

# DEVELOPMENT OF SECONDARY HIGHWAY ACCIDENT COUNTERMEASURES THROUGH INDUCED EXPOSURE ANALYSIS WITH CENSUS INFORMATION

(Phase 2 of Accidents on Secondary Highways and Counter-measures)

### FINAL REPORT



Prepared by

Nikiforos Stamatiadis Giovanni Puccini and Lisa Aultman-Hall

Department of Civil Engineering University of Kentucky

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Development of Secondary
Highway Accident
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#### **EXECUTIVE SUMMARY**

This report presents the findings of the second phase of an analysis to determine the factors that affect crash occurrence in low-volume roads in the Southeast and identify possible countermeasures. The main objective of this study is to define at-risk groups according to personal, socioeconomic and roadway characteristics and identify potential counter-measures that could enhance the road safety of these groups. The findings are based on an analysis of human factors that combined socioeconomic conditions of the drivers, obtained from the Census database. The socioeconomic variables were extracted and related to the crash database utilizing the driver's zip code information as the common link.

The quasi-induced exposure method was utilized here to determine relative crash involvement for specific groups of drivers. The groups of interest for the analysis were disaggregated based on particular variables (crash or socioeconomic variables) or from a combination of them. This way, specific at-risk driver groups could be identified based on their crash involvement. These groups were then used to establish a set of countermeasures aiming to reduce their crash rates on secondary highways. The countermeasures discussed here focus on proposing action plans aimed to minimize the propensity that certain at-risk groups have for being involved in crashes. In order to determine the effect of socioeconomic conditions on secondary highway crashes, several variables were incorporated into the crash database, which contained a total of 56,638 crashes for Kentucky between 1993 and 1995.

The main objective for this project was to establish countermeasures that could improve the safety level of secondary, low-volume roads in the southeastern United States. Many of the countermeasures indicated here are those that could be implemented in general and would impact traffic safety on all roadways. The patterns of accident propensity for younger and older drivers found here for low volume roads, are similar to the trends found overall. Countermeasures to address these and other general safety issues include stricter enforcement of traffic laws, higher penalties for traffic violations, increased education programs, more frequent driver testing, and efforts to reduce travel and automobile usage. Even though these measures could have an impact on overall safety, the remainder of this section addresses countermeasures indicated by the specific analyses undertaken here.

The analyses identified two at-risk groups of drivers, young and old, with somewhat diverse crash characteristics. A plan to improve safety of younger drivers could require all potential drivers to successfully complete a drivers' education program before receiving a license. Even though there are conflicting results regarding the impact of driver education on crash rates of young drivers, more states are requiring young drivers to increase their education levels prior to obtaining a driver license. Another method would be to limit the driving

privileges of drivers under 18. By giving the drivers specific time intervals most of the drivers will be off the roadways during the night and on weekends when most teenage driving fatalities occur. Such efforts are addressed through the graduated license programs that several states, including Kentucky, have implemented recently. Parental supervision of teenage drivers has shown promises regarding crash involvement of young drivers indicating a possible change in the way young drivers drive when their parents are present. Thus, such a requirement could be an integral part of any graduated license program.

The other at-risk group was the older drivers, over 65 years of age who were found to be more involved in multi-vehicle crashes. One option in dealing with older drivers is to require a mandatory re-testing of driving skills at driver license renewal. This option would require older drivers to renew their driver license more frequently than other drivers, for example every two years instead of the four-year renewal of other drivers. Elderly driving can be improved by better roadways, wider lanes and shoulders and also by road sign posting such as, hills and sharp curve signs. These would enable older drivers with slower reflexes to be preparing for a sharp turn or hill before they encounter it, thus reducing the number of single-vehicle accidents on these roadways.

The higher crash rates in what is classified today as rural areas may also be a result of continuous urban sprawl. As suggested by the distance to work results here (people who travel further to work were more likely to cause accidents), two-lane, two-way rural roads may be used by urban workers as commute routes and by increasing their commute / travel times they may become more susceptible to fatigue, inattention, driving faster to shorten their trip times. Therefore, although such roads continue to carry low volumes, as defined in this study with ADT of less than 5,000 vehicles, but they have become commute routes and thus, drivers may exhibit different driving behavior. Drivers who travel further to work may be more tired and prone to sleepiness while behind the wheel. They may also drive the road at higher speeds than those who are less familiar with the route.

The results that higher income individuals and people with more vehicles per household cause more crashes is concerning. It is impossible to imagine that socioeconomic variables themselves are the cause of this higher crash propensity. Therefore, in order to suggest countermeasures one must consider the possible risk factors that would correlate with higher socioeconomic levels. These risk factors may include: use of telephones while driving vehicles, televisions, stereos or other distracting vehicle features. While these devices are certainly not used only on low volume roads, the geometric standards (narrow shoulder and lanes, sharp curves) provide very little forgiveness if the vehicle moves out of the lane during a moment of distraction.

In conclusion, there are very few specific countermeasures that state/local agencies can direct at improving the safety of low volume roads. The countermeasures recommended here are for the most part the same as those which would improve the safety of all roads. The one area where a specific action can be recommended is that of rural land use planning. Care is needed to ensure development in rural areas does not create peak work-related travel that is far beyond that appropriate for the design standards of the road. Furthermore, the rural elderly may need special attention in terms of rural public transit or other options to ensure mobility

#### 1. INTRODUCTION

The majority of roadway mileage in the US consists of two-lane, two-way roads that carry low volumes. The nationwide crash reports however indicate that these roadways have significantly higher crash rates than other roads. Based on 1992 data, secondary roads had 188 crashes per million vehicle-miles which is almost twice the crash rate (99 crashes per million vehicle-miles) of all roads (1). The fact that crash rates are higher in the southeast, when compared to the nationwide average rate, combined with the large mileage of low volume roads prompted this research. The first phase of the study focused on identifying factors and contributing circumstances that affect crash rates on these roadways based on data from the statewide crash databases in Kentucky and North Carolina (2). The main objective of this second phase of the study is to define at-risk groups according to personal, socioeconomic and roadway characteristics and identify potential counter-measures that could enhance the road safety of these groups. The identification of these groups at risk will provide state and federal agencies with a set of possible countermeasures that can be implemented to reduce the crash rates on secondary roads.

The results of this research effort are presented in this document and possible countermeasures to reduce crashes on secondary highways are discussed. These findings are based on the factor analysis obtained in the first phase as well as on more detailed analysis of human factors that combined socioeconomic conditions of the drivers, obtained from the Census database, and education/enforcement characteristics, obtained from studies conducted by the Kentucky Transportation Center. These new variables were extracted and related to the crash database utilizing the driver's zip code information as the common link. Consequently, several relationships involving these new variables and previously identified at-risk driver groups were examined in order to establish a broad set of countermeasures.

The quasi-induced exposure method was utilized here to determine relative crash involvement for specific groups of drivers. Crash rates disaggregated into such groups would be useful metrics for establishing the relative safety among them and would provide direction for policy development aimed at improving highway safety (3). The groups of interest for the analysis were disaggregated based on particular variables (crash, socioeconomic or enforcement variables) or from a combination of them. This way, specific at-risk driver groups could be identified based on their crash involvement. These groups were then used to establish a set of countermeasures aiming to reduce their crash rates on secondary highways. The countermeasures discussed here focus on proposing action plans aimed to minimize the propensity that certain at-risk groups have for being involved in crashes.

At-risk driver groups with higher propensity to be involved in crashes and higher percent involvement in the total number of crashes suggest that they would require a higher priority countermeasure. Thus, information regarding the distribution of the at-fault drivers can also be utilized by considering its relative importance for prioritizing these countermeasures.

Previous research has shown that there is a link between socioeconomic indicators and fatal vehicle crashes for the southeastern region of the US (4). The study showed that drivers who lived in areas with lower socioeconomic characteristics were more likely to be involved in single-vehicle crashes. This finding could support the hypothesis that lower socioeconomic conditions affect the age of vehicles owned (older, less safe vehicles), the type of vehicles driven, the condition of these vehicles (not properly maintained), and the attitudes of the drivers towards

safety and risk taking behaviors. Even though a correlation between socioeconomic variables and fatal crashes was not established for multi-vehicle crashes, multivariable analysis indicated different socioeconomic influences for several of the at-risk groups. Most, of these influences, could be attributed to socioeconomic conditions that could affect differently specific combinations of groups at risk with regards to fatal crashes.

Socioeconomic characteristics seem to influence crash involvement and, possibly, occurrence. Therefore, several socioeconomic variables were studied in this phase of research in order to complement results obtained in the previous phase of the project.

This report is organized in four sections. Following this introduction, the methodology used in the analysis is presented. Section 3 presents the results of the analysis and leads to the proposed countermeasures and section 4 presents and discusses the possible countermeasures. Appendices also follow that provide the complete set of variables examined.

#### 2. METHODOLOGY

#### 2.1. Introduction

The quasi-induced exposure method was also utilized in this phase of the study to determine specific groups at risk. In order to apply the analysis and to determine the effect of socioeconomic conditions on secondary highway crashes, several variables were incorporated into the existing database, which contained a total of 56,638 crashes for Kentucky between 1993 and 1995. The study was limited only to the state of Kentucky because the crash report of North Carolina did not have information regarding driver's zip code and thus, no socioeconomic variables could be extracted for these drivers.

For each variable, two types of analysis were performed: the at-fault driver frequency distribution and the propensity to cause crashes based on exposure. The basic assumption in the quasi-induced exposure method is that in a two-vehicle crash there is a driver who is mostly responsible for the crash--at-fault driver. These drivers are identified based on contributing human factors and possible citations given after the crash. Crashes where the at-fault driver cannot be clearly identified--both or neither driver had any contributing human factors--were excluded from the analysis. The at-fault driver frequency distribution identified the contribution of each group to the total number of crashes. However, these distributions do not consider the relative presence of the driver on the roadway, i.e. exposure, and thus, they do not allow for a complete identification of the most responsible motorists. On the other hand, determining the propensity to cause a crash helps to define the effect of one particular group and its tendency to cause more crashes than being involved in. The crash propensity analysis was performed utilizing the quasi-induced exposure method, in which relative accident involvement ratios (RAIR) were computed for the selected groups. The first part of this study presented a detailed discussion regarding the quasi-induced exposure method and the way to compute the RAIR (2).

#### 2.2. Variables

The accident database developed during the first phase of the study was utilized also in this phase of the research. However, several of the variables included in the previous study were not utilized here, since they were not considered as strong contributors to the crash occurrence and propensity of at-risk driver groups. Moreover, additional variables, more relevant to this phase of the research, were added in their place. The new set of independent variables to be analyzed include the following:

- 1. Crash characteristics (from Kentucky's crash reports): year of the crash, type of driver (at-fault or not at-fault), driver injury, driver gender, driver age, driver zip code, vehicle type, vehicle age, time, day, shoulder type, shoulder width, grade classification, lane width, and curve classification.
- 2. Socioeconomic variables (from the US 1990 Census database): percentage of rural population, percentage of English speaking households, average travel time to work, percentage of school enrollment, educational attainment index, unemployment rates (for people who are eligible to be in labor force), median household income, per capita income, percentage of population below the poverty level, average time that the householder has lived in the units, and average number of vehicles per household.
- 3. Enforcement characteristics from the "Analysis of Traffic Accident Data in Kentucky", (5): percentage of alcohol convictions per number of alcohol related crashes, percentage of reckless convictions per total number of crashes, and percentage of speeding convictions per total number of crashes.

#### 2.3. Data Compilation

For this phase of the research, a major part of data compilation involved recovering and adding information to the existing database. First, the zip code of the drivers was retrieved from the crash reports. Then, socioeconomic variables were extracted from the zip code US 1990 Census database for localities in Kentucky and used to create a new database. In order to capture the characteristics of the drivers according to their locality, composite values were calculated for some of these socioeconomic variables. For example, the original information for education attainment was given by the percent of population who attained each different level of education for each zip code; those numbers were then converted to a weighted score to allow for comparing characteristics between different localities. Third, the three variables utilized to measure the enforcement characteristics were obtained at county level. Finally, the three databases were combined in a final database to be used in this study.

#### 2.4. Data Analysis

Based on the objectives proposed for this phase of research, the analysis for the new variables involved four stages:

1. A single-variable analysis was performed, in which RAIR's were computed for the new socioeconomic variables. This type of analysis established a direct correlation between crashes and each independent variable. In this way, specific groups at risk were also identified based on their propensity to be involved in crashes;

- 2. A two-way variable analysis was conducted involving the computation of RAIR's for driver age, vehicle type, and vehicle age in combination with the most significant socioeconomic, roadway, and enforcement variables. This analysis identified the influences of other potential factors on specific groups at risk;
- 3. Logistic regression was preformed to obtain the statistical significance of the results; and
- 4. An analysis of the results was conducted and a set of countermeasures was developed based on the identified groups at risk.

The quasi-induced exposure method was utilized to perform the first two stages of the analysis. The method is based on the assumption that not at-fault drivers are a sample of the driving population for single- and multi-vehicle crashes and thus they could be used as a measure of exposure (3). The unit utilized to represent this propensity is the relative accident involvement ratio (RAIR), which is determined by dividing the percentage of at-fault drivers for a particular group by the percentage of not at-fault drivers for the same group. This computation is made for both types of crashes: single- and multi-vehicle crashes.

For the crash involvement ratios computed here, the Minitab statistical software was used to perform the statistical tests using logistic regression at the 5% confidence level. Logistic regression was utilized to investigate the relationship between a categorical response variable and one or more predictors. In this case, the response variable had two values representing whether a driver was at fault (binary variable), and the predictors were the categorical crash variables, socioeconomic variables, or a combination of both (factors). In order to establish whether the results shown in the following sections of the report are statistically significant (in other words, to see whether there is enough evidence that the predictor variables have influences on the response variable), logistic regression models were computed for each case. One major parameter was utilized (p-value of the G-test) to determine whether there was a statistical significance in the results. The G-test tests the hypothesis that all slopes associated with the different factors in the logistic regression model were equal to zero. If the probability that all slopes are relatively high (p-value > 5%), then there is not enough evidence that the predictors have an effect on the response variable. In this case, the hypothesis can not be rejected and thus, no statistical significance can be attributed to the results.

#### 2.5. Criteria to Establish Countermeasures

Having identified the at-risk groups, the countermeasures to be presented later consist of an action plan that aims to minimize the higher accident propensity of these groups. Therefore, the analysis of results should indicate possible explanations of why those groups have higher accident propensity compared to other groups. This explanation, along with ideas derived from the numerical results, is used to formulate possible action plans.

Information regarding at-fault driver frequency distributions could help to prioritize such action plans. For instance, in the case of having two different countermeasures for two groups at risk with similar crash propensity, the countermeasure for the group with the highest contribution to crashes should be implemented first. This way, a safety program based on countermeasures

and their priority could be formed, which would have a stronger impact on reducing crashes. Therefore, considerations regarding the group's contribution to crashes are also presented.

#### 3. RESULTS

#### 3.1. Introduction

This section of the report presents the correlations found between the added variables and crashes, which includes single- and two-variable analyses. Single-variable analysis relates independent socioeconomic variables with crashes (step 1), while two-variable analysis correlates the effect of combining at-risk groups for driver age, driver gender, and vehicle age with socioeconomic and roadway environment variables (step 2). The results presented here were statistically significant at a 5% confidence level. Appendix A shows graphically all the combinations tested.

#### 3.2. Socioeconomic variable analysis

An overview of the socioeconomic variables selected for this study is presented in this section. Table 1 summarizes the average of the socioeconomic characteristics for the state of Kentucky by Census tract.

SOCIOECONOMIC VARIABLE	Average KY	
Rural population (%)	48.18	
Average time to work (min)	20.74	
Education attainment score (Index)	1.17	
Unemployment rate (%)	7.37	
Median Household Income (\$)	22,534	
Population below poverty level (%)	19.03	
Average number of vehicles	2.57	

Table 1. Average of the socioeconomic characteristics for the State of Kentucky by Census tract

#### 3.2.1. Median Household Income

The household income is considered a more accurate indicator of the drivers' economic conditions than the per capita income, since it represents the financial status of the entire household. It considers the income of all persons above 15 years in the household and thus

includes drivers from the age groups of higher risk (i.e. teenagers) whose income usually depends on their parents.

Figures 1 and 2 present the distribution of the at-fault drivers and the crash involvement rates, respectively. Figure 1 indicated that the median household group of 15K-20K comprised approximately 35% of both single- and multi-vehicle crashes. This figure also indicates that a larger percentage of drivers at fault lived in areas with median household income lower than the state average (\$22,534). However, Figure 2, which is considering normalized data based on the amount of driving, indicates that the likelihood of a driver to be involved in single-vehicle crashes is increased when median household income increases. On the other hand, no statistical correlation was found between median household income and multi-vehicle crashes.

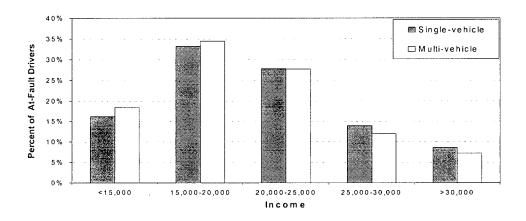


Figure 1. Percentage of at-fault drivers versus the median household income

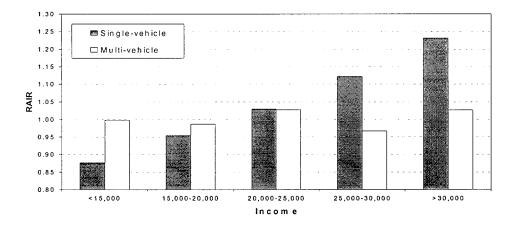


Figure 2. Relative accident involvement ratio versus median household income

The conclusion drawn from Figure 2, which considered exposure, indicates that socioeconomic conditions have a different effect on single-vehicle crashes than on multi-vehicle crashes. In previous research (4), a different correlation between median household income and crashes was found for fatal crashes in the Southeast United States, where the drivers' propensity to cause crashes increased as the median household income decreased. This kind of trend was

supported by the hypothesis that lower socioeconomic conditions may affect negatively the age, type, and maintenance of the vehicles, and thus severe collisions may have higher consequences for people with lower household income. However, the results here indicate an opposite trend for secondary highway crashes.

The increase in single-vehicle crashes, seen in the higher income groups, could be possibly explained by either of the two following reasons. First, people with higher income would probably acquire higher-end vehicles, which in turn have more speeding capabilities and distracting features. Specific features that would distract these individuals include car or cellular phones, high-tech stereos, GPS, car TVs, cruise control, and so forth. On the other hand, individuals with higher income may drive faster to reach their destination in a more timely fashion and thus, be involved more often in single-vehicle crashes on secondary roads, an environment more conducive for these types of crashes.

#### 3.2.2. Unemployment rate

Unemployment is an economic variable that could provide a regional estimate of the well being of the region's population. It affects the economic conditions of not only those individuals who are unemployed but also their families. Unemployment could affect the temporal travel activities, i.e. time a trip is taken, the distance of the trip, i.e. people are required to travel farther to get to their jobs, and the amount of persons traveling in the zone, i.e. more people in a high unemployment area are likely to travel to other areas to be employed. Therefore, unemployment could have a direct influence on the crash occurrence on secondary roads, since it could increase both frequency and distance of trip.

The at-fault driver frequency distribution for unemployment seems to follow the state distribution, in which the majority of drivers live in areas close to the average of 7.37% for the state (Figure 3). Considering crash exposure (Figure 4), the propensity to be involved in single-vehicle crashes increases with the drop in unemployment rates. Multi-vehicle crashes are not affected by the level of unemployment, since differences between the rates are not statistically significant. These results follow the same pattern observed for median household income and confirm a congruent trend between economic variables and crashes on secondary highways: single-vehicle crashes increase for drivers residing in more affluent localities.



Figure 3. Percent of at-fault drivers versus unemployment rate

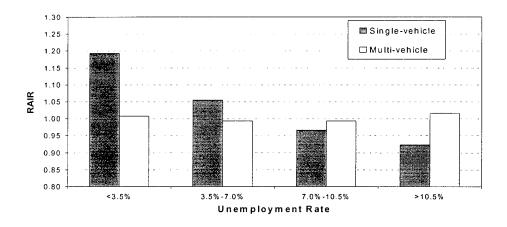


Figure 4. Relative accident involvement ratio versus employment rate

#### 3.2.3. Population below poverty level

The percentage of population below the poverty level, as defined by the Census, was used as an additional economic indicator for crashes on secondary highways. As the data in Figures 5 (drivers at fault distribution) and 6 (crash ratios) indicate, this variable shows congruent results with the other two economic variables. For single-vehicle crashes, the crash propensity ratio increased when the percentage of population below poverty status was reduced. Multi-vehicle crashes, on the other hand, did not present any statistical differences.

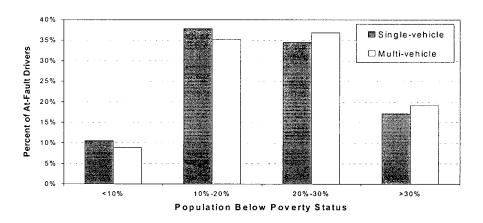


Figure 5. Percent of at-fault drivers versus population below poverty status

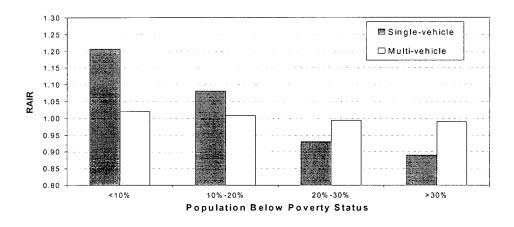


Figure 6. Relative accident involvement ratio versus population below poverty level

#### 3.2.4. Average number of vehicles

The average number of vehicles could also be considered as an indirect socioeconomic variable if it is assumed that people with higher income are more likely to buy more cars. Similar to the other three direct economic variables, this one also indicated the same pattern: crash propensity increased when the number of vehicles increased for single-vehicle crashes and no statistical significance was observed for multi-vehicle crashes. Figures 7 and 8 show the at-fault driver and the RAIR distributions for the independent analysis of this variable, respectively.

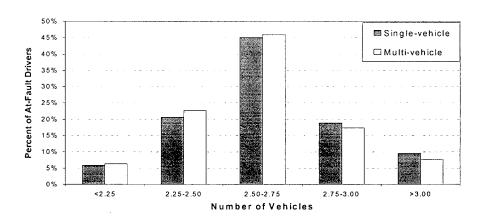


Figure 7. Percent of at-fault drivers versus number of vehicles

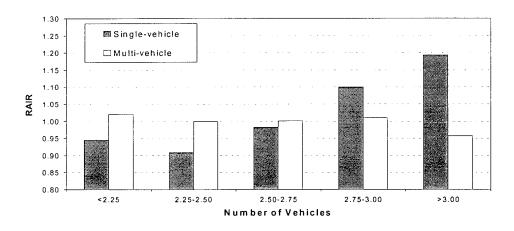


Figure 8. Relative accident involvement ratio versus number of vehicles

#### 3.2.5. Educational Attainment

Educational attainment for the driver location was considered to determine a correlation between levels of education and crashes on secondary highways. A weighted score was calculated to determine quantitatively the impact of education in vehicle crashes on secondary highways. Indexes, which are weighted average numbers, were computed for five educational levels: Non-high school (0), high school degree (1), some college (2), bachelor degree (3), and graduate degree (4). A greater index indicates higher education level, but it is not arithmetically scaled.

Figure 9 shows that most of the drivers (80 percent) causing crashes on secondary highways lived in localities where the educational index was below the state average (1.2). However, the crash propensity analysis (Figure 10) showed statistically significant differences indicating that drivers of higher educational level were more likely to be involved in single-vehicle crashes. On the other hand, no statistical significance was observed for multi-vehicle crashes on secondary highways.

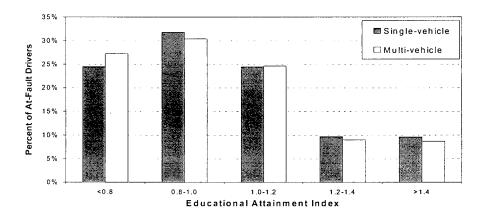


Figure 9. Percent of at-fault drivers versus educational index

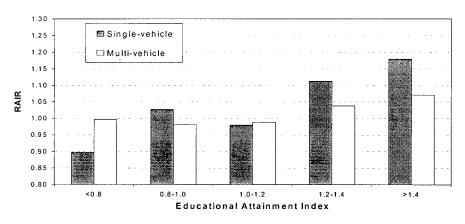


Figure 10. Relative accident involvement ratio versus educational index

#### 3.2.6 Rural Population

Rural conditions are important characteristics in this analysis, since a large percentage of secondary highways are rural roads. Additionally, more severe crashes (e.g. fatal) occur on rural secondary highways. Figure 11 confirms the expected distribution indicating that close to 50% of the at-fault drivers live in areas where the rural population is higher than 90%. The crash propensity trends show, however, a pattern in which drivers from urban areas are more likely to cause multi-vehicle crashes (Figure 12). This result is also expected since secondary highways close to urban locations generally carry a higher volume and thus, the chance to hit another vehicle is higher. Single-vehicle crashes did not show any statistical significance in the results.

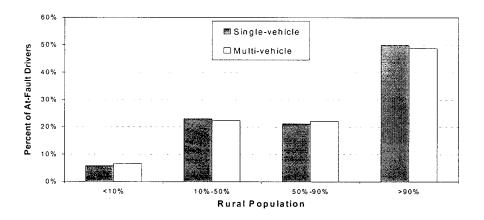


Figure 11. Percent of at-fault drivers versus rural population

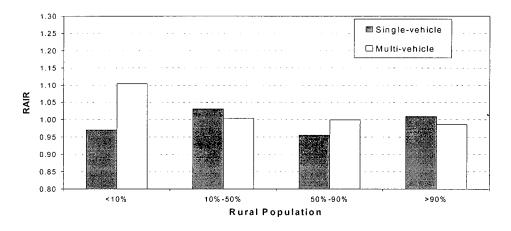


Figure 12. Relative accident involvement ratio versus rural population

#### 3.3. Enforcement variable analysis

In order to measure the level of enforcement at a locality, ratios between the total number of alcohol, speeding and reckless convictions and the number of crashes were computed per locality. These ratios were computed first utilizing crash information at the county level. To use these ratios at the zip code level it was assumed that the county values were constant throughout the county and thus, could be transferred to the lower level. Even though this assumption may not be very accurate, the lack of additional detailed data prevented a more detailed analysis. The ratio, for alcohol convictions, was computed by dividing the total number of alcohol convictions by the total number of alcohol related crashes. The other two ratios (reckless driving and speeding) were computed by dividing the total number of convictions by the total number of crashes.

In order to evaluate how enforcement activity might potentially affect crashes, three categories were utilized based on low, medium or high conviction ratios per each variable. As Figures 13 to 18 indicate, even though enforcement seems to have an intensive impact on crashes on secondary highways, the results did not show any statistically significant differences for either single- or multi-vehicle crashes. It should be also noted that the information utilized here was very general. Therefore, it is suggested that future research in this field should obtain additional specific enforcement conditions on various roads to perform a more accurate analysis.

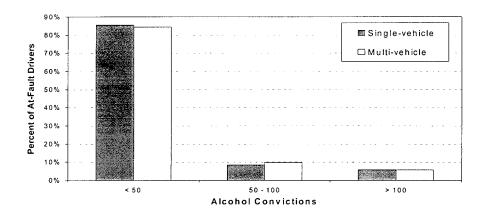


Figure 13. Percent of at-fault drivers versus alcohol convictions

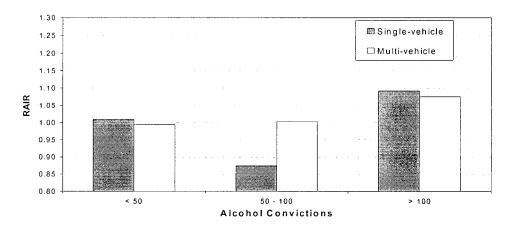


Figure 14. Relative accident involvement ratio versus alcohol convictions

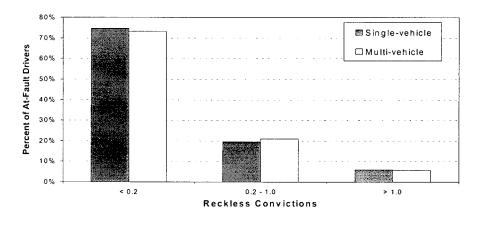


Figure 15. Percent of at-fault drivers versus reckless driving convictions

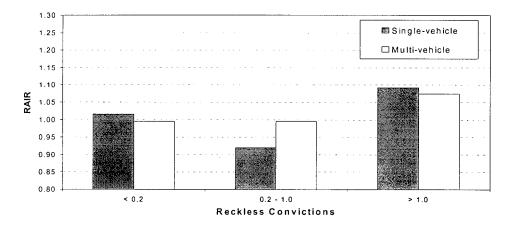


Figure 16. Relative accident involvement ratio versus reckless driving convictions

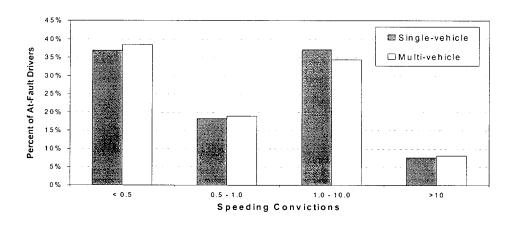


Figure 17. Percent of at-fault drivers versus speeding convictions

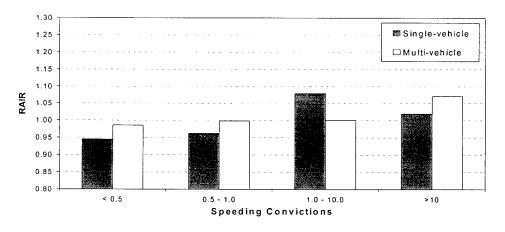


Figure 18. Relative accident involvement ratio versus speeding convictions

#### 3.4. Multi-variable Analysis

A series of multi-variable analyses were performed to identify the specific effects of socioeconomic variables and roadway environment when combined with driver age, driver gender and vehicle age. Approximately 80 combinations of variables were tested (See appendix A); however, the results discussed in this section are only for those variables and relationships that showed statistical significance.

#### 3.4.1. Driver age and socioeconomic variables

A significant correlation was identified between driver age and socioeconomic variables. Accident propensity ratios computed for driver age in conjunction with the economic variables (income, poverty and unemployment) showed a common pattern for younger drivers in single-vehicle crashes. The youngest age group (under 25 years old) is more likely to cause single-vehicle crashes when their economic conditions increase (Figures 19 and 20). Analyzing driver age and education attainment, the youngest age group also seems to be more likely to cause single-vehicle crashes when those drivers lived in areas with higher education levels. On the other hand, the oldest age group (above 65) and the rural population showed a statistically significant result for multi-vehicle crashes. In this case, urban older drivers seem to cause more multi-vehicle crashes. Finally, no statistical significance was observed for the results in the remaining combinations of driver age and socioeconomic variables (Figures 21 and 22).

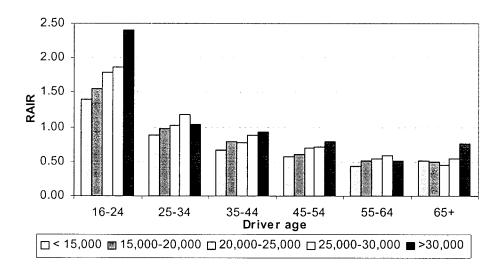


Figure 19. Relative accident involvement ratio versus driver age and income

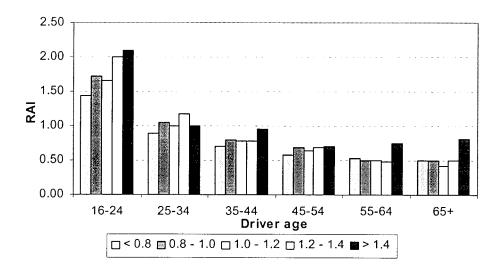


Figure 20. Relative accident involvement ratio versus driver age and education level

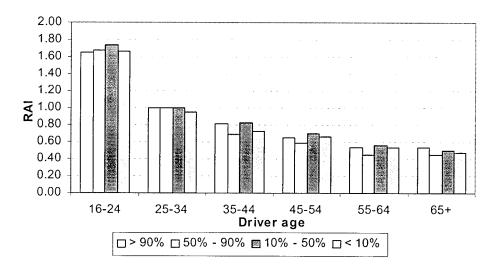


Figure 21. Relative accident involvement ratio versus driver age and rural population for single vehicle crashes

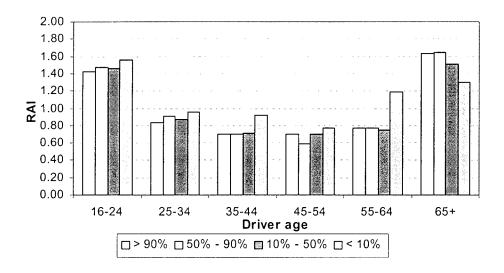


Figure 22. Relative accident involvement ratio versus driver age and rural population for multi-vehicle crashes

The correlation between economic conditions and younger drivers in crashes on secondary highways can be possibly explained by the fact that driving exposure is more sensitive for this at-risk age group. If economic conditions increase, younger drivers, who usually are students, may be more inclined to drive differently based on the trip purpose. It could be hypothesized that when they drive for pleasure, they may drive in a more risky manner, while they are more careful when driving for other purposes. Moreover, a recent study showed that the type of passenger has an influence on the type of crashes young drivers are involved in and this may also have an impact on the crash rates observed here (6). Therefore, higher economic conditions may result in higher crash propensity for this age group. This hypothesis can also be supported by the results observed from the combination of driver age and education attainment, where higher educational levels--more young drivers complete their education--lead to higher crash propensity.

Results observed for rural older drivers showed that they have a higher propensity for causing multi-vehicle crashes on secondary highways. This trend could be explained by the hypothesis that rural older drivers, who are typically more actively involved in the working force, might use secondary highways more often than older urban drivers. In addition, these individuals, whose reaction time is generally reduced, may drive dangerously (e.g. extremely slow) in relation to others, thus making them more likely to be involved in multi-vehicle crashes. Therefore, rural older driver might constitute an at-risk group in accidents on secondary highways.

It is important to indicate two major points based on the results observed here. Socioeconomic conditions seem to highly influence at-risk age groups, and this influence on crashes is similar to that observed during the one-dimensional socioeconomic variable analyses. Consequently, it can be stated that the pattern observed for socioeconomic variables is mainly attributed to at-risk age groups specifically the youngest age group, in single-vehicle crashes and oldest age group in multi-vehicle crashes.

#### 3.4.2. Driver gender and socioeconomic variables

When analyzing driver gender and socioeconomic variables, both genders followed the same pattern observed for socioeconomic conditions: crash propensity increases when socioeconomic conditions increase. Therefore, socioeconomic conditions influence similarly both genders. However, statistical differences between genders were observed for the average number of vehicles and the average time to work. Females seem to be more likely to cause multi-vehicle crashes than males when the vehicle availability increases in the household (Figure 23). These results could reflect the socioeconomic factors associated with genders and vehicle ownership. Higher income households are more likely to have both husband and wife working and own more than one vehicle. Therefore, in those households where cars are shared, no differences are noted while the crash propensity of females increases for households where sharing cars is not required. On the other hand, females were also found more likely to cause single-vehicle crashes when their average time to work increases (Figure 24). A possible explanation might be related to the fact that in general women tend to do household related shopping and transport their children to school and other activities, which not only makes their trips longer but also add more distractions in the vehicle. Therefore, it could be speculated that females become more distracted or tired in driving long distances or during longer intervals of time than males. For the rest of the socioeconomic variables, no statistical significance was observed between genders.

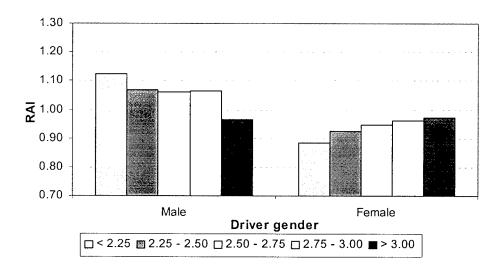


Figure 23. Relative accident involvement ratio versus driver gender and number of cars for multi-vehicle crashes

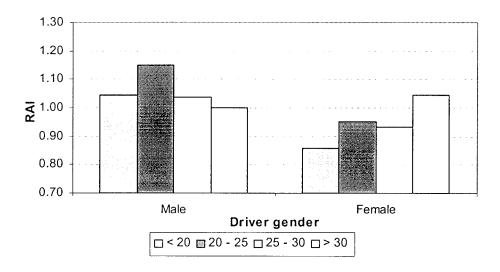


Figure 24. Relative accident involvement ratio versus driver gender and time to work for single-vehicle crashes

#### 3.4.3. Vehicle age and socioeconomic variables

For all vehicle ages, influences were similar to those observed for socioeconomic conditions in single-vehicle crashes, and thus adding the age of the vehicle identified no additional specific effects. On the other hand, for multi-vehicle crashes, the oldest vehicle age group was found more likely to cause crashes when poverty level and unemployment rates were lower. This result was expected, since it is reasonable to assume that there is a higher concentration of older vehicles in areas with lower economic conditions. Additionally, urban newer cars seem to be more likely to be involved than newer rural vehicles in multi-vehicle crashes. A plausible explanation of this may be that urban drivers are more affected by the winding curves, small shoulders and narrow lanes that characterize most secondary highways. Finally, a significant decrease in the crash propensity ratios was found for the oldest vehicle age group (above 15 years old) when the average number of vehicles per household increases. This result can be explained considering that having older vehicles in addition to other vehicles may be an indication of "antique" or more expensive older vehicles that are driven in a safer manner.

#### 3.4.4. Driver age and roadway environment variables

The time of crash occurrence showed an impact on driver age groups for single-vehicle crashes. The data showed that all age groups were more likely to cause single-vehicle crashes during night, but as the driver age decreased, the nighttime driving affected drivers more. All age groups of drivers were also more likely to be involved in single-vehicle crashes during weekends and this influence was higher as driver age decreased as well. These findings were expected because such secondary roads as those considered here are likely to be used for recreational purposes. Younger drivers might be more affected by nighttime conditions due to the time and purpose of the trip. For example, students often travel to visit their parents' home on the

weekends and during nighttime. On the other hand, time of the day and day of the week did not show any new statistical influence on driver age in multi-vehicle crashes.

Roadway geometric characteristics also influenced some driver age groups in single-vehicle crashes. All age groups were negatively affected in single-vehicle crashes as lane width decreased and the grade and curve sharpness increased. These results were expected since it is reasonable to assume that adverse conditions might affect a driver's ability, which is more notable in single-vehicle crashes. In addition, geometric conditions were an important contributing factor to single vehicle crashes involving younger drivers, perhaps because they tend to speed more and lack driving experience. However, an unexpected relationship was observed when the driver age was combined with the shoulder width. In this case, higher propensity in single-vehicle crashes was found for shoulders between 1 to 5 feet wide for all age groups. This effect was also higher as the driver's age decreased. Even though wider shoulders, above 5 feet wide, presented the safest condition for all the age groups, shoulders less than 1 foot were also safe, perhaps because drivers drive more carefully under the narrowest or no shoulders conditions.

Finally, the oldest age group of drivers was found less likely to be involved in multi-vehicle crashes as the sharpness of the curve increased. A reasonable explanation of this finding is that these individuals, who generally drive slower, may exhibit a compensatory action by increasing their attention level when other vehicles are present. Moreover, their increased involvement in single-vehicle crashes as the sharpness increases is an indication of possible judgement errors regarding speed and curvature.

#### 3.4.5. Driver gender and roadway environment variables

Few differences were noted when the driver gender was related to the roadway environment. Males were more likely to cause single-vehicle crashes at nighttime than females. On the other hand, females seemed to be more likely to be involved in multi-vehicle crashes during weekdays. The rest, of the confounding factors previously identified, have a similar effect on both genders.

#### 3.4.6. Vehicle age and roadway environment variables

In general, roadway conditions seem to be a stronger contributing factor in crash occurrence than the vehicle age and just a few additional correlations were identified when both variables were analyzed simultaneously. The 10-15 years old vehicle group seems to be highly affected when roadway conditions are highly graded and curved, for both single and multi-vehicle crashes. At the same time, this vehicle age group was previously found more likely to be involved in single- and multi-vehicle fatal crashes (4). The 10-15 year old vehicles seem to be a critical vehicle age group, in which vehicle factors might have an influence on crashes.

#### 3.5. Summary of findings

The results presented in this study identified at-risk groups of drivers and vehicle variables that influence the occurrence of single- and multi-vehicle crashes on secondary highways in Kentucky. Socioeconomic conditions of the drivers were analyzed and some

common correlation was noticed for several variables. Specific findings for groups at risk were identified in the combination of driver age, driver gender, and vehicle age with socioeconomic and roadway environment variables.

Driver age is the human factor that has the strongest correlation on crash occurrences on secondary highways. The youngest age group (under 25 years old) was found as the most likely to cause single-vehicle crashes, and the second most likely in causing multi-vehicle crashes. The oldest age group (above 65 years old) was found as the most likely to cause multi-vehicle crashes. The remaining age groups did not show any other significant involvement. When driver age was combined, with socioeconomic and roadway environment variables, additional information was identified for these two groups at risk. Based on the multivariable analysis, Figure 25 shows the interrelation between the two age groups at risk with other socioeconomic and roadway factors for single- and multi-vehicle crashes.

#### A. Driver age in single-vehicle crashes

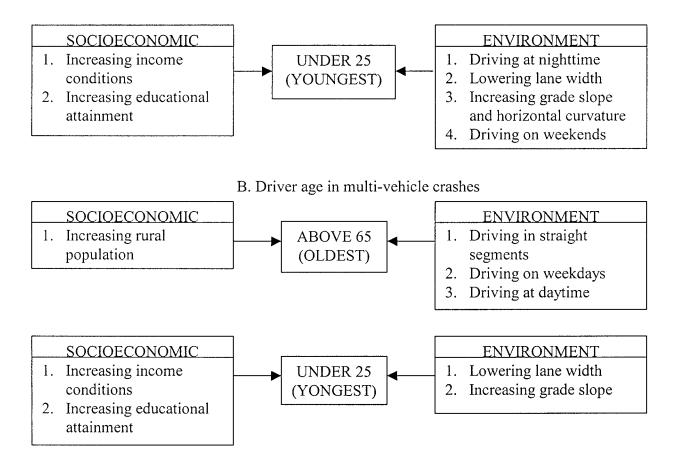


Figure 25. Socioeconomic and other factors increasing crash propensity

Another important finding of this study was the correlation found between single-vehicle crashes and socioeconomic characteristics. For all the economic indicators, drivers who live in

areas with higher income and higher educational attainment were found more likely to cause single-vehicle crashes. This was originally explained by the assumption that people with higher income would probably acquire more high-end vehicles, which in turn have more speeding capabilities and distracting features. However, when combining economic variables and vehicle age, it was noticed that the impact of the socioeconomic variables was the same regardless of the vehicle age. Therefore, it is reasonable to assume that socioeconomic variables affect individual behavior more than the vehicle age. For example, people, with higher income, may drive faster to reach their destination due to time constraints. Moreover, when driver age and socioeconomic conditions were combined, this trend was attributed mainly to the youngest age group, since driving exposure is more sensitive for this at-risk age group. If economic conditions increase, younger drivers, who usually are students, may exhibit different driving habits when driving for pleasure than for work and thus, have different crash propensities for single- and multi-vehicle crashes. Therefore, higher economic conditions may result in higher crash propensity for this age group. This hypothesis can also be supported by the results observed in the combination between driver age and education attainment in which higher educational levels lead to higher crash propensity as well.

Few differences were observed for driver gender. Females have an increased tendency to cause both single and multi-vehicle crashes when the vehicle availability is increased in the household. Females were also found more likely to cause single-vehicle crashes when their average time to work increases, and females seem to be more likely to be involved in multi-vehicle crashes during weekdays. On the other hand, males were more likely to cause single-vehicle crashes at nighttime. These trends may be explained by the traditional roles between genders: females tend to drive children around, while males drive the longer distance trips.

Finally, some additional crash factors were identified for the vehicle age. In general, higher propensity was observed as vehicle age increased in multi-vehicle crashes. For this type of crash, the oldest vehicle age group was found more likely to cause crashes when poverty level and unemployment rates were low. This result was expected, since it is reasonable to assume that there is a higher concentration of older vehicles in areas with lower economic conditions. In addition, it was observed that the 10-15 years old vehicle group seems to be highly affected when roadway conditions were highly graded and curved, for both single and multi-vehicle crashes.

#### 4. COUNTERMEASURES

The main objective for this project was to establish countermeasures that could improve the safety level of secondary, low-volume roads in the southeastern United States. Many of the countermeasures indicated here are those that could be implemented in general and would impact traffic safety on all roadways. The patterns of accident propensity for younger and older drivers found here for low volume roads, are similar to the trends found overall. Countermeasures to address these and other general safety issues include stricter enforcement of traffic laws, higher penalties for traffic violations, increased education programs, more frequent driver testing, efforts to reduce travel and automobile usage, and so forth. Even though these measures could have an impact on overall safety, the remainder of this section addresses countermeasures indicated by

the specific analyses undertaken here.

The analyses presented here identified two at-risk groups of drivers, young and old, with somewhat diverse crash characteristics. There are many actions that can be taken in order to reduce the number of crashes caused by or involving underage drivers. Another plan would be to require that all potential drivers successfully complete a drivers deducation program before receiving a license. Even though there are conflicting results regarding the impact of driver education on crash rates of young drivers (7), more states are requiring young drivers to increase their education levels prior to obtaining a driver license (8). What is also important in such education efforts is the program content, which should focus on developing skills (9). Finally, a less severe method would be to limit the driving privileges of drivers under 18. By giving the drivers specific time intervals, most of the drivers will be off the roadways during the night and on weekends when most teenage driving fatalities occur. Such efforts are addressed through the graduated license programs that several states, including Kentucky, have implemented recently. Parental supervision of teenage drivers has shown promises regarding crash involvement of young drivers indicating a possible change in the way young drivers drive when their parents are present (6). Thus, such a requirement could be an integral part of any graduated license program. These countermeasures would address safety on all roads not just those low volume roads studied here.

The other at-risk group was the older drivers; over 65 years of age who were found to be more involved in multi-vehicle crashes. This trend is similar to past research that examined age effects on crash involvement (3,10). One option in dealing with older drivers is to require a mandatory re-testing of driving skills at driver license renewal. This option would require older drivers to renew their driver license more frequently than other drivers, for example every two years instead of the four-year renewal of other drives. Such programs are in effect in few states and vary in degree of requirements of the four-year renewal of the rolling to knowledge and road tests (11). Finally, elderly driving can be improved by better roadways, wider lanes and shoulders and also by road sign posting such as, hills and sharp curve signs. These would enable older drivers with slower reflexes to be preparing for a sharp turn or hill before they encountered it, thus reducing the number of single-vehicle accidents on these roadways.

The higher crash rates in what is classified today as rural areas may also be a result of continuous urban sprawl. As suggested by the distance to work results here (people who travel further to work were more likely to cause accidents), two-lane, two-way rural roads may be used by urban workers as commute routes and by increasing their commute / travel times they may become more susceptible to fatigue, inattention, and driving faster to shorten their trip times. Therefore, although such roads continue to carry low volumes, as defined in this study with ADT of less than 5,000 vehicles, but they have become commute routes and thus, drivers may exhibit different driving behavior. Drivers who travel further to work may be more tired and prone to sleepiness while behind the wheel. They may also drive the road at higher speeds than those who are less familiar with the route.

The results that higher income individuals and people with more vehicles per household cause more accidents are concerning. It is impossible to imagine that socioeconomic variables themselves are the cause of this higher accident propensity. Therefore, in order to suggest countermeasures one must consider the possible risk factors that would correlate with higher socioeconomic levels. These risk factors may include: use of telephones while driving vehicles, televisions, stereos or other distracting vehicle features. While these devices are certainly not

used only on low volume roads, the geometric standards (narrow shoulder and lanes, sharp curves) provide very little forgiveness if the vehicle moves out of the lane during a moment of distraction.

In conclusion, there are very few specific countermeasures that state/local agencies can direct at improving the safety of low volume roads. The countermeasures recommended here are for the most part the same as those, which would improve the safety of all roads. The one area where a specific action can be recommended is that of rural land use planning. Care is needed to ensure development in rural areas does not create peak work-related travel that is far beyond that appropriate for the design standards of the road. Furthermore, the rural elderly may need special attention in terms of rural public transit or other options to ensure mobility for this group who may be taking risks on roads they can no longer competently drive.

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## APPENDIX A MULTIVARIABLE ANALYSIS

A.1. DRIVER AGE AND SOCIOECONOMIC VARIABLES

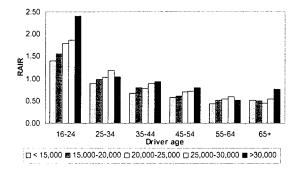
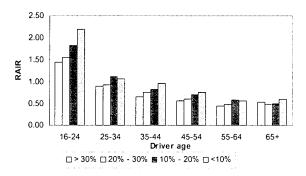
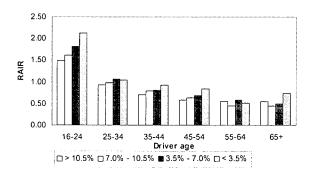


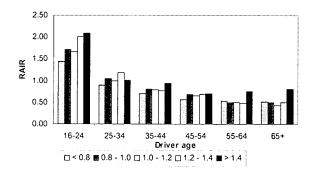
Figure A.1.1. Single-vehicle crash ratio by driver age and median household income



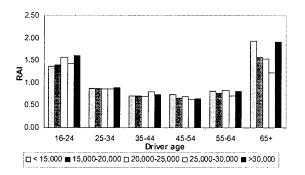
**Figure A.1.3.** Single-vehicle crash ratios by driver age and population below poverty level



**Figure A.1.5.** Single-vehicle crash ratios by driver age and unemployment rate



**Figure A.1.7**. Single-vehicle crash ratios by driver age and educational attainment index



**Figure A.1.2.** Multi-vehicle crash ratio by driver age and median household income

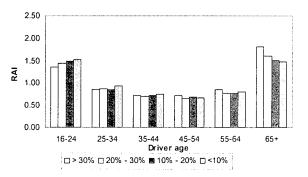
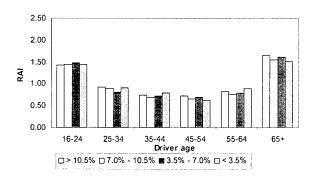


Figure A.1.4. Multi-vehicle crash ratios by driver age and population below poverty level



**Figure A.1.6.** Multi-vehicle crash ratios by driver age and unemployment rate

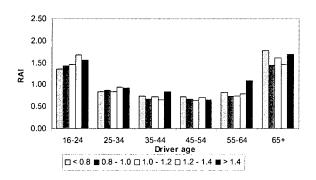
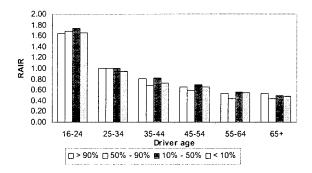


Figure A.1.8. Multi-vehicle crash ratios by driver age and educational attainment index



**Figure A.1.9**. Single-vehicle crash ratios by driver age and percentage of rural population

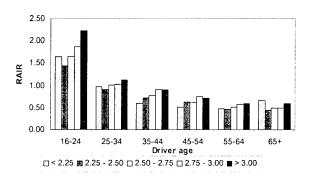


Figure A.1.11. Single-vehicle crash ratios by driver age and average number of vehicles

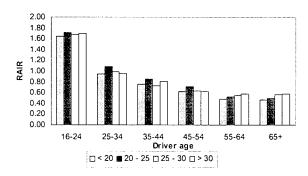
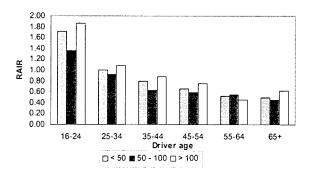


Figure A.1.13. Single-vehicle crash ratios by driver age and average time to work



**Figure A.1.15.** Single-vehicle crash ratios by driver age and alcohol convictions ratios

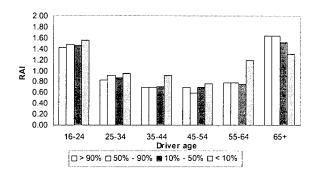
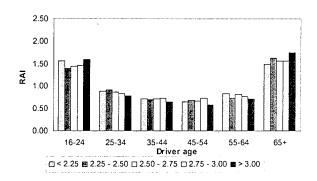
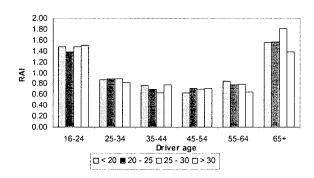


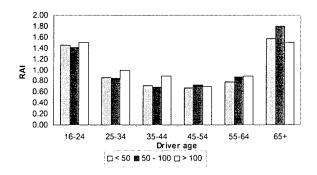
Figure A.1.10. Multi-vehicle crash ratios by driver age and percentage of rural population



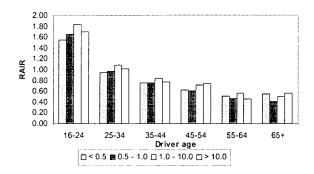
**Figure A.1.12.** Multi-vehicle crash ratios by driver age and average number of vehicles



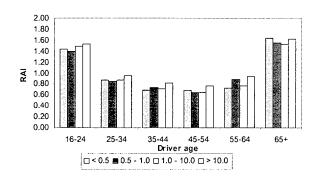
**Figure A.1.14.** Multi-vehicle crash ratios by driver age and average time to work



**Figure A.1.16.** Multi-vehicle crash ratios by driver ago and alcohol conviction ratios



**Figure A.1.17.** Single-vehicle crash ratios by driver age and speeding conviction ratios



**Figure A.1.18.** Multi-vehicle crash ratios by driver age and speeding conviction ratios

A.2. DRIVER GENDER AND SOCIOECONOMIC VARIABLES

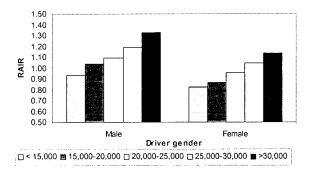
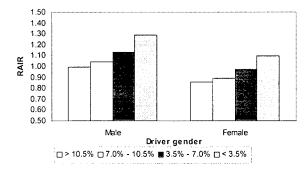


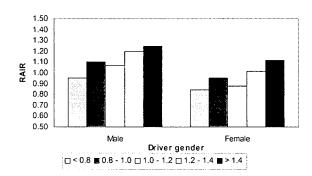
Figure A.2.1. Single-vehicle crash ratios by driver gender and median household income



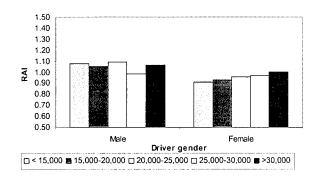
**Figure A.2.3.** Single-vehicle crash ratios by driver gender and population below poverty level



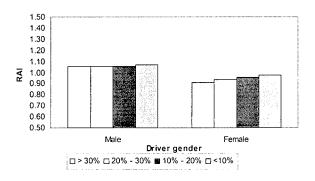
**Figure A.2.5.** Single-vehicle crash ratios by driver gender and unemployment rate



**Figure A.2.7.** Single-vehicle crash ratios by driver gender and educational attainment index



**Figure A.2.2.** Multi-vehicle crash ratios by driver gender and median household income



**Figure A.2.4.** Multi-vehicle crash ratios by gender and population below poverty level

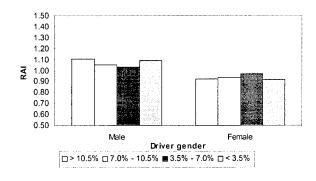
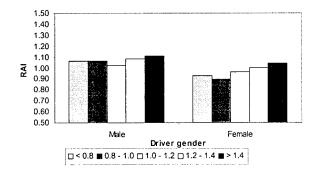
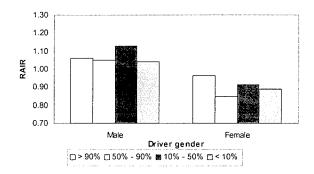


Figure A.2.6. Multi-vehicle crash ratios by driver gender and unemployment rate



**Figure A.2.8.** Multi-vehicle crash ratios by driver gender and educational attainment index



**Figure A.2.9.** Single-vehicle crash ratios by gender and rural population



**Figure A.2.11.** Single-vehicle crash ratios by driver gender and average number of vehicles

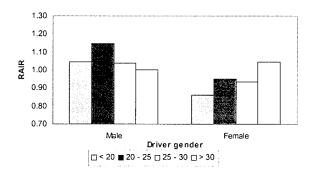
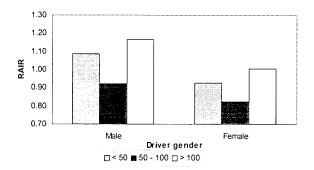


Figure A.2.13. Single-vehicle crash ratios by driver gender and average time to work



**Figure A.2.15.** Single-vehicle crash ratios by driver gender and alcohol conviction ratios

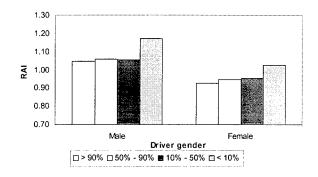
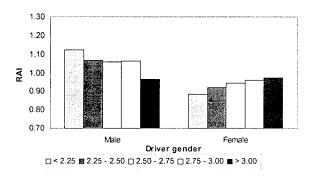


Figure A.2.10. Multi-vehicle crash ratios by driver gender and rural population



**Figure A.2.12.** Multi-vehicle crash ratios by driver gender and average number of vehicles

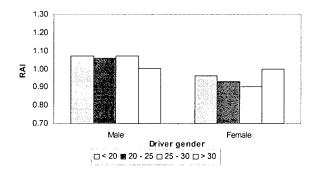
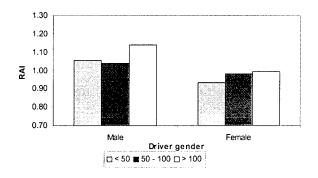
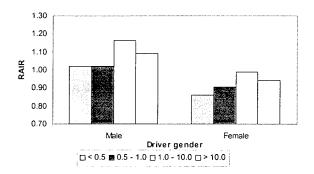


Figure A.2.14. Multi-vehicle crash ratios by driver gender and average time to work



**Figure A.2.16.** Multi-vehicle crash ratios by driver gender and alcohol conviction ratios



**Figure A.2.17.** Single-vehicle crash ratios by driver gender and speeding conviction ratios

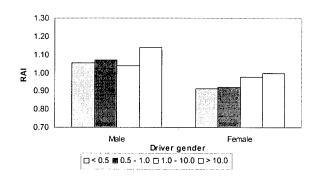
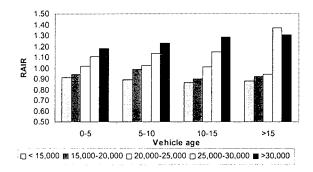
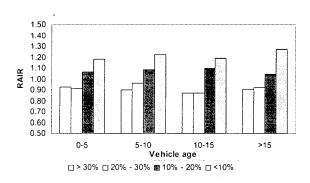


Figure A.2.18. Multi-vehicle crash ratios by driver gender and speeding conviction ratios

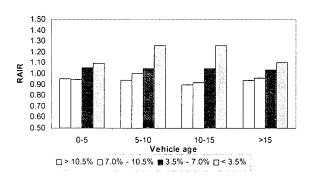
A.3. VEHICLE AGE AND SOCIOECONOMIC VARIABLES



**Figure A.3.1.** Single-vehicle crash ratios by vehicle age and median household income



**Figure A.3.3.** Single-vehicle crash ratios by vehicle age and population below poverty level



**Figure A.3.5.** Single-vehicle crash ratios by vehicle age and unemployment rate

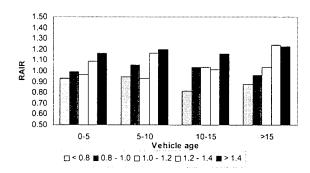
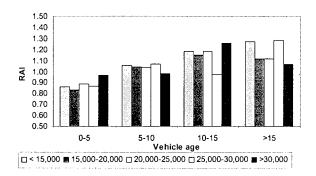
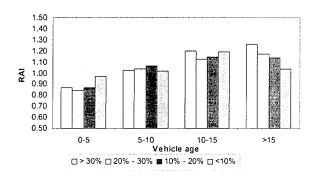


Figure A.3.7. Single-vehicle crash ratios by vehicle age and educational attainment index



**Figure A.3.2.** Multi-vehicle crash ratios by vehicle age and median household income



**Figure A.3.4.** Multi-vehicle crash ratios by vehicle age and population below poverty level

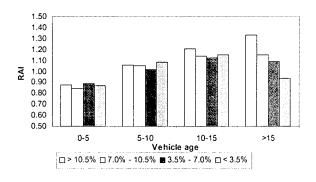
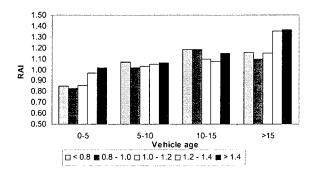


Figure A.3.6. Multi-vehicle crash ratios by vehicle age and unemployment rate



**Figure A.3.8.** Multi-vehicle crash ratios by vehicle age and educational attainment index

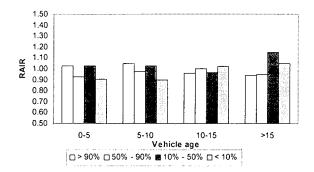
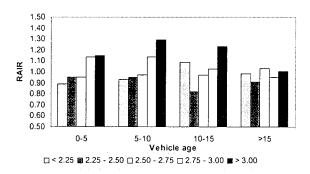
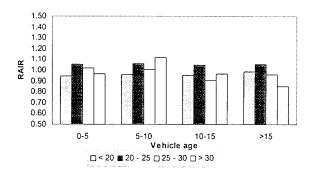


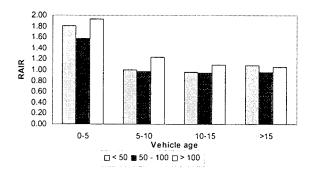
Figure A.3.9. Single-vehicle crash ratios by vehicle age and percentage of rural population



**Figure A.3.11.** Single-vehicle crash ratios by vehicle age and average number of vehicles



**Figure A.3.13.** Single-vehicle crash ratios by vehicle age and average time to work



**Figure A.3.15.** Single-vehicle crash ratios by vehicle age and alcohol conviction ratios

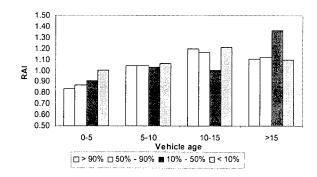


Figure A.3.10. Multi-vehicle crash ratios by vehicle age and percentage of rural population

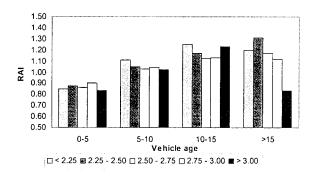
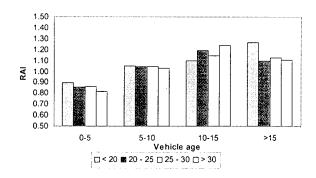
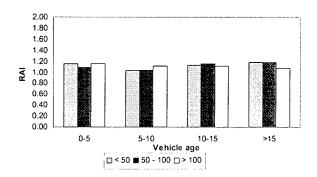


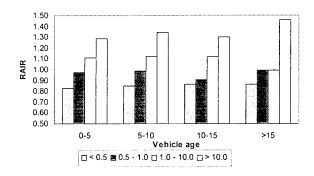
Figure A.3.12. Multi-vehicle crash ratios by vehicle age and average number of vehicles



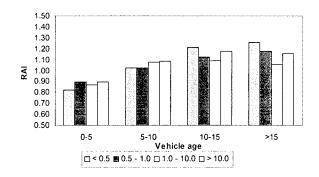
**Figure A.3.14.** Multi-vehicle crash ratios by vehicle age and average time to work



**Figure A.3.16.** Multi-vehicle crash ratios by vehicle age and alcohol conviction ratios



**Figure A.3.17.** Single-vehicle crash ratios by vehicle age and speeding conviction ratios



**Figure A.3.18.** Multi-vehicle crash ratios by vehicle age and speeding conviction ratios

A.4. DRIVER AGE AND ROADWAY ENVIRONMENT VARIABLES

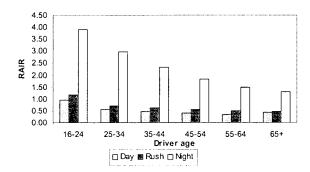
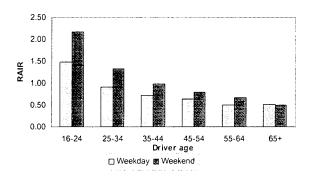
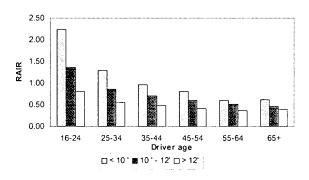


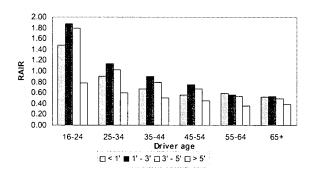
Figure A.4.1. Single-vehicle crash ratios by driver age and time of the day



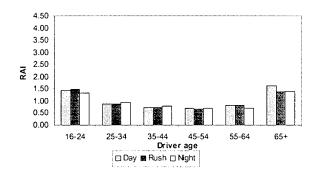
**Figure A.4.3.** Single-vehicle crash ratios by driver age and day of the week



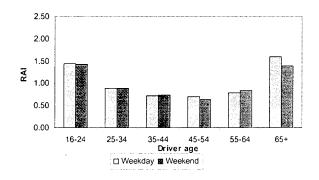
**Figure A.4.5.** Single-vehicle crash ratios by driver age and lane's width



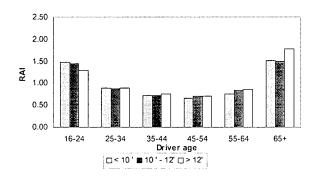
**Figure A.4.7.** Single-vehicle crash ratios by driver age and shoulder width



**Figure A.4.2.** Multi-vehicle crash ratios by driver age and time of the day



**Figure A.4.4.** Multi-vehicle crash ratios by driver age and day of the week



**Figure A.4.6.** Multi-vehicle crash ratios by driver age and lane's width

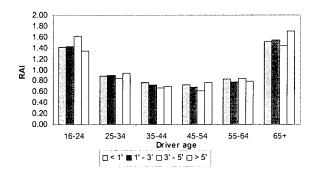
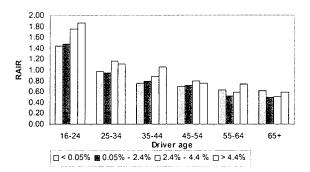
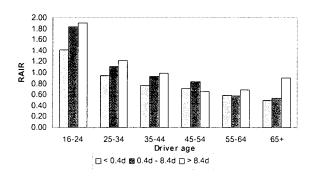


Figure A.4.8. Multi-vehicle crash ratios by driver age and shoulder width



**Figure A.4.9.** Single-vehicle crash ratios by driver age and grade classification



**Figure A.4.11.** Single-vehicle crash ratios by driver age and curve classification

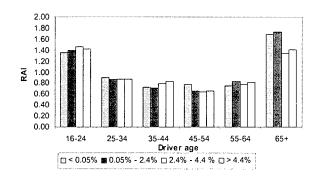
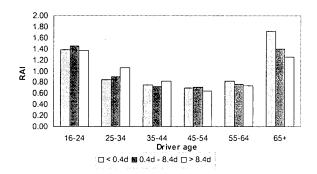
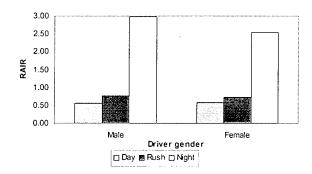


Figure A.4.10. Multi-vehicle crash ratios by driver age and grade classification

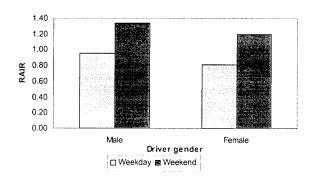


**Figure A.4.12.** Multi-vehicle crash ratios by driver age and curve classification

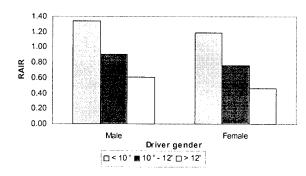
A.5. DRIVER GENDER AND ROADWAY ENVIRONMENT VARIABLES



**Figure A.5.1.** Single-vehicle crash ratios by driver gender and time of the day



**Figure A.5.3.** Single-vehicle crash ratios by driver gender and day of the week



**Figure A.5.5.** Single-vehicle crash ratios by driver gender and lane width

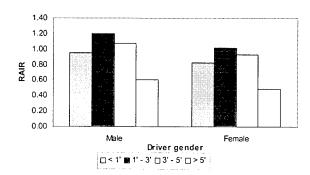
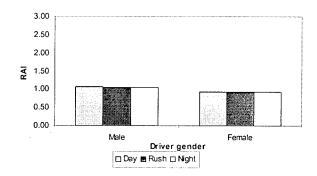
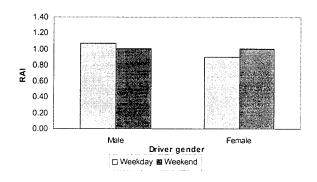


Figure A.5.7. Single-vehicle crash ratios by driver gender and shoulder width



**Figure A.5.2.** Multi-vehicle crash ratios by driver gender and time of the day



**Figure A.5.4.** Multi-vehicle crash ratios by driver gender and day of the week

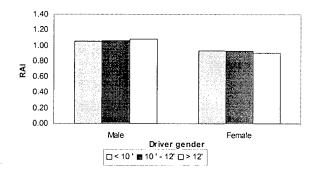
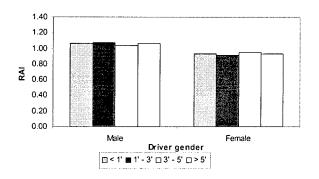


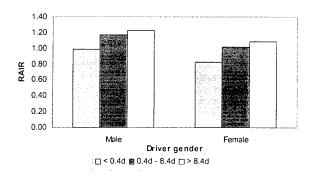
Figure A.5.6. Multi-vehicle crash ratios by driver gender and lane width



**Figure A.5.8.** Multi-vehicle crash ratios by driver gender and shoulder width



**Figure A.5.9.** Single-vehicle crash ratios by driver gender and grade classification



**Figure A.5.11.** Single-vehicle crash ratios by driver gender and curve classification

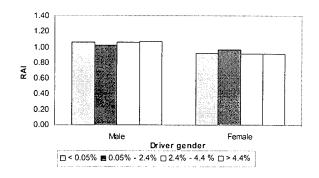
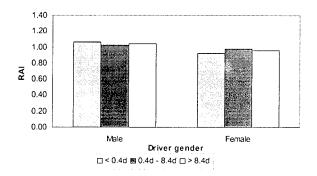
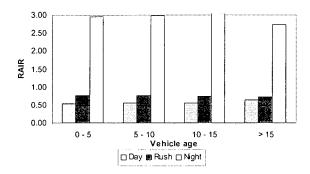


Figure A.5.10. Multi-vehicle crash ratios by driver gender and grade classification

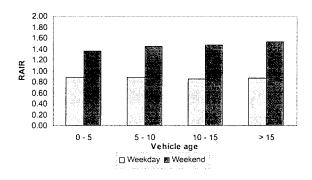


**Figure A.5.12.** Multi-vehicle crash ratios by driver gender and curve classification

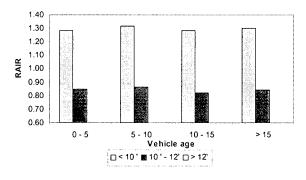
A.6. VEHICLE AGE AND ROADWAY ENVIRONMENT VARIABLES



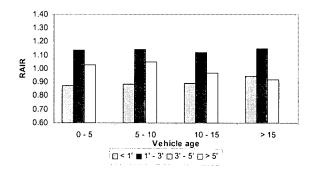
**Figure A.6.1.** Single-vehicle crash ratios by vehicle age and time of the day



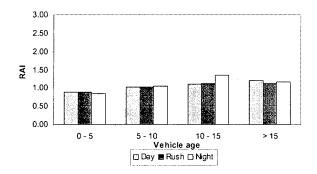
**Figure A.6.3.** Single-vehicle crash ratios by vehicle age and day of the week



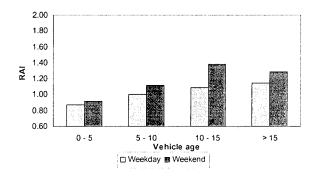
**Figure A.6.5.** Single-vehicle crash ratios by vehicle age and lane width



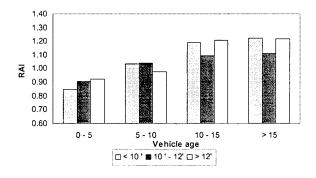
**Figure A.6.7.** Single-vehicle crash ratios by vehicle age and shoulder width



**Figure A.6.2.** Multi-vehicle crash ratios by vehicle age and time of the day



**Figure A.6.4.** Multi-vehicle crash ratios by vehicle age and day of the week



**Figure A.6.6.** Multi-vehicle crash ratios by vehicle age and lane width

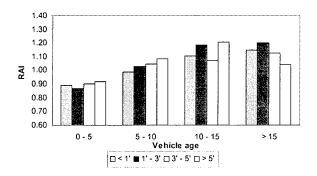
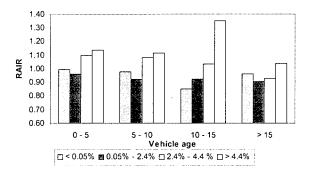
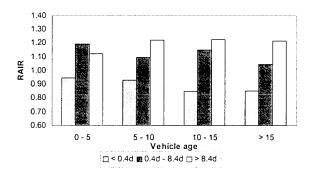


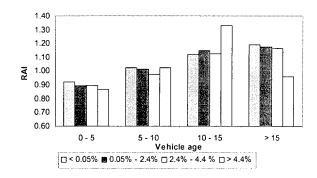
Figure A.6.8. Multi-vehicle crash ratios by vehicle age and shoulder width



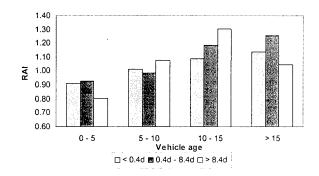
**Figure A.6.9.** Single-vehicle crash ratios by vehicle age and grade classification



**Figure A.6.11.** Single-vehicle crash ratios by vehicle age and curve classification



**Figure A.6.10.** Multi-vehicle crash ratios by vehicle age and grade classification



**Figure A.6.12.** Multi-vehicle crash ratios by vehicle age and curve classification