2-4% of the factors involved in accidents. Other, possibly more important predictors of future accidents, such as stress, have not been included because such data are not readily available on driver license and history files or have not yet been identified as causes of accidents. Even questionnaires do not supplement the drivers record data sufficiently to result in a correlation large enough to account for most of the variability involved in accidents (Peck, McBride, & Coppin, 1970). To the extent that accidents result from transient or unknown causes, it will remain virtually impossible to develop a model with high predictive power.

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APPENDIX A
POISSON REGRESSION MODEL

APPENDIX A

POISSON REGRESSION MODEL

It is assumed that the number of accidents experienced by an individual follows a Poisson distribution, which can be expressed as:

$$\Pr\{Y(t) = y\} = p(y,t) = \frac{e^{-\lambda t} (\lambda t)^y}{y!}, \quad y = 0, 1, 2, \dots$$

$$\lambda > 0, t > 0,$$

where λ is defined as the accident rate potential of an individual.

Assuming that λ can be expressed as a linear function of k independent variables, then λ can be given as:

$$\lambda = E[Y(t)/t] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k$$

where the x_i represent the independent variables and the β_i represent the corresponding parameters. Then $p(y,t)$ is given as

$$p(y,t) = \frac{\exp \left\{ -t \sum_{i=0}^k \beta_i x_i \right\} (t \sum_{i=0}^k \beta_i x_i)^y}{y!}, \quad y = 0, 1, 2, \dots$$

$$t > 0,$$

where $x_0 = 1$.

Estimates for the parameters β_i from the regression equation

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k$$

will be obtained using a weighted least squares procedure in an iterative fashion. For simplicity, let $t = 1$. Then in matrix notation,

$$E(\underline{y}) = \underline{\lambda} = X\underline{\beta} \text{ and } \text{Cov}(\underline{y}) = V$$

where the diagonal elements of V are given as

$$V_{jj} = \sum_{i=0}^k \beta_i x_{ij} \text{ for } j = 1, 2, \dots, n,$$

and the off-diagonal elements are all equal to 0. The minimum variance unbiased estimator of β is given as

$$\hat{\underline{\beta}} = (\underline{X}'\underline{V}^{-1}\underline{X})^{-1}\underline{X}'\underline{V}^{-1}\underline{y},$$

and the variance-covariance matrix is given as

$$\text{Cov}(\hat{\underline{\beta}}) = (\underline{X}'\underline{V}^{-1}\underline{X})^{-1}.$$

For further detail, see Theil (1971).

Since $\underline{V}$ is unknown, estimates will be obtained using an iterative procedure. Let $\hat{\underline{V}}_m$ denote the estimates obtained from the m -th iteration. Let $\underline{V}_0$ be the identity matrix. That is, compute the initial estimates using ordinary least squares. Updates in the estimate for $\underline{V}$ are obtained by defining

$$\hat{\underline{V}}_{m+1} = \text{diag} \left[\underline{X}\underline{b}_m \right]$$

The iterative procedure is continued until $\hat{\underline{V}}_m$ converges, that is, until $\underline{b}_{m+1} = \underline{b}_m$ and $\hat{\underline{V}}_{m+1} = \hat{\underline{V}}_m$. Let $\underline{b}$ and $\underline{V}$ be represented by those estimates obtained from the final iteration. Then the best asymptotically normal estimate, as pointed out by Jorgenson (1961) is

$$\underline{b} = (\underline{X}'\hat{\underline{V}}\underline{X})^{-1} \underline{X}'\hat{\underline{V}}^{-1} \underline{y}.$$

The predicted values $\hat{\underline{\lambda}}$ are given as $\hat{\underline{\lambda}} = \underline{X}\underline{b}$ with variance of $\underline{x}'_h(\underline{X}'\underline{V}^{-1}\underline{X})\underline{x}_h$ where $\underline{x}'_h$ represents the h -th row of $\underline{X}$. Tests of hypotheses about $\underline{\beta}$ can be performed in the following manner. Let $\underline{L}$ be an $\ell \times (k+1)$ matrix of contrasts on $\underline{\beta}$. The null hypothesis is given as $\underline{L}\underline{\beta} = \underline{\gamma}$. Then $(\underline{L}\underline{b} - \underline{\gamma})' \left[\underline{L}(\underline{X}'\hat{\underline{V}}^{-1}\underline{X})^{-1}\underline{L}' \right]^{-1} (\underline{L}\underline{b} - \underline{\gamma})$ is asymptotically distributed as chi-square with ℓ degrees of freedom.

A more detailed discussion of the above procedure is provided by Weber (1970, 1971). Additional papers of interest on Poisson regression are Frome, Kutner, and Beauchamp (1973), Gart (1964), Jorgenson (1961), and Pyne (1979).

APPENDIX B
DATA ANALYSES

APPENDIX B

DATA ANALYSES

Introduction

Preliminary analyses using ordinary least squares (OLS) indicated that males and females should be treated as two separate populations. The variables considered for entry into the model are provided in Table B1.

TABLE B1 VARIABLES	
IAGE	1/AGE (females)
CAGE	1/(AGE) ³ (males)
DRIV-EDU (driver education)	0 no 1 yes
LISC-CO (commercial license)	0 no 1 yes
LISC-CH (chauffer's license)	0 no 1 yes
LISC-MO (motorcycle license)	0 no 1 yes
NBSPEED	(speeding violations)
NBRSFYRW	(failure to yield right of way)
MISC	(all other violations)
NBMVA	(negligent multi-vehicle accidents)
NNBMVA	(non-negligent multi-vehicle accidents)
NBSVA	(negligent single vehicle accidents)
NNBSVA	(non-negligent single vehicle accidents)

The analyses were performed using Poisson regression as defined by Weber (1971). For a brief outline of the methodology refer to Appendix A. A discussion from an applied standpoint will also be provided in the following section.

Poisson Regression

Starting values for the Poisson regression are obtained using OLS. All variables which were not even marginally significant according to the OLS were deleted. An OLS was then run with the reduced set of variables to obtain starting values.

Define the regression as

$$y_j = \sum_{i=0}^k \beta_i x_{ij}$$

where x_0 is a vector of 1's. Denote the estimates for β_i ($i = 0, 1, \dots, k$) as $b_i^{(s)}$ where s represents the estimate obtained after the s -th iteration. Here y represents the observed number of after accidents. y is assumed to be Poisson with mean and variance of $\sum \beta_i x_i$.

Parameter estimates will be obtained using an iterative weighted least squares (WLS) with $\sum \beta_i x_{ij}$ in the $(s+1)$ -th regression replaced by $\sum b_i^{(s)} x_{ij}$. Weights for the variance-covariance matrix for the WLS are given as $1/\sum b_i^{(s)} x_{ij}$. The WLS can be performed using an OLS program with w defined as

$$w_j = \frac{1}{\sum_i b_i^{(s)} x_{ij}}$$

The OLS regression equation is given as

$$y_j w_j = \sum b_i x_{ij} w_j.$$

Since x_{0j} represents a vector of 1's, b_0 will represent a coefficient for w_j . Therefore, it must be specified that there is no intercept term in order to obtain the WLS using OLS. The regression is performed iteratively

with the WLS parameter estimates from a previous run used to update the weights for the following run. Convergence is obtained when $b_i^{(s)} = b_i^{(s+1)}$. For the analyses performed here, the iterations were stopped after equality had been obtained to five significant digits.

Analysis of Males

Preliminary analyses indicated that DRIV-EDU and LISC-MO did not contribute significantly and they were therefore dropped from the regression. Convergence was obtained after four iterations. The estimates for each iteration are provided in Table B2.

TABLE B2
PARAMETER ESTIMATES

PARAMETER	$b_i^{(0)}$	$b_i^{(1)}$	$b_i^{(2)}$	$b_i^{(3)}$	$b_i^{(4)}$
INTERCEPT	0.05616	0.05810	0.05797	0.05798	0.05798
CAGE	1084.33	1032.09	1034.93	1034.80	1034.81
LISCO-CO	0.03021	0.02675	0.02679	0.02678	0.02678
LISC-CH	0.05736	0.05396	0.05414	0.05414	0.05414
NBSPEED	0.02403	0.02595	0.02598	0.02598	0.02598
NBRSFYRW	0.04678	0.04522	0.04521	0.04520	0.04520
MISC	0.05197	0.05249	0.05263	0.05263	0.05263
NBMVA	0.07204	0.07077	0.07078	0.07078	0.07078
NNBMVA	0.04968	0.04523	0.04526	0.04525	0.04525
NBSVA	0.08405	0.08165	0.08165	0.08165	0.08165
NNBSVA	0.06466	0.06720	0.06737	0.06737	0.06737

Chi-square tests for the significance of each coefficient are provided in Table B3. The chi-square tests (outlined in Appendix A) may be obtained using the $(X'V^{-1}X)^{-1}$ matrix provided in Table B4. Chi-square tests obtained using Table B4 may differ slightly from the values presented in Table B3 due to rounding error.

TABLE B3
ANALYSIS OF INFORMATION

SOURCE	CHI-SQUARE	D.F.
INTERCEPT	1168.44	1
CAGE	316.71	1
LISC-CO	83.41	1
LISC-CH	85.09	1
NBSPEED	320.87	1
NBRSFYRW	85.63	1
MISC	89.31	1
NBMVA	201.70	1
NNBMVA	119.99	1
NBSVA	61.78	1
NNBSVA	20.72	1

TABLE B4
 $(X'V^{-1}X)^{-1}$ MATRIX

	INTERCEPT MISC	CAGE NBMVA	LISC_CO NNBMVA	LISC_CH NBSVA	NBSPEED NNBSVA	NBRSFYRW
INTERCEPT	0.0000029 -4.0000E-07	-0.0503523 -5.0000E-07	-0.0000018 -6.0000E-07	-0.0000016 1.0000E-07	-3.0000E-07 -2.0000E-07	-3.0000E-07
CAGE	-0.0503523 -0.0178949	3381.17 -0.0175204	0.0083895 -0.0187691	0.0020269 -0.0382172	-0.02002 -0.0265898	-0.026534
LISC_CO	-0.0000018 -1.0000E-07	0.0083895 -2.0000E-07	0.0000086 -3.0000E-07	0.0000017 -4.0000E-07	-3.0000E-07 -7.0000E-07	0
LISC_CH	-0.0000016 -4.0000E-07	0.0020269 -5.0000E-07	0.0000017 -7.0000E-07	0.0000344 -5.0000E-07	-3.0000E-07 -0.0000011	-3.0000E-07
NBSPEED	-3.0000E-07 -6.0000E-07	-0.02002 -4.0000E-07	-3.0000E-07 -4.0000E-07	-3.0000E-07 -7.0000E-07	0.0000021 -5.0000E-07	-7.0000E-07
NBRSFYRW	-3.0000E-07 -0.0000019	-0.026534 -0.0000011	0 -7.0000E-07	-3.0000E-07 -0.0000015	-7.0000E-07 -1.0000E-06	0.0000239
MISC	-4.0000E-07 0.000031	-0.0178949 -0.0000015	-1.0000E-07 -5.0000E-07	-4.0000E-07 -0.0000029	-6.0000E-07 -0.0000017	-0.0000019
NBMVA	-5.0000E-07 -0.0000015	-0.0175204 0.0000248	-2.0000E-07 -9.0000E-07	-5.0000E-07 -0.0000019	-4.0000E-07 -0.0000017	-0.0000011
NNBMVA	-6.0000E-07 -5.0000E-07	-0.0187691 -9.0000E-07	-3.0000E-07 0.0000171	-7.0000E-07 -8.0000E-07	-4.0000E-07 -9.0000E-07	-7.0000E-07
NBSVA	1.0000E-07 -0.0000029	-0.0382172 -0.0000019	-4.0000E-07 -8.0000E-07	-5.0000E-07 0.0001079	-7.0000E-07 -0.0000024	-0.0000015
NNBSVA	-2.0000E-07 -0.0000017	-0.0265898 -0.0000017	-7.0000E-07 -9.0000E-07	-0.0000011 -0.0000024	-5.0000E-07 0.0002191	-1.0000E-06

It should be noted that even an accident considered to be non-negligent contributes more to the likelihood of a future accident than any single violation. It should also be noted that negligent accidents contribute more to the likelihood of a future accident than do non-negligent accidents. Although there may be doubt that the majority of non-negligent accidents are truly non-negligent, the classification non-negligent probably does represent a lower degree of culpability.

Analysis of Females

Preliminary analyses using OLS indicated that DRIV-EDU, LISC-MO, and NNBSVA were not even marginally significant. These variables were then deleted from the analysis. Convergence for the Poisson regression was obtained after four iterations. The parameter estimates after each iteration are provided in Table B5. Chi-square tests for each parameter are provided in Table B6. LISC-CO was found to be not significant with $\chi^2 = 1.26$ with 1 degree of freedom.

LISC-CO was then deleted, and the Poisson regression was rerun. Convergence was obtained after four iterations. Parameter estimates after each iteration are provided in Table B7.

The chi-square tests for significance of each parameter are provided in Table B8. The $(X'V^{-1}X)^{-1}$ matrix is provided in Table B9. Again, it should be noted that due to rounding error, tests of significance obtained using Table B10 may differ slightly from the values provided in Table B9.

Non-negligent accidents were found to be less significant than for males, but a single negligent accident still made a greater contribution towards the likelihood of future accidents than did any single violation. As was the case for males, negligent accidents contribute more to the likelihood of a future accident than do non-negligent accidents.

TABLE B5					
PARAMETER ESTIMATES					
PARAMETER	$b_i^{(0)}$	$b_i^{(1)}$	$b_i^{(2)}$	$b_i^{(3)}$	$b_i^{(4)}$
INTERCEPT	0.02059	0.02189	0.02182	0.02182	0.02182
IAGE	1.54867	1.49425	1.49676	1.49664	1.49665
LISC-CO	0.02053	0.01579	0.01548	0.01546	0.01546
LISC-CH	0.04292	0.04212	0.04236	0.04233	0.04233
NBSPEED	0.02978	0.03107	0.03110	0.03110	0.03110
NBRSFYRW	0.04210	0.03676	0.03676	0.03675	0.03675
MISC	0.04759	0.04672	0.04667	0.04667	0.04667
NNBMVA	0.04787	0.04730	0.04727	0.04727	0.04727
NNBMVA	0.02370	0.02519	0.02517	0.02517	0.02517
NBSVA	0.04910	0.04915	0.04962	0.04963	0.04963

TABLE B6		
ANALYSIS OF INFORMATION		
SOURCE	CHI-SQUARE	D.F.
INTERCEPT	64.46	1
IAGE	182.27	1
LISC-CO	1.26	1
LISC-CH	12.65	1
NBSPEED	178.61	1
NBRSFYRW	33.61	1
MISC	27.23	1
NBMVA	80.29	1
NNBMVA	35.81	1
NBSVA	12.44	1

TABLE B7					
PARAMETER ESTIMATES					
PARAMETER	$b_i^{(0)}$	$b_i^{(1)}$	$b_i^{(2)}$	$b_i^{(3)}$	$b_i^{(4)}$
INTERCEPT	0.02075	0.02195	0.02188	0.02188	0.02188
IAGE	1.54717	1.49496	1.49719	1.49706	1.49707
LISC-CH	0.04293	0.04199	0.04223	0.04223	0.04223
NBSPEED	0.02984	0.03117	0.03119	0.03119	0.03119
NBRSFYRW	0.04216	0.03677	0.03677	0.03676	0.03676
MISC	0.04758	0.04667	0.04662	0.04663	0.04663
NBMVA	0.04790	0.04728	0.04726	0.04726	0.04726
NNBMVA	0.02370	0.02522	0.02519	0.02519	0.02519
NBSVA	0.04916	0.04934	0.04979	0.04980	0.04980

TABLE B8		
ANALYSIS OF INFORMATION		
SOURCE	CHI-SQUARE	D.F.
INTERCEPT	64.84	1
IAGE	182.28	1
LISC-CH	12.60	1
NBSPEED	179.56	1
NBRSFYRW	33.63	1
MISC	27.19	1
NBMVA	80.26	1
NNBMVA	35.86	1
NBSVA	12.51	1

TABLE B9
 $(X^{-1}V^{-1}X)^{-1}$ MATRIX

	INTERCEPT MISC	IAGE NBMVA	LISC_CH NNBMVA	NBSPEED NBSVA	NBRSFYRW
INTERCEPT	0.00000738 -2.9000E-07	-0.00027856 -1.6000E-07	3.2000E-07 5.0000E-08	4.6000E-07 1.8000E-07	3.1000E-07
IAGE	-0.00027856 -0.00001393	0.0122955 -0.00002371	-0.00004755 -0.00003443	-0.00004527 -0.00003661	-0.00004055
LISC_CH	3.2000E-07 -0.00000112	-0.00004755 -6.8000E-07	0.00014152 -4.8000E-07	-4.4000E-07 -6.3000E-07	-4.4000E-07
NBSPEED	4.6000E-07 -0.00000101	-0.00004527 -6.9000E-07	-4.4000E-07 -5.7000E-07	0.00000542 -7.5000E-07	-9.7000E-07
NBRSFYRW	3.1000E-07 -0.00000209	-0.00004055 -9.2000E-07	-4.4000E-07 -8.0000E-07	-9.7000E-07 -0.00000101	0.00004018
MISC	-2.9000E-07 0.00007996	-0.00001393 -0.00000144	-0.00000112 -7.3000E-07	-0.00000101 -0.00000204	-0.00000209
NBMVA	-1.6000E-07 -0.00000144	-0.00002371 0.00002783	-6.8000E-07 -6.3000E-07	-6.9000E-07 -0.00000176	-9.2000E-07
NNBMVA	5.0000E-08 -7.3000E-07	-0.00003443 -6.3000E-07	-4.8000E-07 0.0000177	-5.7000E-07 -6.7000E-07	-8.0000E-07
NBSVA	1.8000E-07 -0.00000204	-0.00003661 -0.00000176	-6.3000E-07 -6.7000E-07	-7.5000E-07 0.00019821	-0.00000101

