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Research Project T9903, Task 16
In-Vehicle Signing and Variable Speed Limit Evaluation

TRAVELAID

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16. ABSTRACT

This report discusses the effectiveness of using variable message signs (VMS) and in-vehicle traffic advisory systems (IVU) on a mountainous pass (Snoqualmie Pass on Interstate 90 in Washington state) for changing driver behavior. As part of this project, variable message and variable speed limit information were placed along a 61-km segment of I-90 between North Bend, Wash., and Cle Elum, Wash. The study area was the region where I-80 passes over the Cascade mountains through the Snoqualmie Pass. The signs, which were implemented during the winter of 1997-98, provided weather and roadway information to motorists with the intention of reducing the number and severity of accidents.

An analysis of accidents on Snoqualmie Pass was conducted with historical accident data. Several accident models were used to estimate accident frequencies severity. The report reviews the analysis of speed data over Snoqualmie Pass and reports on lane-mean speeds and deviations.

Next, the potential users' needs for variable message information and their willingness to use in-vehicle information were assessed. A survey was distributed and analyzed to explore these questions. An econometric analysis was performed of potential speed reductions for various weather conditions. A second set of analyses was then performed on the surveys to investigate the characteristics associated with drivers who would use an in-vehicle system and those who would not use the information provided by the in-vehicle unit.

A laboratory experiment was conducted on the use of an in-vehicle system and VMS. A driving simulator was used for this study. Mean speed and deviation from the mean speed were analyzed, as was the effectiveness of the systems over each 4.68-km (3-mile) stretch. The effect of VMS on the relationship between mean speeds and speed deviations was analyzed.

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Executive summary

Introduction

This report provides the details for the work conducted on the *TravelAid* project at the University of Washington, in conjunction with Washington State Transportation Center (TRAC), Washington State Department of Transportation (WSDOT), U.S. Department of Transportation (USDOT), and Federal Highway Administration (FHWA). The studies discussed, focus on the effectiveness of using variable message signs (VMSs) and in-vehicle traffic advisory systems (IVUs) on a mountainous pass (Snoqualmie Pass on Interstate 90 in Washington State) for changing driver behavior. As part of this project, variable message signs and variable speed limit signs have been placed along a 61 km segment of I-90 between North Bend, WA (milepost 33), and Cle Elum, WA (milepost 71). The study area is the region where I-90 passes over the Cascade mountains through Snoqualmie Pass. The signs, which were implemented during the winter of 1997-98, provide speed limit, weather, and roadway information to motorists with the intention of reducing the number and severity of accidents at this location.

Objectives

Variable message signs (VMSs), including variable speed limits, and in-vehicle traffic advisory system are expected to reduce speed, reduce the number of accidents, and reduce the severity of accidents that occur. It is not obvious that they do. The objectives of the TravelAid research project are to develop a research framework to accurately evaluate the effectiveness of such information systems. To that end, the speed profile of vehicles, their mean speed and the deviations from mean speed, was studied. VMSs may reduce speed but by doing so they may cause increased deviations from mean speed. Such an effect can be detrimental and can increase the frequency of accidents. The research project has also studied accident frequencies and accident severities. There are three basic parts to achieving this research goal:

First, a picture of the before-conditions is formed, by studying the mean speeds, speed deviations, accident frequencies, and accident severities before the installation of the signs.

Second, the probable effects of the information systems, variable message signs and in-vehicle units, are studied in a controlled experiment using a driving simulator.

Third, the after-conditions, after the installation of the variable message signs, must be studied to compare with the before-conditions. A study of the effects of the signs on the mean speed and speed deviation of vehicles in the area is a part of the project and has been completed.

Short summary of project

A model framework for studying accident frequencies and severities was developed. Models relating accident frequency and severity to roadway and environmental factors were developed. These models allow the study of how different factors affect accident frequency or severity. Comparable models based on data collected after the installation of VMSs can then be compared to these models to see what changes have occurred, and what factors were most affected by the VMSs.

The driving simulator studies suggest that giving drivers messages that suggest the conditions ahead are good increases mean speed beyond the mean speed of drivers that don't get information. However, when drivers received messages that suggested adverse conditions and reduced the speed limit, they obeyed and drove slower than drivers that didn't get information. Another result from the driving simulator study is that drivers that get information have a tendency towards higher speed deviation, meaning greater variations in speed, than drivers that don't get information. This can possibly increase the probability of accidents.

The current signs only show messages during adverse conditions. This makes it harder to see the actual effect of the signs. Drivers are driving more slowly because of the adverse conditions, so the drop in speed is not necessarily because of the signs. A model framework was developed that untangles these effects and the results show that drivers that receive cautionary messages and a new lower speed limit do indeed slow down beyond what they would without such information. However, the study also shows that the effect does not last long after the signs stop appearing. Drivers soon pick up the pace and return to their desired speed. The signs may therefore contribute to an increase in risk during this acceleration zone after the signs stop.

Future research must be performed to study the effects of the variable message signs on the accident frequencies and accident severities in the area. Without such a study an important part of the analysis of the effectiveness of the variable message signs is missing, and the key-conclusions of the effectiveness of the program cannot be drawn. Such a study is needed to see if there is a difference between the before- and after-conditions, and to see if there is a significant increase in accident risk in the area where drivers accelerate to their desired speed after having temporarily slowed down because of the messages.

Summary of results and implications

The analysis of the historical accident data lead to a general model that can be used to examine accident frequency as a function of geometric and weather-related variables. This model can be used to examine the effect of VMSs and IVUs on accident frequency by collecting accident data after these systems have been introduced and then estimating a model similar to the ones done in this research. The coefficients, or factors, in the model can then be compared to examine the effect of the VMSs and IVUs. If accident frequencies have changed, this method will also show why by showing which coefficients have been significantly changed. This is important to ensure accuracy of the comparison of before and after data. It is also possible to perform an analysis of coefficient elasticities. The elasticity of a coefficient, tells by how many percent the outcome changes when the input is changed by 1%. This gives more information about the actual size of the effect of the VMSs and IVUs.

Some of the general results of this research were that sections with grade exceeding 2% have a significantly higher number of accidents than flatter sections. Maximum rainfall and the number of rainy days significantly increase accident frequency.

The historical accident data was also used in a model that analyses accident severity as a function of various geometric, weather and human factors. The model can be used to examine if the VMSs lead to a significant shift towards less severe accidents when it is compared with a comparable model using data collected after the installation of VMSs. This can provide basis for research into changes of accident cost, which can lead to information regarding accident cost savings with the use of the VMSs.

Speed data was collected at a single site and used to examine lane mean speeds and speed deviations from the mean before the introduction of VMSs and IVUs. Relationships between lane speeds and speed deviations were found and they were statistically valid. Lane speed is affected by adjacent lane speed and the lane speed deviations are affected by adjacent lane speed deviations, the speed in the lane and the speeds in adjacent lanes. This research shows that this method of modeling mean speeds is promising. Future research should explore variations in the geometric, seasonal, and weather variables that may vary between different sites. Also, more microscopic data could be used to try to uncover dynamic effects in the traffic flow. The study performed here offers generic information and it would be beneficial for planning purposes with the added understanding of cause-effect relationship between lane mean speed and lane speed deviations.

Among the studies performed on the data from the simulation experiment was the modeling of mean speed and deviation by estimating an endogenous system of equations. That study focused on the effect of geometric and socioeconomic variables on mean speed and deviation along a 12 mile stretch of a computer simulated version of I-90 at Snoqualmie Pass. The effects of VMSs and IVUs were also tested. The effect is seen through the variable speed limit set by the messages on the VMSs and IVUs. The drivers with IVU only were found to have higher mean speeds than the other drivers. They do change their speed when the IVU message informs of an upcoming snowplow but, still, have a higher mean speed than those without a system. The drivers with VMSs only have higher mean speeds than those with neither system in the areas without snowplows but their mean speed is similar in the snowplow regions. Drivers with both IVU and VMSs drive slower than the other drivers. Their speed deviations where higher than for drivers with IVU only, VMS only, or drivers without a system. This indicates that drivers put some trust in the system and drive faster when the system does not indicate danger than do drivers without a system, which must be on the lookout themselves. It is interesting that the mean speed was lower for those with both IVU and VMSs and the deviation was highest for this group. These results must be taken with a grain of salt, because they stem from a simulator study and the drivers know they will not be injured or harmed by reckless driving. They also know there are no other vehicles on the road except for snowplows. These results indicate that erroneous messages may prove to be more dangerous than no messages. Further research into the effect of inaccurate messages on drivers is therefore needed. These results also show that the VMSs and IVUs may increase speed deviation. This can lead to safety concerns, especially if the traffic stream is mixed, that is, made up of drivers without information systems and drivers with systems, because these two groups are likely to have different speed profiles and this may incrase accident risk. Further research into the effect of IVUs in a mixed traffic stream is therefore necessary.

To further analyze the accident frequency and severity a model of reported speed reduction under adverse weather conditions was estimated by using survey data. This study found that drivers reported driving at very diverse speeds under adverse conditions such as on wet or icy road. It is hoped that the installation of VMSs and/or IVUs that set variable speed limits would limit this diversity and therefore increase safety.

However, as was found by the previously mentioned simulation study the speed deviation of drivers using VMSs and/or IVUs was larger than for those without such a system. There are two comments on this. First, it is not the difference between drivers with IVUs and those without IVUs that is expected to be reduced, but rather, the speed deviation within the whole group of drivers using the system. To find this a much larger sample of subjects must be used for it to be statistically valid to compare them to each other. Another angle that might be taken to analyze this further would be to examine the mean speed and speed deviation on a smaller scale to isolate the speed between messages from the message areas. Such research might answer the hypothesis that drivers with VMSs and/or IVUs drive with less speed deviation as a group on the sections between messages, but if there is a message giving a different speed limit in a section the speed deviation is increased for that section.

The survey study found many relationships between the socioeconomic factors and the reported speed reductions. One general conclusion was that drivers generally drive as fast as the law allows and give little consideration to road conditions. The variable speed limits set by the VMSs and IVUs should therefore increase safety by setting the limits according to the current conditions. This will, however, not work if drivers get the feeling that the VSLs are merely suggestions but not a legal limit that is enforced. Enforcement is therefore likely to play a big part of the success of VSLs.

The survey was also used to analyze whether drivers would use an IVU and what socioeconomic factors contribute to that decision. It was found that perception of conditions played a big role. Drivers indicated that they would generally only obey if they conditions warranted, especially for the command to put on chains. Putting on chains is so onerous that drivers need more than an IVU telling them to put them on if they do not perceive their need. These results can then be compared with the results from a similar survey collected from the participants in the simulator study.

In-service evaluation of variable message signs on mean speeds and speed deviations showed that the endogenous relationship between mean speed and speed deviation was significant and valid under ITS. The variable message signs (VMS) were shown to significantly reduce mean speed but they also significantly increased speed deviation. The increase in speed deviation can possibly work towards increasing accident frequencies at the VMS site and thereby tempering the effect of the lower mean speeds, which work to reduce accident severities and frequencies. The effect of the VMSs is not found to be significant at a site 10 km west of the VMS site. This, along with the simple aggregate results for average mean speeds and average speed deviation, suggests that drivers show compensatory behavior. The difference in average mean speed at the non-VMS site is small between the times when VMSs are on and off at the VMS site, and the lack of significance of the VMSs in the models at the non-VMS site support that. To achieve this, drivers must accelerate more quickly between the VMS site and the non-VMS site when the VMSs are on to compensate for their lower mean speed, as compared to when the VMSs are off.

Compensatory behavior like this could increase accident frequencies in the area between the sites and reduce or negate the safety benefits of lower mean speeds when the VMSs are on. A separate study to examine this effect is necessary to fully understand the safety effects of the VMSs on I-90 at Snoqualmie Pass, Washington.

Organization of report

This report is separated into several Parts to reflect the work done at various stages of the project. Chapter 1 provides an overview of the project scope and objectives. After that, an analysis of accidents on the pass was conducted using historical accident data for the Snoqualmie Pass (Part I). Several different accident models were estimated to evaluate accident frequencies (Chapter 2) and accident severity (Chapter 3). Part II reviews the analysis of speed data over Snoqualmie Pass and reports specifically on lane-mean speeds and deviations (Chapter 4). Once the historical data on the study site was collected and analyzed, it was time to assess potential users' needs for variable message information and their willingness to use in-vehicle information.

A survey was distributed and analyzed to explore these questions and findings are presented in Part III. The survey is shown in Appendix A. In Part III, the survey is described (Chapter 5) followed by the econometric analyses of potential speed reductions for various weather conditions (Chapter 6). A second set of analyses on the survey was then performed to look at the characteristics associated with drivers who would use an in-vehicle system as well as those who would not use the information provided by the in-vehicle unit (Chapter 7).

Part IV provides the methodology and analysis of the results of a laboratory experiment on the use of an in-vehicle system (the Trafficmaster) and variable message signs (VMSs). Since a driving simulator was used for this study, other simulator work is described in Chapter 8 to familiarize the reader with research done in the field. This is followed by the methodology followed in the driving simulator experiment (Chapter 9). The analysis of the data is separated into two chapters — the analysis of mean speed and deviation from the mean speed (Chapter 11), and the effectiveness of the systems over each 4.68 kilometer (or 3 mile) stretch (Chapter 12).

Part V reports on recent research that has been performed after the installation of VMSs on I-90 at Snoqualmie Pass, WA. The Part contains in Chapter 13 an analysis of the effect of VMSs on the relationship between mean speeds and speed deviations.

The results are summarized in Part VI along with a discussion on research implications and future research.

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Glossary

2SLS: Two Stage Least Squares Regression

3SLS: Three Stage Least Squares Regression

ANOVA: Analysis of Variance

APTS: Advanced Public Transportation Systems

ATIS: Advanced Traveler Information Systems

ATMS: Advanced Traffic Management Systems

AVCS: Advanced Vehicle Control Systems

BNL: Binomial Logit

CVO: Commercial Vehicle Operations

FHWA: Federal Highway Administration

FIML: Full-Information Maximum Likelihood

GLS: Generalized Least Squares

GPS: Geographical Positioning System

HMD: Heads Mounted Display

Hz: Hertz, s^{-1}

ILS: Indirect Least Squares

ITS: Intelligent Transportation Systems

IVHS: Intelligent Vehicle-Highway Systems

IVU: In-Vehicle Unit

km/h: Kilometers per hour

LIML: Limited-Information Maximum Likelihood

ML: Maximum Likelihood

MNL: Multinomial Logit

mph: Miles per hour

OLS: Ordinary Least Squares

SAS: Statistical Analysis Software.

SGI: Silicon Graphics Image

SST: Statistical Software Tools

TravTek: Travel Technology

VMS: Variable Message Sign

VSL: Variable Speed Limit

WSDOT: Washington State Department of Transportation

Chapter 1

Overview

1.1 Background

Freeway accidents are common phenomena in the United States and other parts of the world. The question of how to reduce the number and severity of accidents has prompted the use of highway patrol persons to enforce recommended speed limits; changes in highway design standards wherever possible to reduce curves and dramatic grades; and allocating resources to investigate the use of better information to drivers on road and weather conditions. This research investigates the effect of the latter alternative. Specifically, to determine if better information, provided in a driver's vehicle will enable drivers to make better driving decisions.

This research is consistent with the goals of the work being conducted under ITS (Intelligent Transportation Systems), formerly IVHS (Intelligent Vehicle-Highway Society of America). ITS is the field of study which involves the service, application and interaction of a group of advanced technologies designed to make our transportation systems operate more safely and efficiently. In 1991, ITS was centered on the technological application aspects (i.e. ATIS, AVCS, ATMS, CVO, and APTS). More recently, the focus has channeled toward 28 user services which are intended to encompass more travel related information that is not limited by a technological application, but rather, enhances the application (IVHS America, 1993). Examples of the 28 user services under the ITS plan include pre-trip travel information, traveler services information, route guidance, and incident management. This research focuses primarily on enroute driver information, and the technologies originally defined by ATIS, by providing information to drivers on roadway congestion, incidents, construction, and environmental hazards while they are in their vehicle.

1.2 Problem statement

On rural roads where geometric configurations are less than desirable, many motorists find themselves wondering what driving strategy would be best for their specific driving situations. Traffic information can provide drivers with knowledge about what to anticipate on the road on a given day and time. However, the traffic information provided by general commercial mediums (i.e. advisory radios, commercial radios, and television) do not provide a complete picture for a driver's individual trip. In the search for real-time information for each driver's needs, researchers are continually examining the use of in-vehicle and out of vehicle systems to assist drivers in getting to their destinations, efficiently and safely. In this report, these alternative methods for helping drivers are explored; by investigating the use of traffic information provided in and out of a driver's vehicle.

In an attempt to provide better information to drivers and reduce the risk of accidents in winter conditions, the Washington State Department of Transportation (WSDOT) in conjunction with USDOT has implemented the *TravelAid* Project.

As part of this project, variable message and speed limit signs are placed along the 61 kilometer segment of Interstate 90 between North Bend, Washington (milepost 33) and Cle Elum (Easton), Washington (milepost 71). This is where I-90 passes over the Cascade mountains through Snoqualmie Pass. The study area is shown on Figure 1.1. The signs will be used to provide weather and roadway information to motorists in hopes that the number and severity of accidents will be reduced.

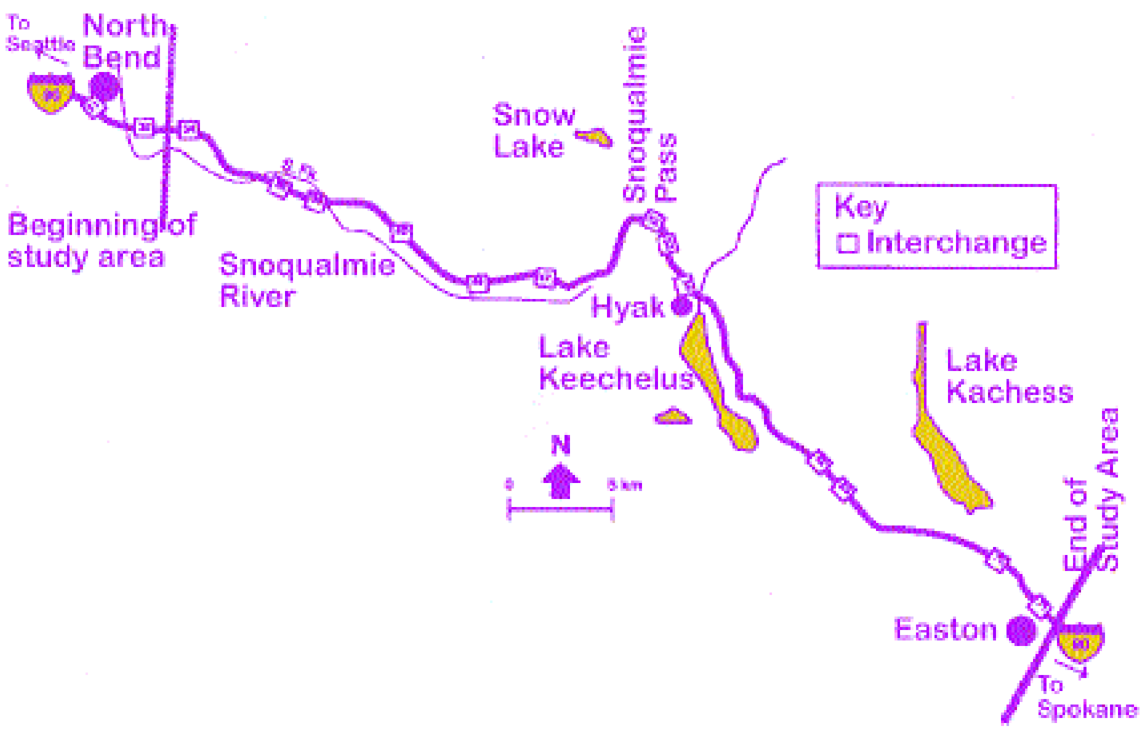

Figure 1.1: Map of study area.

Snoqualmie Pass is an important link between the western and eastern parts of Washington state. It is one of the most heavily traveled east-west routes, used by commercial vehicle operators, recreational drivers (i.e. skiers, and holiday travelers), and commuters. The Snoqualmie Pass section of I-90 is prone to harsh weather conditions with fog and rain in the summer and in the winter, ice and snow. These conditions make for severe and frequent accidents. Past data have shown that the number of accidents increases dramatically over the winter months due to the severe weather conditions and geometric configurations of the mountainous pass (Larson *et al.,* 1992).

The use of intelligent transportation systems such as variable message signs and in-vehicle information systems, gives rise to concerns relating to the impacts it may have on vehicular safety. While intelligent transportation systems have elements that are common to more traditional safety-oriented countermeasures, they present unique technological and human factors concerns that must be dealt with. Addressing these additional concerns does not present an unusually difficult conceptual or methodological problem, but it does necessitate that consideration be given the wide-range of factors that may affect overall safety.

The University of Washington has performed research to evaluate the project, which is funded by the Federal Highway Administration (FHWA) and USDOT. The intent of the evaluation is described in the *TravelAid* evaluation plan. The evaluation seeks to answer the following questions with regard to in-vehicle units (IVUs), variable message signs (VMSs), and variable speed limits (VSLs):

1. What impact do the IVUs, VMSs and VSLs have on the driver and driving task?
2. What impact do IVUs, VMSs and VSLs have on collision severities and type of collisions?
3. How effective are IVUs in terms of safety relative to VMSs and VSLs alone?
4. What would be the safety and operational impacts if all vehicles were equipped with IVUs?

To answer these questions, field and laboratory data has been collected and analyzed using econometric techniques. The research has shown that IVUs have a significant impact on the average speed and the deviation from the mean speed.

1.3 Summary

This research report describes the studies that have been, and are being, conducted at the University of Washington. There have been studies to better understand driver behavior and performance on Snoqualmie Pass before the implementation of the *TravelAid* project (see Morse, 1995; Boyle, 1998). The historical accident frequency (see Shankar *et al.,* 1995) and severity (see Shankar *et al.,* 1996) on Snoqualmie Pass and the factors that affect it have also been studied. The focus of these accident studies is on the non-behavioral determinants of accident risk, specifically roadway geometrics and weather conditions. There has also been research into mean speed and speed deviations using loop detector data (see Shankar and Mannering, 1997) and data from a survey and a driving simulator (see Ulfarsson, 1997). Simulator and survey data has also been used to analyze driver behavior in the presence of the *TravelAid* traffic advisory systems (see Boyle, 1998). Finally, an in-service assessment of the impacts of variable message signs on mean speeds and speed deviations was also conducted (Ulfarsson, Shankar and Vu, 2001). The focus of this research was on assessing the marginal impact of variable message signs on mean speeds and speed deviations, and examining the spatial transferability of speed-speed deviation relationships under ITS.

Part I

Historical Accident Analysis

To guide the evaluation and determine the ultimate effectiveness of IVUs, VMSs, and VSLs, a thorough understanding of the previous accident history of the study area is needed. Details of our work to date are provided in the next two chapters.

The section of Interstate 90 shown in Figure 1.1 experiences a high number of vehicular accidents as a result of challenging roadway geometrics (i.e. small horizontal curve radii and steep grades) and adverse weather conditions. The climate in the vicinity of the Snoqualmie Pass summit is severe. At an elevation of over 900 meters above sea level, the area receives an average of over 100 centimeters of rainfall and over 1700 centimeters of snowfall, annually. Snowfall occurs during every month except July and August. During a large portion of the year, residual snow and ice accumulated on the ground contribute to adverse driving conditions. Factors that contribute to the accidents include driver behavior, geometric characteristics (e.g., grade and curve radii), weather-related variables (e.g., rainfall and snowfall, intensity of snowfall and rainfall), interactions between geometrics and weather elements, and seasonal effects such as traffic volume, precipitation and ambient temperature-related variations.

The statistical analysis that we have undertaken to date focuses on the investigation of non-behavioral determinants of accident occurrences, specifically roadway geometrics and weather conditions. We present an appropriate methodology to establish an explicit relationship between geometric and weather-related elements and accidents. In the next two chapters, we describe the analysis of accident frequencies and present the analysis of accident severities.

Chapter 2

Accident frequencies

2.1 Introduction

The intent of this Chapter is to focus on the non-behavioral determinants of accident risk, specifically roadway geometrics and weather conditions. The Chapter begins with a review of previous research on accident frequencies in terms of their relationship to geometric and weather-related elements. On the basis of this review, we present an appropriate methodology to establish an explicit relationship between geometric and weather-related elements and accidents. This is followed by a description of available data and a discussion of model estimation results. Finally, a summary of model findings and implications is presented.

2.2 Previous research

Previous research, for the most part, has dealt with modeling relationships between accident occurrences and geometric elements. Examples of this include the work of Wong and Nicholson (1992). They observed that modifications to roadway geometrics were important because of the strong association between adverse geometric elements and high-accident locations. This association has been confirmed in studies by Boughton (1975), National Cooperative Highway Research Program (1978), and the Federal Highway Administration (1982). Other empirical relationships between vehicle accidents and highway geometrics have been studied through the use of statistical models to investigate accident involvement rate, accident probability, geometric design variables critical to safety, and the accident reduction potential of geometric improvements (National Cooperative Highway Research Program, 1978; Hammerslag *et al.,* 1982; Okamoto and Koshi, 1981; Miaou *et al.,* 1991).

In terms of the relationship between accidents and weather elements, a number of important studies have been conducted (Ivey *et al.,* 1981; Jovanis and Delleur, 1981; Mori and Uematsu, 1967; Snyder, 1974). This past work studied the effect of rainfall and snowfall on accident occurrences and attempted to quantify the contribution of these environmental elements to increasing accident likelihoods. Other types of methodologies have also been applied to the problem of accident analysis. For example, risk-based approaches, applied to the prediction of wet-weather accidents, have also been documented (Brodsky and Hakkert, 1988) and, recently, the effect of winter pavement maintenance on accident rates has been investigated (Hanbali, 1992). Finally, seasonal variations in weather elements coupled with corresponding variations in traffic volumes have been examined (Jones *et al.,* 1991) in a multi-variate framework.

Although past research work has provided insight into the effect of weather on accident rates and frequencies, efforts to investigate the interaction of weather and geometric elements, and their consequent impact on accident likelihoods, have been minimal. The study of such interactions is important because it could shed light on the impact of weather on critical geometric design elements and serve as a guide in the design of roadway geometrics so as to minimize accident likelihoods in the presence of varying climatic conditions. This concept contrasts with present roadway geometric design practice which applies a uniform nationwide standard in terms of assumed weather impacts on geometric design (Mannering and Kilareski, 1990). Presumably, much could be gained by adjusting this standard to account for weather conditions that deviate greatly from the norm.

In addition to weather and geometrics, it may be argued that human factors contribute significantly to accident occurrences and hence warrant inclusion in the modeling effort. Previous research (Treat, 1980; Sabey and Taylor, 1980) indicates that human factors are involved in 95% of all traffic accidents, either alone or in combination with other factors. However, other research (Massie *et al.,* 1993) tempers the criticism of research excluding human factors by pointing out that the human factors approach ignores the problem associated with classifying collisions and their related causes, be it human or otherwise. The authors add that such an approach fails to address the issue of helping drivers avoid collisions. Identification of geometric and weather-related factors and their interrelationship can be used to assist the driver in reducing the chances of a collision by offsetting the ignorance factor caused by unanticipated changes in roadway geometrics and their interrelation with adverse weather conditions.

From a methodological perspective, attempts to model accident frequencies have varied from the use of least squares regression techniques to methods involving exponential distribution families including the Poisson and negative binomial models. Previous research on Poisson and least squares (Jovanis and Chang, 1986; Joshua and Garber, 1990; Miaou and Lum, 1993) indicates the inappropriateness of least squares techniques to modeling of accident frequencies, and recommends the employment of the Poisson distribution. The Poisson distribution, however, suffers from an important limitation, namely that the mean and variance are constrained to be equal. Over-dispersion (variance greater than the mean) or under-dispersion (variance less than the mean) of data violates this constraint and leads to biased coefficient estimates. A more general distribution, such as the negative binomial, has been employed in such situations (Engel, 1984; Lawless, 1987; Manton, Woodbury and Stallard, 1981) to relax this constraint. Negative binomial distributions have been employed frequently in physics, medical sciences and marketing. Documented use of the negative binomial distribution in the field of traffic engineering includes applications in trip generation (Frisbie, 1980) and transportation economics (Hellerstein, 1991). In terms of applying the negative binomial distribution to model accident occurrences, research has been conducted on accident proneness (Bates and Neyman, 1952), accident migration (Maher, 1987; 1990), accident "blackspots" identification (Senn and Collie, 1988) and accident frequencies (Miaou, 1994; Maher, 1991; Poch and Mannering, 1994).

The body of extant literature provides important methodological direction for our study of the interrelationship between roadway geometrics and weather and accident frequencies. Details of this methodological direction are discussed in the following section.

2.3 Methodology

Count data are often modeled by assuming Poisson distributions (Cameron and Trivedi, 1986). The Poisson distribution is a useful starting point because; (1) it lends itself well to the modeling of count data by virtue of its discrete, non-negative, integer-distribution characteristics, and (2) can be generalized to more flexible distributional forms. In terms of accident frequencies, in this study we will focus on modeling the number of accidents occurring on a specified section of roadway in a one month time period. In such a case, the Poisson distribution gives

$$P(n_{ij}) = e^{-\lambda_{ij}} \lambda_{ij}^{n_{ij}} / n_{ij}!, \tag{2.1}$$

where $P(n_{ij})$ is the probability of n accidents occurring on roadway section i in month j and λ_{ij} is the expected number of accidents on roadway section i in month j. Given a vector of geometric, traffic and weather data, λ_{ij} can be estimated by the equation

$$\ln \lambda_{ij} = \mathbf{X}_{ij}\beta , \tag{2.2}$$

where **X** is a vector of geometric, traffic and weather data for roadway section i in month j and β is a vector of estimable coefficients. As mentioned in our review of previous research, the Poisson distribution constrains the mean and variance to be equal, (i.e. $E[n_{ij}] = Var[n_{ij}]$). As previously mentioned, estimation using a Poisson distribution violating this assumption (i.e. when data are overdispersed or underdispersed) results in biased estimates of β. It is well known, based on the findings of many previous research efforts, that accident frequency data tend to be over-dispersed, with the variance being significantly greater than the mean. Consequently, the Poisson distribution can lead to erroneous coefficient estimates and erroneous inferences can be drawn. To overcome this, the negative binomial distribution, which includes a gamma-distributed error term, is appropriate because it relaxes the Poisson's mean-variance equality constraint. The negative binomial model is derived by re-writing equation (2.2) as,

$$\ln \lambda_{ij} = \mathbf{X}_{ij}\beta + \varepsilon_{ij}, \tag{2.3}$$

where ε_{ij} is a gamma-distributed error term. This results in the mean-variance relationship,

$$\mathrm{Var}[n_{ij}] = E[n_{ij}][1 + \alpha E[n_{ij}]]. \tag{2.4}$$

If α is significantly different from zero, the data are over-dispersed or underdispersed. If α is equal to zero the negative binomial reduces to the Poisson distribution.

The resulting probability distribution under the negative binomial assumption is,

$$P(n_{ij}) = \frac{\Gamma(\theta + n_{ij})}{\Gamma(\theta) n_{ij}!} u_{ij}^{\theta}(1 - u_{ij})^{n_{ij}}, \tag{2.5}$$

where $u_{ij} = \theta/(\theta+\lambda_{ij})$, $\theta = 1/\alpha$, and $\Gamma(.)$ is a value of the gamma function. Estimation of λ_{ij} can be conducted through standard maximum likelihood (ML) procedures (see Greene, 1993). Using equation (2.5), the likelihood function (the product of probabilities) for the negative binomial is,

$$L(\lambda_{ij}) = \prod_{i=1}^{N}\prod_{j=1}^{T} \frac{\Gamma(\theta + n_{ij})}{\Gamma(\theta) n_{ij}!} \left[\frac{\theta}{\theta + \lambda_{ij}}\right]^{\theta} \left[\frac{\lambda_{ij}}{\theta + \lambda_{ij}}\right]^{n_{ij}}, \tag{2.6}$$

where T is the last month of accident data and N is the total number of roadway sections. This function is maximized to obtain coefficient estimates for β and α.

Careful attention must be paid to the appropriateness of the negative binomial distribution in the case of overdispersed data. For example, equation (2.3) may hold while the distribution of n_{ij} conditioned on $\mathbf{X}_{ij}$ may not be negative-binomial distributed. In such a case, the coefficient estimates will be consistent though less efficient than those for the correct distribution. Importantly, the asymptotic variance-covariance matrix will be incorrect and likely underestimated. However, in practice, this underestimation is not likely to affect substantive conclusions drawn from model estimation (see Lawless, 1987).

In addition to maximum likelihood estimation procedures, other methods such as quasilikelihood, weighted least squares (McCullagh and Nelder, 1983), moment estimation techniques (Breslow, 1984) and regression-based estimation (Cameron and Trivedi, 1986; 1990) are available. Examples of the application of the moment method and regression-based estimation in accident modeling indicates that these methods should be used with caution (Miaou, 1994). Indications from statistical research on the estimation of α, the dispersion coefficient, suggest that for large samples (N > 20) the quasilikelihood and maximum likelihood methods perform best (Piegorsch, 1990).

2.4 Empirical setting

The study area consists of the 61 kilometer portion of I-90 described in the introduction to this report (see Figure 1.1). This portion of Interstate 90 generally consists of a three-lane (3.66 meter lanes) cross-section, in each direction, with 3.05 meter shoulders and a 104.6 km/h speed limit. Virtually no variation in travel lane and shoulder widths exists in the study area.

Data from a number of sources were gathered over the period from January 1988 to May 1993. Precipitation data were assembled from the Desert Research Institute and Western Regional Climate Center and the geometric attributes of the roadway and accident data were obtained from the Washington State Department of Transportation. The available precipitation data consisted of information relating to monthly rainfall and snowfall including average monthly snowfall and rainfall, maximum daily snowfall and rainfall and number of snowy and rainy days per month. Three weather stations located at Snoqualmie Falls, Stevens Pass and Cle Elum (all in Washington State near the study area) were used as the sources of climatic data. Weather data were assigned to sections based on their geographic proximity and elevation levels[1].

Geometric characteristics included: number of horizontal curves, number of horizontal curves underdesigned (those curves with design speeds less than 112.6 km/h, less than 96.5 km/h, and less than 80.45 km/h), maximum and minimum horizontal radii, number of vertical curves and maximum and minimum grades.

With this data in hand, the issue of dividing the study area into manageable sections of roadway must be addressed. The existing literature addresses several important issues relating to roadway section length determination in a linear regression context (Okamoto and Koshi, 1989). The findings of these studies show that great care must be taken in determining roadway section lengths because of two model estimation concerns; (1) the possibility of heteroskedasticity (i.e.

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1 As a result, several contiguous sections shared the same weather information (this can be seen in Table 2.1). Shared weather data raises the issue of serial correlation of model error terms. Weather information shared by contiguous sections causes any shocks in data to propagate through sections common to that data, thereby causing spatial correlation. To date, the effect of such spatial correlation has not been specifically investigated in a count data model context. However, based on experiences in linear regression contexts, it can be reasonably assumed that spatial correlation could cause some loss of efficiency of parameter estimates. Studies have shown that, in most practical contexts, this is not a major concern (Mannering 1995).

error terms are not identically distributed), and (2) the possibility of biased model coefficients. Heteroskedasticity, especially in the context of a negative binomial specification (as opposed to a Poisson specification), is an important issue due to the incorporation of the gamma-distributed error term.

The most popular alternatives for determining roadway section lengths are the use of fixed-length sections or homogeneous sections (i.e. sections with homogeneous geometric characteristics, see Miaou *et al.,* 1991). With regard to homogeneous sections (both in terms of geometrics and weather), several important problems arise. One of these problems is that roadways with numerous horizontal curves and grades tend to produce sections that are less than 1 kilometer in length (i.e. to ensure homogeneity in geometrics). This can result in locational error problems because accidents, in most states, are locationally reported to the nearest milepost (1.609 kilometers). Potential bias resulting from such accident-reporting locational error is clearly undesirable.

Homogeneity of weather data presents a different problem. Weather data, by virtue of their geographic characteristics, usually encompass much larger areas and, if allowed to govern section lengths, are likely to result in long geometrically diverse sections, thus violating geometric homogeneity.

Finally, the unequal length of sections that will result from the homogeneity requirement may exacerbate potential heteroskedasticity problems (i.e. unequal sample sizes, see Mannering, 1995) and lead to a loss in estimation efficiency. The resulting increase in the standard errors of model coefficients could lead the analyst to draw erroneous inferences with regard to the effects of model covariates.

The disadvantages of using fixed-length sections, relative to homogeneous sections, are far less severe. In fact, most potential disadvantages can be overcome by accounting for the non-homogeneity of geometric and weather-related variables by including detailed measures of the variability across sections in the model specification (e.g., number of curves, maximum grade and number of underdesigned curves, and so on). If such data are available, there is little need to constrain the analysis to homogeneous sections. Moreover, fixed-length sections may offer other advantages such as being able to mitigate the effects of the accident migration which is a phenomenon involving the migration of accidents to a different portion of a hazardous roadway section after corrective measures have been taken on some other portion of the roadway (see Boyle and Wright, 1984; McGuigan, 1985; Maher, 1987). If one were to use geometrically homogeneous sections, it would be exceedingly difficult to account for the effect that changes in accident likelihoods on one section would have on others (due to accident migration). However, the use of fixed-length, non-homogeneous sections accounts for the possibility of accident migration, to some extent, because the migration across the homogeneous "sub-sections" that comprise the fixed length section is internalized.

As a result of the above discussion, the sections considered in this study were determined to be fixed, equal-length sections. Thus, accident frequencies and associated geometric and weather data were compiled along ten sections, of equal length, over the 61 kilometer study area (i.e. each section is 6.1 kilometers in length). Accident frequencies and roadway geometrics for both roadway directions (eastbound and westbound) were used[1]. A total of 2,225 reported accidents occurred in the study area between January 1988 and May 1993[2]. Accidents were sorted by year and month and integrated with geometric and monthly weather data into one database. The consolidated database, after accounting for some missing weather data (which resulted when weather stations were not functioning due to mechanical failures) consisted of 464 observations with some sections experiencing zero accidents in some months[3]. The implicit specification of accident frequency per month as the dependent variable allows the modeling of seasonal variations in traffic volumes, ambient temperature and other environmental data such as daylight duration.

Table 2.1 summarizes the averages of the variables measured in this study. Mean section accident frequency per month was 3.26 (Figure 2.1 shows average per-month accident frequencies by section) with an observed monthly minimum of zero and maximum of 28 (the observed monthly variance was 16.32). Other values worthy of note include the high number of horizontal curves on the ten sections. The twelve horizontal curves in section 6 (sections 6 and 7 are near the summit) suggests complex geometrics in the area (i.e. about two horizontal curves per kilometer). Also the average monthly snowfall, observed to be 145.78 centimeters in

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1 Interstate 90 has divided cross-sections with different grades and horizontal curve attributes in three of the ten study sections. By combining both east and west directions, we constrain the β's to be the same. An empirical test of this assumption revealed that this constraint is statistically valid.

2 In this analysis we include only those accidents reported to the Washington State Highway Patrol (WSP). Although this section of highway is heavily patrolled by WSP, it is likely that some minor accidents are never reported.

3 Note that our data has repeated observations from the same section of roadway. That is, each section produces as many as 12 observations (corresponding to 12 months) per year. Such data raises the possibility of error term correlation among observations produced by the same section, with observations from the same section sharing unobserved factors that may impact accident likelihoods (e.g., a scenic distraction). A likely consequence of such correlation is some loss in efficiency of coefficient estimates. However, research by Mannering and Winston (1991) indicates that the efficiency loss from this source is small, particularly if section-specific constants are included in the model specification (as will be the case in this study).

sections 5-8, is quite high and reflects the severe climate resulting from the relatively high elevation.

Table 2.1: Sample summary statistics (section averages).

Variable	Section number 1	2	3	4	5	6	7	8	9	10
Accident frequency (per month)	1.80	2.25	1.66	2.49	7.81	8.35	5.92	4.15	2.81	2.86
Number of curves with a design speed less than 128.7 km/h	1	3	1	3	1	5	9	2	8	2
Number of curves with a design speed less than 96.5 km/h	0	1	1	0	1	4	6	2	7	1
Number of curves with a design speed less than 80.5 km/h	0	0	0	0	1	1	1	0	0	0
Number of horizontal curves in section	8	8	10	9	10	12	10	9	10	4
Maximum horizontal curve radius in section (m)	3030	3636	909	3030	1515	3030	695	1736	1736	1818
Minimum horizontal curve radius in section (m)	636	595	595	606	333	333	347	347	347	788
Number of vertical curves in section	7	8	9	10	8	5	16	7	15	5
Maximum grade in section	5.00	3.00	1.76	3.63	5.29	4.22	2.00	2.60	3.83	5.00
Minimum grade in section	0.03	0.27	0.14	0.46	3.29	0.67	0.43	0.08	0.20	0.74
Average monthly rainfall (cm)	5.01	5.01	5.01	5.01	8.70	8.70	8.70	8.70	1.93	1.93
Maximum daily rainfall in the month (cm)	2.73	2.73	2.73	2.73	5.28	5.28	5.28	5.28	1.40	1.40
Number of rainy days in the month	1.09	1.09	1.09	1.09	2.11	2.11	2.11	2.11	0.56	0.56
Average monthly snowfall (cm)	1.70	1.70	1.70	1.70	145.78	145.78	145.78	145.78	8.5	8.5
Maximum daily snowfall in the month (cm)	1.28	1.28	1.28	1.28	27.65	27.65	27.65	27.65	3.30	3.30
Number of snowy days in the month	0.20	0.20	0.20	0.20	10.31	10.31	10.31	10.31	1.24	1.24

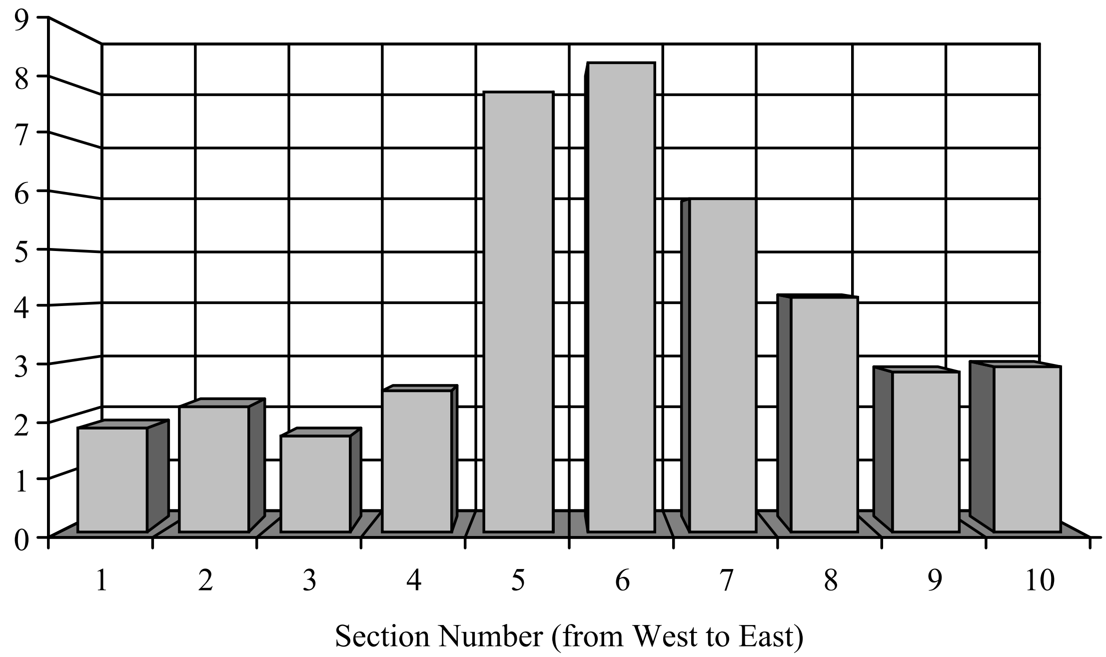

Figure 2.1: Average monthly accident frequencies on the 10, 6.1 kilometer sections. (Sections numbered sequentially from West to East in the study area).

2.5 Model estimation

The negative binomial estimation of section-accident frequencies is presented in Table 2.2. This table shows that all variables are of plausible sign with reasonably high statistical significance. Table 2.2 shows that the majority of independent variables specified in this model positively affect accident frequency indicating a likelihood in increase in frequency with increasing variable values. The number of curves variable provides some insight into potential geometric hazards. The number of curves with design speeds between 96.5 km/h and 128.7 km/h appears to have a greater effect (0.117) than those designed under 96.5 km/h (0.046). The higher coefficient value for higher design-speed curves is likely capturing the tendency of drivers to slow down for curves with low design speeds due to a combination of the visual effect of the curve and speed reduction signs usually found in those locations.

Grade appears to have a strong positive effect on accident frequency, although in a stepwise, as opposed to a continuous, manner. In comparison to those sections with grades less than 2 percent, those with maximum grades exceeding 2 percent will experience a significant increase in accident frequency. Intuitively, this captures the effect of speed differentials that play a significant role in accident occurrences, although, to some extent, the presence of climbing lanes offsets the detrimental impact of grades especially those impacts caused by slow-moving heavy vehicles. In the present context, however, a geometric variable accounting for climbing lane effects was not found to be significant because there is little variation in this variable across sections. A review of the data showed that any vertical grade reasonably long (longer than 2 kilometers) and exceeding 2 percent had a climbing lane.

Maximum rainfall played a significant, positive role in accident occurrences. Employed as an indicator variable, it captures not only the effect of intensity of rainfall and potential hydroplaning of vehicles but also may be capturing the effects of exposure and pavement condition. For example, the pavement surface is likely to remain wet or icy during the night or early morning when daily rainfall exceeds 2.54 centimeters.

The number of rainy days played a significant, positive role in accident occurrences. This variable appears to capture exposure effects such as exposure to wet pavements and lower visibility effects. More interestingly, given the fact that the Seattle area generally experiences intermittent rainfall throughout the year, drivers may be inclined to pay less attention to the risk of an accident during rainy weather. The number of rainy days variable could possibly be playing a surrogate role for increased accident risk arising from driver complacency.

Maximum daily snowfall intuitively captures the positive effect that snow plays in accident occurrences. Maximum snowfall exceeding 5.08 centimeters, employed as an indicator variable, appears to account for traction and lane-marking-related problems caused by increasing snow depth on the pavement. In combination with grades, as evidenced by the interaction term, it positively impacts accident frequency. This illustrates the dangerous combination of traction, lane-markings and speed differentials. In addition, it also suggests that the effect of climbing lanes could likely be annulled by the obliteration of lane markings on snow-covered pavements. In the presence of under designed horizontal curves, the snowfall variable portrays a stronger effect than the grade interaction by virtue of its higher coefficient.

The section location indicator variable shows that the middle portion of the study corridor (sections 5, 6, 7, and 8, which include the summit and the immediate area surrounding it) is associated with lower accident rates with all other factors held constant[1]. This is likely the result of changes in driver behavior, with drivers becoming more cautious as they gain elevation and approach/depart from the Snoqualmie Pass Summit.

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1 Note that this does not imply that these sections of the study area have lower overall accident rates (see Figure 2.1). It only indicates that these sections have lower than expected accident rates when the accumulated effects of geometrics and weather have been taken into account.

Table 2.2: Negative binomial estimation results (total section accident frequency).

Variable	Estimated coefficient	t-statistic	p-value
Number of horizontal curves designed between 96.5 km/h and 128.7 km/h	0.117	2.437	0.015
Number of horizontal curves designed below 96.5 km/h	0.046	2.205	0.027
Maximum grade in section indicator (1 if greater than 2%, 0 otherwise)	0.133	2.748	0.006
Maximum rainfall indicator (1 if greater than 2.54 centimeters on any given day in the month, 0 otherwise)	0.209	1.401	0.161
Number of rainy days in the month	0.018	1.975	0.048
Rainfall-Curve interaction indicator (1 if maximum rainfall greater than 2.54 centimeters on any given day in the month and at least one horizontal curve has a design speed less than 96.5 km/h, 0 otherwise)	0.184	1.239	0.215
Maximum daily snowfall in the month	0.033	2.231	0.026
Snowfall-Grade interaction indicator (1 if maximum snowfall greater than 5.1 centimeters on any given day in the month and grade greater than 2%, 0 otherwise)	0.291	1.930	0.053
Snowfall-Curve interaction indicator (1 if maximum snowfall greater than 5.1 centimeters on any given day in the month and at least one horizontal curve has a design speed less than 96.5 km/h, 0 otherwise)	0.387	2.137	0.032
Section location indicator (1 if section number is 5, 6, 7 or 8, 0 otherwise)	-0.466	-1.812	0.070
Year of occurrence indicator (1 if 1988, 0 otherwise)	0.273	2.330	0.020
Year of occurrence indicator (1 if 1990, 0 otherwise)	-0.167	-1.410	0.159
α (dispersion coefficient)	0.418	8.463	0.000
Number of observations	464		
Log-likelihood at zero	-2193.39		
Log-likelihood at convergence	-970.93		
ρ^2	0.56		

The year 1988 was found to positively affect accident frequencies. Although normal precipitation levels were observed during this year, the positive coefficient value captures unobserved effects such as unusually cold ambient temperatures resulting in ice-covered pavements and construction-related effects such as lane closures[1].

The year 1990, in a similar manner, was specified as an indicator variable. The negative effect of this variable seems to account for some decrease in traffic volumes as well as extra caution used by drivers in the presence of adverse driving conditions created by abnormally high levels of precipitation that occurred during the year.

Finally an examination of ρ^2 (0.52) for the model indicates a good statistical fit, while the dispersion coefficient, α, was estimated to be significantly different from zero ($t = 8.463$) indicating over dispersion of data, a phenomenon that can not be handled by a Poisson distribution[2].

Other issues worthy of note in the estimation context pertain to the impact of weather-related variables on pertinent variables such as traffic volume, temperature and daylight time. The high level of significance of the weather-related variables coupled with their interaction with geometric variables suggests that they capture seasonal trends in traffic volume, temperature and daylight time as well[3]. The significance of weather-related variables and their use as surrogates for traffic volumes is corroborated in previous research (Jones *et al.,* 1991).

It should also be noted that we tried to include a variety of other interactions between two variables and among three or more variables in our model (e.g., rainfall exceeding 2.54 centimeters on any given day in the month, at least one horizontal curve with less than 96.5 km/h design speed, and a grade greater than 2 percent). However, all such variables produced statistically insignificant coefficients and were thus excluded from our final specification.

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[1] It should be noted that since I-90 is a captive corridor with few alternate routes to/from Eastern Washington, construction activities did not cause significant decreases in traffic volumes in the study corridor .

[2] It is interesting to note that several variables that were found to be significant in a Poisson specification of our model turned out to be insignificant under the negative binomial assumption. This occurred because the Poisson specification underestimated coefficient variances due to the inherent overdispersion of data. Variables found significant in the Poisson but insignificant in the negative binomial included average daily rainfall for the month, number of snowy days in the month, average snowfall in the month and curve radii.

[3] The absence of traffic volume, temperature, and other variables in the model raises the possibility of a model specification error (i.e., an omitted variables bias). To test for this we used a series of month indicator variables (e.g., January, February, etc.) and time of year variables (e.g., winter, summer, spring, and autumn). These variables are highly correlated with traffic volumes (and their seasonal variation), temperature variations, and other possible omitted variables. These indicator variables were all statistically insignificant, suggesting the possible omitted variables bias is not playing a significant role in our model.

Elasticities of independent variables were estimated to determine the impact of those variables on accident frequency. Elasticities can be roughly interpreted as the percentage change in the average frequency of accidents λ_{ij} due to a one percent change in the independent variable. Elasticity of accident frequency λ_{ij}, with respect to x_{ijk} (the kth independent variable for section i in month j) is defined as,

$$E_{x_{ijk}}^{\lambda_{ij}} = \frac{\partial \lambda_{ij}}{\lambda_{ij}} \cdot \frac{x_{ijk}}{\partial x_{ijk}} . \tag{2.7}$$

Using equations (2.3), and (2.7) gives,

$$E_{x_{ijk}}^{\lambda_{ij}} = \beta x_{ijk} , \tag{2.8}$$

where β is the coefficient corresponding to covariate x_{ijk}.

With equation (2.8), elasticities of λ_{ij} for each section observation were computed and sample averages were then estimated. Note that the elasticities of indicator variables are not meaningful, so only the elasticities of continuous variables are presented in Table 2.3.

Table 2.3 provides some interesting insights. For example, a 1 percent increase in the number of rainy days in a month causes a 0.26 percent increase in accident frequencies. Similarly, a 1 percent increase in the maximum daily snowfall in a month results in a 0.10 percent increase in accident frequencies. This suggests that, at least for these two variables, accident likelihoods may be more sensitive to rain than snow. However, these are not the only snow/rain variables in the model (i.e. indicator variables are not included in Table 2.3) and, as will be shown, indicator variables that show an interaction between climatic conditions and roadway geometrics have a large impact on accident frequencies.

Table 2.3: Accident frequency elasticity estimates.

Elasticity with respect to:	Value
Number of rainy days in the month	0.2624
Maximum daily snowfall in the month	0.1012
Number of horizontal curves designed between 96.5 km/h and 128.7 km/h	0.1346
Number of horizontal curves designed below 96.5 km/h	0.0968

Finally, it is also important to point out that all variables shown in Table 2.3 are inelastic (elasticity less than unity). This suggests that, while the effect of these variables on accident frequencies is statistically significant, they may be nearing thresholds where accident frequencies have relatively low sensitivity to any changes in the explanatory variables.

To gather some understanding of the relative importance of the indicator variables included in the model, a numerical computation can be performed to provide an idea of the relative effect of indicator variables on average accident frequency. This is accomplished by using a ratio of coefficients. For example, the average accident frequency λ_{ij} for section i in month j can be said to increase 14.0% ($e^{0.133}/e^{0}$), if the maximum grade on the section is raised to exceed 2%, assuming the error terms are independent of x_{ij} and remain unchanged. Table 2.4 presents the change in the average accident frequency caused by threshold changes in the indicator variables.

Table 2.4 shows that snowfall-horizontal curve and snowfall-grade indicators have a large effect on accident frequencies (47.3% and 33.8% respectively). Rainfall indicators also strongly impact accident frequencies. These findings underscore the importance of accounting for weather/geometric interactions when assessing accident likelihoods.

2.6 Implications of findings

The proposed model accounts for plausible and intuitive geometric and weather-related factors that influence accident frequencies. Specifically, the model offers insight into the combined effect of weather and geometric elements through interaction variables. The employment of indicator-type interaction variables allows designers to determine thresholds of geometric variables, such as maximum grade, beyond which their interaction begins to significantly affect accident frequencies.

The findings of this research have significant implications for highway design standards. Current standards establish geometric design criteria on the basis of pavement-tire interactions on wet pavements. Our findings show that, in order to reduce accident likelihoods in areas that frequently experience adverse weather, the basis of establishing design criteria should be expanded beyond wet-pavements. Specifically, great effort should be expended to avoid steep grades and horizontal curves with low design speeds in areas with adverse weather. Intuitively, this seems obvious, but our model provides a method of quantifying the impacts of these geometric characteristics. For example, for our study area, eliminating all horizontal curves with a design speed less than 96.5 km/h on a roadway section that experiences at least 5.1 cm of snowfall, one or more days in a month, can reduce the monthly accident frequency by 47.3% (see Table 2.4). Although our model results are site-specific, a more global application of our approach could serve as a basis for a cost-benefit analysis that could guide geometric design policy more effectively than the current wet-pavement approach[1].

Table 2.4: Percentage change in accident frequencies due to indicator variables.

Variable	Percentage Change in mean accident frequency, λ_{ij}
Maximum grade in section indicator (1 if greater than 2%, 0 otherwise)	14.2
Maximum rainfall indicator (1 if greater than 2.54 centimeters on any given day in the month, 0 otherwise)	23.2 to 48.1[a]
Rainfall-Curve interaction indicator (1 if maximum rainfall greater than 2.54 centimeters on any given day in the month and at least one horizontal curve has a design speed less than 96.5 km/h, 0 otherwise)	20.2
Snowfall-Grade interaction indicator (1 if maximum snowfall greater than 5.1 centimeters on any given day in the month and grade greater than 2%, 0 otherwise)	33.8
Snowfall-Curve interaction indicator (1 if maximum snowfall greater than 5.1 centimeters on any given day in the month and at least one horizontal curve has a design speed less than 96.5 km/h, 0 otherwise)	47.3
Section location indicator (1 if section number is 5, 6, 7 or 8, 0 otherwise)	-32.3
Year of occurrence indicator (1 if 1988, 0 otherwise)	31.4
Year of occurrence indicator (1 if 1990, 0 otherwise)	-15.4

a It is assumed that the change in one indicator variable will not be accompanied by a simultaneous change in any other variable with the exception of the interaction variables. For example, a change in the maximum monthly rainfall variable (to greater than 2.54 cm) does not affect the location dummy. However, by virtue of the monthly rainfall's interaction with horizontal curves, maximum rainfall could have an additive effect because it could influence two variables. This explains the percentage range shown for maximum rainfall.

In terms of using our model results to evaluate the proposed use of variable message signs, variable speed-limit signs and in-vehicle signing to warn drivers of weather and traffic-related dangers in the study corridor, a comparison of our "before" estimation results (as shown in Table 2.2) can be made with similar estimations conducted using data collected after the signing system has been implemented. A series of likelihood ratio tests can be conducted to test for

[1] A more global application would be a negative binomial accident frequency model estimated with roadway sections that had widely varying geometric, traffic flow, and access control characteristics (as opposed to the comparatively homogeneous sections used in this study). Such an application would likely find that variables such as lane widths, shoulder widths, peak hour traffic volumes, daily traffic volumes, percentage of trucks, type of road indicators (i.e., urban freeway, rural arterial, etc.), and type of interchange/intersection indicators, play a role in the frequency of accident occurrence.

overall coefficient stability (between before and after data) and individual coefficient stability can be evaluated on estimated coefficients such as grade, snowfall, snow-grade interactions, snow-horizontal curve interactions, and the various rainfall variables (see Mannering *et al.,* 1994 for an application of such coefficient stability tests). The finding of statistically significant instability in coefficients could then be attributed to the variable message/speed-limit signing and the in-vehicle signing systems. Such an analysis is important because we are not simply testing for differences in before and after accident frequencies, but isolating the true causality of these differences by controlling for the complex interaction between geometrics and weather conditions. A more simplistic comparison of before and after data could easily lead to erroneous conclusions. For example, one could conclude that the signing system was ineffective in reducing accidents but slight variations in weather between before and after data could be masking the system's effectiveness.

Finally, in addition to being able to determine whether or not the proposed signing system was effective in reducing accident frequencies, an analysis of changes in coefficient elasticities and the magnitudes of indicator variables will allow us to more precisely isolate the effectiveness of the signing system. For example, we may be able to specifically state that the signing system mitigated the adverse effects high snowfall on grades greater than 2 percent. Such specificity is needed to make definitive statements regarding ITS technologies.

2.7 Accident frequency models

In addition to modeling overall accident frequency on highway sections (i.e. as demonstrated above) separate regressions of specific accident types will also provide valuable information. Separate regression models have the potential for providing greater explanatory power relative to a single, overall frequency model because separate models allow coefficient estimates to vary by the type of accident. Intuitively, such variation is seems reasonable. For example, we would expect a steep grade to have a different effect on the likelihood of an overturn accident than it would on a rear-end accident.

To evaluate the impacts of geometrics and weather on specific accident types, models were estimated for accidents classified as, sideswipes, rear-end, parked vehicles, fixed object, overturns, and same direction (all others). Estimation results for these models are presented in Tables 2.5-10. All models were negative binomial regressions except the overturn accident frequency model which was a Poisson regression (i.e. statistically the overturn data were not over dispersed). Interpretations of the results shown in Tables 2.5 through 2.10 are then presented.

Table 2.5: Negative binomial estimation results monthly section "sideswipe" accident frequency.

Variable	Estimated coefficient	t-statistic	p-value
Constant	-2.772	-4.011	0.000
Number of horizontal curves designed below 96.5 km/h	0.102	1.977	0.048
Lowest horizontal curve radius in section (meters)	0.01027	1.104	0.269
Number of rainy days in the month	-0.019	-1.132	0.258
Maximum rainfall indicator (1 if greater than 2.54 centimeters on any given day in the month, 0 otherwise)	0.959	3.910	0.000
Number of snowy days in the month	0.029	1.290	0.197
Snowfall-Grade interaction indicator (1 if maximum snowfall greater than 5.1 centimeters on any given day in the month and grade greater than 2%, 0 otherwise)	0.930	3.869	0.000
Year of occurrence indicator (1 if 1988, 0 otherwise)	0.483	2.013	0.044
α (dispersion coefficient)	0.396	1.420	0.155
Number of observations	464		
Log-likelihood at zero	-498.78		
Log-likelihood at convergence	-298.14		
ρ^2	0.40		

Variable: Number of horizontal curves designed between 96.5 km/h and 128.7 km/h

Finding: Tendency to increase same direction (all others) and fixed object collisions

This finding suggests that curves under designed between 96.5 km/h and 128.7 km/h do not create the visual impact on drivers to decrease speeds. The result is an increase in both lane violations (resulting in vehicular collisions) and vehicles running off the roadway and colliding with fixed objects. From a severity viewpoint, fixed object collisions are more likely to result in serious injuries than vehicular collisions in the same direction. Consideration should then be given to upgrading marginally under designed curves (96.5 km/h to 128.7 km/h) if fixed object collisions show increasing trends at certain locations.

Table 2.6: Negative binomial estimation results monthly section "rear-end" accident frequency.

Variable	Estimated coefficient	t-statistic	p-value
Constant	-4.368	-5.346	0.000
Number of horizontal curves designed below 96.5 km/h	0.080	1.679	0.093
Maximum grade in section	0.310	2.211	0.027
Maximum grade in section indicator (1 if greater than 2%, 0 otherwise)	1.271	1.732	0.083
Maximum rainfall on any given day in the month	-0.381	-1.902	0.057
Number of rainy days in the month	-0.048	-1.741	0.082
Average daily rainfall in any given month	0.149	2.324	0.020
Rainfall-Curve interaction indicator (1 if maximum rainfall greater than 2.54 centimeters on any given day in the month and at least one horizontal curve has a design speed less than 96.5 km/h, 0 otherwise)	0.983	3.309	0.001
Maximum daily snowfall in the month (1 if maximum snowfall greater than on 5.1 centimeters on any given day in the month)	3.468	3.215	0.001
Snowfall-Grade interaction indicator (1 if maximum snowfall greater than 5.1 centimeters on any given day in the month and grade greater than 2%, 0 otherwise)	-1.964	-2.382	0.017
Snowfall-Curve interaction indicator (1 if maximum snowfall greater than 5.1 centimeters on any given day in the month and at least one horizontal curve has a design speed less than 96.5 km/h, 0 otherwise)	-1.707	-2.262	0.023
Section location indicator (1 if section number is 5, 6, 7 or 8, 0 otherwise)	0.815	2.408	0.016
Section location indicator (1 if section number is 5, 6, 7 or 8, 0 otherwise)	0.815	2.408	0.016
Section location indicator (1 if section number is 5, 6, 7 or 8, 0 otherwise)	0.815	2.408	0.016
Year of occurrence indicator (1 if 1988, 0 otherwise)	0.747	2.797	0.005
Year of occurrence indicator (1 if 1989, 0 otherwise)	0.762	2.908	0.004
α (dispersion coefficient)	0.910	3.023	0.002

(Continued)

Table 2.6: Negative binomial estimation results monthly section "rear-end" accident frequency. (Continued).

Number of observations	464
Log-likelihood at zero	-544.59
Log-likelihood at convergence	-310.84
ρ^2	0.43

Table 2.7: Negative binomial estimation results monthly section "parked vehicle" accident frequency.

Variable	Estimated coefficient	t-statistic	p-value
Constant	-3.290	-5.523	0.000
Number of horizontal curves designed below 96.5 km/h	-0.167	-1.741	0.082
Maximum rainfall indicator (1 if greater than 2.54 centimeters on any given day in the month, 0 otherwise)	0.906	2.274	0.023
Maximum daily snowfall (1 if greater than 5.1 centimeters on any given day in the month, 0 otherwise)	2.500	3.705	0.000
Snowfall-Grade interaction indicator (1 if maximum snowfall greater than 5.1 centimeters on any given day in the month and grade greater than 2%, 0 otherwise)	-1.381	-2.294	0.022
Year of occurrence indicator (1 if 1988, 0 otherwise)	0.629	1.385	0.166
Year of occurrence indicator (1 if 1989, 0 otherwise)	1.273	3.179	0.001
Spring/Summer month indicator (1 if April, May, June, July or August, 0 otherwise)	-0.819	-1.607	0.108
α (dispersion coefficient)	1.505	2.375	0.018
Number of observations	464		
Log-likelihood at zero	-487.54		
Log-likelihood at convergence	-177.51		
ρ^2	0.64		

Table 2.8: Negative binomial estimation results monthly section "fixed object" accident frequency.

Variable	Estimated coefficient	t-statistic	p-value
Constant	-2.156	-5.515	0.000
Number of horizontal curves designed between 96.5 km/h and 128.7 km/h	0.154	1.957	0.050
Number of horizontal curves designed below 96.5 km/h	-0.130	-2.737	0.006
Number of horizontal curves in section	0.285	5.032	0.000
Maximum rainfall indicator (1 if greater than 2.54 centimeters on any given day in the month, 0 otherwise)	0.423	1.932	0.053
Number of rainy days in the month	0.023	1.821	0.069
Rainfall-Curve interaction indicator (1 if maximum rainfall greater than 2.54 centimeters on any given day in the month and at least one horizontal curve has a design speed less than 96.5 km/h, 0 otherwise)	-0.507	-2.144	0.032
Maximum snowfall indicator (1 if greater than 5.1 centimeters on any given day in the month, 0 otherwise)	0.654	3.198	0.001
Number of snowy days in the month	0.050	2.604	0.009
Section location indicator (1 if section number is 1, 2, 3 or 4, 0 otherwise)	-1.431	-4.349	0.000
Section location indicator (1 if section number is 5, 6, 7 or 8, 0 otherwise)	-1.017	-3.257	0.001
Year of occurrence indicator (1 if 1988, 0 otherwise)	0.283	2.206	0.027
Spring/Summer month indicator (1 if April, May, June, July or August, 0 otherwise)	-0.294	-2.081	0.037
α (dispersion coefficient)	0.282	3.078	0.002
Number of observations	464		
Log-likelihood at zero	-845.42		
Log-likelihood at convergence	-610.79		
ρ^2	0.28		

Table 2.9: Poisson estimation results monthly section "overturn" accident frequency.

Variable	Estimated coefficient	t-statistic	p-value
Constant	-3.288	-7.961	0.000
Average spacing of horizontal curves in section (meters)	0.00784	4.636	0.000
Lowest horizontal curve radius in section (meters)	-0.00461	-2.857	0.004
Maximum rainfall indicator (1 if greater than 2.54 centimeters on any given day in the month, 0 otherwise)	0.692	3.030	0.002
Rainfall-Curve interaction indicator (1 if maximum rainfall greater than 2.54 centimeters on any given day in the month and at least one horizontal curve has a design speed between 96.5 km/h and 128.7 kilometers per hour, 0 otherwise)	-0.727	-2.952	0.003
Number of snowy days in the month	0.039	2.264	0.023
Snowfall-Curve interaction indicator (1 if maximum snowfall greater than 5.1 centimeters on any given day in the month and at least one horizontal curve has a design speed between 96.5 km/h and 128.7 kilometers per hour, 0 otherwise)	0.970	4.771	0.000
Section location indicator (1 if section number is 1, 2, 3 or 4, 0 otherwise)	2.260	4.119	0.000
Year of occurrence indicator (1 if 1988, 0 otherwise)	0.465	2.868	0.004
Number of observations	464		
Log-likelihood at zero	-509.17		
Log-likelihood at convergence	-368.75		
ρ^2	0.28		

Variable: Number of horizontal curves in section

Finding: Tendency to increase same direction (all others) and fixed object collisions

This finding suggests two separate phenomena. Vehicular collisions in the same direction tend to increase on sections as the number of horizontal curves increase because speeds on curves do not decrease enough to avoid lane violations. The fact that fixed object collisions tend to increase with the total number of curves in a section indicates the increased likelihood of fixed objects, such as guardrails, being present on sections with more curves. The presence of such objects prevents a more severe type of accident, such as a vehicle overturn, from occurring. The caveat stemming from this finding is that it is preferable to design longer but fewer horizontal curves where the terrain makes construction of straight sections impossible.

Table 2.10: Negative binomial estimation results monthly section "same direction (all others)" accident frequency.

Variable	Estimated coefficient	t-statistic	p-value
Constant	-4.007	-7.819	0.000
Number of horizontal curves designed between 96.5 km/h and 128.7 km/h	0.471	3.381	0.001
Maximum grade in section	0.344	2.939	0.003
Rainfall-Curve interaction indicator (1 if maximum rainfall greater than 2.54 centimeters on any given day in the month and at least one horizontal curve has a design speed less than 96.5 km/h, 0 otherwise)	0.787	3.857	0.000
Maximum daily snowfall (1 if greater than 5.1 centimeters on any given day in the month)	2.923	7.128	0.000
Snowfall-Grade interaction indicator (1 if maximum snowfall greater than 5.1 centimeters on any given day in the month and grade greater than 2%, 0 otherwise)	-0.901	-2.218	0.027
Snowfall-Curve interaction indicator (1 if maximum snowfall greater than 5.1 centimeters on any given day in the month and at least one horizontal curve has a design speed between 96.5 km/h and 128.7 km/h, 0 otherwise)	-1.232	-3.338	0.001
Spring/Summer month indicator (1 if April, May, June, July or August, 0 otherwise)	-0.805	-2.881	0.004
Year of occurrence indicator (1 if 1988, 0 otherwise)	0.577	2.253	0.024
Year of occurrence indicator (1 if 1989, 0 otherwise)	0.412	1.647	0.100
α (dispersion coefficient)	0.562	2.524	0.011
Number of observations	464		
Log-likelihood at zero	-540.84		
Log-likelihood at convergence	-307.04		
ρ^2	0.43		

Variable: Average spacing of horizontal curves in section

Finding: Tendency to increase overturn collisions

This finding uncovers an effect of roadway geometrics that was not distinguishable in the overall accident frequency model. The very significant t-statistic (4.636) indicates the significant effect that spacing of horizontal curves in a section has on driver speeds. Intuitively, if curves are spaced farther apart, vehicular speeds are likely to climb as a result of lower caution being exhibited by drivers. Consequently, there is a greater risk of an overturn if curves are spaced farther apart in a section. Careful attention should be paid to the application of corrective measures in this regard. The obvious interpretation is to decrease the spacing of curves to decrease the frequency of overturn accidents; however, it would appear counterintuitive to physically locate curves nearer as a countermeasure. The surrogate action is to place more advance warning signs in sections with longer curve spacing. By placing more advance warning signs and strategically locating them, the spacing of curves in the driver's mind is subliminally altered.

Variable: Lowest horizontal curve radius in section

Finding: Tendency to increase sideswipe collisions and decrease overturn collisions

The lowest horizontal radius suggests the type of terrain the section is located in. Sections with higher minimum radii could lull the driver into lane violations that result in sideswipes. However, low radii curves are usually associated with winding sections of highway which decrease the likelihood of gathering sufficient speed for an overturn accident.

Variable: Maximum grade in section

Finding: Tendency to increase rear-end and same direction (all others) collisions

This finding suggests several processes stemming from the presence of grades in a section. Between any two sections, the section with the steeper maximum upgrade will experience a greater number of rear-end and other same direction accidents. In addition, rear-end accidents will increase substantially if the maximum grade exceeds 2% in that section. Both effects are explained by speed differentials occurring due to the impact of grades. The impact of grades is reversed in the presence of downgrades. Between any two sections, the section with the steeper maximum downgrade will experience fewer rear-end and other same direction accidents, presumably from lower speed differentials. Much of the effect of the higher braking distance on downgrades appears to be offset by the visual impact of brake lights warning drivers of the potential slowing of vehicles ahead. In contrast, drivers are unlikely to use brakes on an upgrade which eliminates a critical warning sign of speed reductions.

Variable: Maximum rainfall on any given day in the month

Finding: Tendency to increase sideswipe, parked vehicle, fixed object and overturn collisions and decrease rear-end collisions

This result reflects some interesting phenomena affecting driver behavior and the driving task. Accidents resulting from the loss of steering control, such as lane violations and running-off-the-roadway, are expected to increase in occurrence with increases in maximum daily rainfall. Maximum rainfall indicates the intensity of rainfall and how that results in water puddles forming in wheel ruts in the pavement. The presence of such puddles contributes to vehicle hydroplaning and also excessive lateral drag resulting in lane violations and off-roadway accidents. On the other hand, as intensity of rainfall increases visibility decreases and drivers maintain greater headways paying more attention to the driving task. Much of this attention is focused on the vehicle ahead and quite likely much less is paid to the area of peripheral vision. This overcompensation on vehicle headways reduces rear-end accident risks but increases other accident types.

Variable: Average daily rainfall in the month

Finding: Tendency to increase rear-end collisions

This likely is an outgrowth of a seasonal effect that is descriptive of pavement condition. As opposed to maximum rainfall on any given day in the month, this variable captures the loss of traction due to wet pavements. An increase in average daily rainfall is indicative of a more prolonged wet-month weather effect. Drivers are less likely to pay attention to prolonged effects as opposed to short-term effects such as thunderstorms. In addition, as mentioned in the discussion of the overall model, the Seattle area receives rainfall for a large portion of the year on an intermittent basis. Drivers in the region may be less likely to acknowledge the hazards of wet pavements.

Variable: Number of rainy days in the month

Finding: Tendency to decrease sideswipe and rear-end collisions and increase fixed object collisions

It is speculated that the findings relating to this variable can be partially attributed to drivers reducing their speed in the presence of other vehicles during rainy periods (so much so that some types of vehicle collisions actually decrease). The positive coefficient for fixed object collisions suggests that this possibility of cautious driving behavior during rainy conditions does not transfer to all driving situations

Variable: Maximum snowfall on any given day in the month

Finding: Tendency to increase rear-end, same direction (all others), parked vehicle, and fixed objects collisions

This finding illustrates a number of consequences associated with intensity of snowfall. Loss of traction, visibility, and obliteration of lane markings act individually or in combination to increase the likelihood of accident types such as rear-end and other collisions in the same direction as well as collisions with parked vehicles and fixed objects.

Variable: Number of snowy days in the month

Finding: Tendency to increase sideswipe, fixed object and overturn collisions

This variable could be capturing a number of effects. For example, the loss of traction, obliteration of lane markings, and seasonal trends in weather and temperature could all be reflected in the significance of this variable.

Variable: Snowfall-Grade Interaction

Finding: Tendency to decrease sideswipe, rear-end, other collisions in the same direction and parked vehicle collisions

The coefficients of the interaction between snowfall and grade on rear-end accidents, other vehicular collisions in the same direction and parked vehicle accidents (as shown in tables 2.6-2.8) appear counterintuitive. However, a closer examination of the estimation results shown in tables 2.6-2.8 indicates that the net effect of snowfall and grade is to increase the frequency of these accident types, a conclusion also drawn from the positive coefficient of the snowfall-grade interaction variable for sideswipe collisions. In order to illustrate the net positive effect of snowfall-grade interaction on rear-end collisions, it is observed in Table 2.6 that the coefficient of the maximum daily snowfall variable is 3.468 which implies that when the daily maximum in any given month exceeds 5.1 centimeters rear-end accident frequencies are expected to increase 32-fold ($e^{3.468}$). In the presence of a significant interaction with grade on the section, (i.e. when maximum grade in the section exceeds 2%) this 32-fold compounding effect is tempered to 4.5-fold ($e^{(3.468-1.964)}$) by the negative coefficient (-1.964) of the interaction between snowfall and grade. This is a very intuitive occurrence indicating that the compounding effect of snowfall is not as severe when grades exceed 2%, quite possibly due to the presence of climbing lanes on upgrades and driver caution on downgrades. Examination of the snowfall-grade coefficient in other relevant accident types indicates a similar pattern. Corrective action then appears to be the construction of climbing lanes in areas where snowfall intensity is severe (exceeding 5.1 centimeters a day) and grades exceed 2%.

Variable: Snowfall-curve interaction

Finding: Tendency to increase rear-end, other collisions in the same direction and overturn collisions

This finding is similar to those described previously for the interaction between snowfall and grade. The net effect of snowfall on curves is tempered in the presence of under designed curves (< 128.7 km/h), presumably due to warning signs and driver caution. Corrective action to mitigate the impact of snowfall appears to be the installation of warning signs in advance of under designed curves advising drivers of poor traction and slower speeds.

Variable: Rainfall-curve interaction

Finding: Tendency to increase rear-end and other collisions in the same direction, and decrease fixed object and overturn collisions

It is likely that this variable is capturing complex interactions among roadway and geometric conditions and driver behavior. To be able to speculate further on the nature of these findings, additional data on other roadway types (e.g., non-freeways) is necessary. This would allow us to isolate the effect of rainfall-curve interactions by providing greater variance in the data.

Variable: Spring/Summer month indicator

Finding: Tendency to decrease same direction-all others, parked vehicle and fixed object collisions

This indicates primarily the effects of seasonal trends such as daylight duration, ambient temperature. These are important determinants of accidents such as vehicular collisions in the same direction and collisions with parked vehicles and fixed objects. The finding illustrates the impact of pavement conditions, such as black ice, as well as visibility. It should be noted that the "Spring/Summer" indicator was found to significantly decrease accident frequencies in spite of increased exposure due to the higher traffic volumes typically observed during the spring and summer months.

Variable: Year of occurrence indicator

Finding: Tendency to increase all accident types

This finding indicates that some unobserved effects (e.g., ice accumulation on the pavement, and within-day temperature variations) were more severe during the subject year than usual, thus tending to increase the likelihood of an accident.

Variable: Section location indicator

Finding: Tendency to increase rear-end and overturn collisions, but decrease fixed object collisions

Section location indicators capture unobserved factors attributable to specific locations within the corridor. Such unobserved factors could include visual distractions and other attributes of the highway section that are difficult to quantify.

In summary, note that the coefficient estimates presented in these tables show that there are significant differences in the magnitudes of the coefficient estimates (and in some cases the signs of the coefficient estimates) among different accident types. The results of these separate accident frequency models can be used in the same way as the overall accident frequency model. That is, to evaluate the effectiveness of highway design improvements and ITS systems in reducing specific types of accidents.

2.8 Conclusions

This research presents an appropriate model to explore the frequency of occurrence of accidents on the basis of a multi-variate analysis of geometrics and weather-related effects. A negative binomial model of overall accident frequency is estimated along with models of the frequency of specific accident types. Interactions between weather and geometric variables are proposed as part of the model specifications and the results of the analysis uncover important determinants of accident frequency. By accounting for interactions between weather and geometric elements, this research offers insight into possible strategies that could be undertaken to counter the adverse effects of weather. This research also presents an important basis for a comprehensive before and after analysis of the effectiveness of safety improvements (e.g., ITS).

In particular, the approach presented herein can be used to thoroughly evaluate the safety impacts of variable-message/speed-limit signs, in-vehicle units, and other ITS technologies. Such evaluations will serve as a cornerstone to justify future ITS expenditures.

Chapter 3

Accident severities

3.1 Introduction

In measuring the impact of an ITS on overall vehicular safety, it is important to establish defensible safety-measurement criteria. Past safety-related research has shown that the frequency and severity of accidents are two such measurement criteria. In the previous Chapter we addressed accident frequencies as they relate to ITS. This Chapter will deal exclusively with accident severities.

The Chapter begins with a discussion of the proposed methodological approach. This is followed by a description of the study area and the data used in model estimation. We then present model estimation results and a detailed discussion of our findings and their implications for accident severity analysis. The Chapter concludes with a summary and directions for future research.

3.2 Previous research

Previous research on accident severity has been diverse and provided important methodological and behavioral insights. Several accident-severity studies conducted have examined particular severity types such as fatalities (Shibata and Fukuda, 1994) or concentrated on crashes involving certain vehicle types such as trucks (Golob *et al.,* 1987; Alassar, 1988). Other studies have concentrated on enforcement issues and their impact on fatal vehicular crashes related to alcohol and seat belt use (see for example Evans, 1986b, 1990; Holubowycz *et al.,* 1994). Such studies have placed a heavy emphasis on the impact of human factors in determining accident severity. However, other elements, such as highway design and environmental conditions, while not receiving the extensive attention given to human factors, have also been recognized as important determinants of accident severity (see Mercer, 1986; Massie *et al.,* 1993). Overall, past research has provided important insights into the range of factors that influence accident severity.

From a methodological standpoint, a variety of approaches have been employed to study accident severity. Using logistic regression techniques, Jones and Whitfield (1988) modeled severity risk as a function of anthropometric measures, car mass, age of driver and restraint system use. Logistic regression was also employed in a study of driver fatalities to model the probability of fatalities conditioned on the occurrence of an accident (Lui *et al.,* 1988). However, the study used a limited number of variables such as driver age, gender, impact points, vehicle crash severity, restraint system use and car mass. Other important aggravating factors such as inclement weather, location of accident (for example, whether the accident occurred on a curve, or off the road) were omitted. Other studies have employed multivariate time-series approaches to successfully develop predictive models of accident severity (Lassarre, 1986). Evans (1986a) employed a double-pair comparison approach to examine how occupant characteristics affect fatality risk. Still other methodologies such as headway-based severity analysis (Glimm and Fenton, 1980), bivariate probit analysis (Hutchinson, 1986) and discriminant analysis (Shao, 1987) have been used. The latter methodologies, especially the probit and discriminant analyses, allow the researcher to model severity in terms of thresholds. These threshold approaches are consistent with the general categorization of accident severity as being either property damage only, possible injury, evident injury, or disabling injury/fatality.

The present study attempts to extend the empirical and methodological contributions of previous work by developing a predictive model of accident severity that can be used to evaluate the safety-related impacts of ITS and other safety-related countermeasures. In so doing, we will address highway design and environmental issues, along with human factors, in a multivariate context using a nested-multinomial logit approach. The empirical focus of our work will be a rural section of interstate 90 in Washington State, which is scheduled to have a ITS operational in Autumn 1996.[1] The section of highway selected is roughly 61 km in length and is located 50 km east of Seattle. The highway is a high-accident area due to its complex roadway geometrics and adverse climatic conditions (it crosses the Cascade mountain range). This research proposes to study past accident severities on this highway in an effort to establish a basis from which the safety effectiveness of the forthcoming ITS can be evaluated. This work follows our previous effort on accident frequencies (Shankar *et al.,* 1995). In combination with models of accident frequencies, the severity models presented in this Chapter will enable us to provide a complete assessment of the possible safety impacts of the forthcoming Interstate-90 ITS

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[1] This ITS will consist of a series of variable message signs (warning drivers of adverse weather and traffic conditions), variable speed limit signs (that will change the speed limits in response to climatic and traffic conditions), and equipping several hundred vehicles with in-vehicle climate and traffic condition warning devices.

3.3 Methodology

We begin by developing a conditional model of accident severity (i.e. conditioned on the fact that an accident has occurred).[1] Severity of an accident is specified to be one of four discrete categories: 1) property damage only, 2) possible injury, 3) evident injury, and 4) disabling injury or fatality.[2] Given these four discrete categories, a statistical model that can be used to determine the probability of an accident having a specific severity level can be derived. We start the derivation with the following probability statement,

$$P_n(i) = P(S_{in} \geq S_{In}) \ \ \forall\, I \neq i, \tag{3.1}$$

where $P_n(i)$ is the probability that accident n is severity i, P denotes probability and S_{in} is a function of covariates that determine the likelihood of accident n being severity i (I is the set of possible severities). To estimate this probability, a function defining the severity likelihoods must be specified. We use a linear form such that,

$$S_{in} = \beta_i X_n + \varepsilon_{in}\ , \tag{3.2}$$

where $\mathbf{X}_n$ is a vector of measurable characteristics that determine the severity (e.g., driver age, driver gender, highway design attributes, prevailing weather conditions, vehicle type, use of seat belts, and so on), β_i is a vector of estimable coefficients, and ε_{in} is an error term that accounts for unobserved factors influencing accident severity. The term $\beta_i\mathbf{X}_n$ in this equation is the observable component of severity determination because the vector $\mathbf{X}_n$ contains measurable variables (e.g., highway design attributes at the location of accident n), and ε_{in} is the unobserved portion.Given equations (3.1) and (3.2), the following can be written,

$$P_n(i) = P(\beta_i\mathbf{X}_n + \varepsilon_{in} \geq \beta_I\mathbf{X}_n + \varepsilon_{In}) \ \ \forall\, I \neq i, \tag{3.3}$$

or,

$$P_n(i) = P(\beta_i\mathbf{X}_n - \beta_I\mathbf{X}_n \geq \varepsilon_{In} - \varepsilon_{in}) \ \ \forall\, I \neq i. \tag{3.4}$$

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1 For a statistical model of the likelihood of an accident occurring, the reader is referred to our earlier work on accident frequencies (Shankar, Mannering, and Barfield, 1995).

2 The determination of this severity is made by the officer at the scene of the accident and reported on the Washington State accident report forms. Also note that accidents are classified based on the most severe consequence of the accident. For example, an accident resulting in both injury and death will be classified as a fatality accident. In addition, it must be noted that total number of classified accidents reported is less than or equal to the number of individual severities since, for example, an injury accident may result in more than one person being injured.

With equation (3.4), an estimable severity model can be derived by assuming a distributional form for the error term. A natural choice would be to assume that this error term is normally distributed. Such an assumption results in a probit model. However, probit models are computationally difficult to estimate (see Ben-Akiva and Lerman, 1985). A more common approach for models of this type is to assume that ε_{in}'s are generalized extreme value (GEV) distributed.[1] The GEV assumption produces a closed form model that can be readily estimated using standard maximum likelihood methods. It can be shown (McFadden, 1981) that the GEV assumption produces the simple multinomial logit model,

$$P_n(i) = \exp[\beta_i \mathbf{X}_n] \Big/ \sum_I \exp[\beta_I \mathbf{X}_n], \tag{3.5}$$

where all variables are as previously defined and the vector β_i is estimable by standard maximum likelihood methods.Unfortunately, the simple multinomial logit model presented in equation (3.5) can lead to serious specification problems because this particular form requires us to assume that the unobserved terms (ε_{in}'s) are independent from one severity type to another. This is not likely to be the case because some of the severity types are likely to share unobserved terms and thus be correlated. For example, property damage only and possible injury accidents may share unobservables such as internal injury or effects associated with lower-severity accidents. In the presence of shared unobservables, the logit formulation will erroneously estimate the coefficient vector and severity probabilities. To circumvent this problem, a more generalized form of the severity probabilities can be derived from the GEV distribution. This is referred to as a nested logit model and has the following form (see McFadden, 1981),

$$P_n(i) = \exp[\beta_i \mathbf{X}_n + \Theta_i L_{in}] \Big/ \sum_I \exp[\beta_i \mathbf{X}_n + \Theta_i L_{In}], \tag{3.6}$$

$$P_n(j \mid i) = \exp[\beta_{j|i} \mathbf{X}_n] \Big/ \sum_J \exp[\beta_{J|i} \mathbf{X}_n], \tag{3.7}$$

$$L_{in} = \ln\left[\sum_J \exp(\beta_{J|i} \mathbf{X}_n)\right], \tag{3.8}$$

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1 Discriminant analysis is another alternative to the approach that we have selected to model accident severity (Shao 1987). However, several studies have shown (see for example Press and Wilson 1978), that logit-based modeling approaches (which include the GEV approach) are superior to discriminant analysis for classification primarily because of the violation of the assumption of normality of disturbances in discriminant analysis. Presence of non-normal variables such as qualitative variables (dummy variables) in classification studies causes such a violation. In the present study, several qualitative variables, as will be shown, play significant roles in the determination of accident severity.

where $P_n(i)$ is the unconditional probability of accident n having severity i (e.g., evident injury), $P_n(j|i)$ is the probability of accident n having severity j conditioned on the severity being in severity category i (e.g., the probability of having property damage only or possible injury given that there was no evident injury), J is the conditional set of severity categories (conditioned on i) and I is the unconditional set of severity categories, L_{in} is the inclusive value (log sum) which is interpreted as the expected value of the attributes that determine severity probabilities in severity category i, Θ_i is an estimable coefficient which must have a value between zero and one to be consistent with the model derivation (see McFadden, 1981).

The structure of the nested logit model eliminates the adverse consequences of shared unobservables because logit models determine probabilities using the difference in functions defining severity (i.e. the S_{in}'s in equation (3.2)). Thus when a logit nest contains only those severity levels that share unobserved effects, the unobserved effects will cancel in the differencing and thereby preserve the assumption of independence needed to derive the model. We will discuss estimation concerns relating to this model and show its suitability for analyzing accident severities in the model estimation section of this Chapter. For further information on the derivation and application of nested logit models the reader is referred to Ben-Akiva and Lerman (1985), Train (1986) and Mannering and Winston (1985, 1991, 1995).

3.4 Empirical setting

In collecting data on the 61 kilometer study section of I-90, six data categories were specified; 1) individual accident data from the Washington State Department of Transportation (WSDOT), 2) weather data, 3) geometric data, 4) pavement surface data, 5) vehicle data and 6) driver-related data. For the purposes of classifying roadway geometric data, the study area was segmented into 10 equal 6.1 kilometer sections (see Shankar *et al.,* 1995). Important accident data included information on primary identified causes, most severe consequence of the accident, time of day of accident, accident location with respect to the traveled way (on or off the roadway, whether the accident occurred on a curve or straight section or a grade, roadway illumination information, types of roadside objects involved in collision, and accident type). Weather data included whether or not the accident occurred during rainy, snowy, or foggy conditions. The geometric data included (for the section of highway in which the accident occurred) radii of horizontal curves, vertical grades, number of horizontal and vertical curves per kilometer, percentage length of horizontal curves. Pavement surface data included information on whether the accident occurred on icy, snowy, wet or dry pavement. Vehicle data included information on number and type of vehicles, restraint system[1] used by driver and occupants at the time of the accident, ejection status of occupants (i.e. whether or not occupants have been ejected from the vehicle) and number of occupants in each vehicle. Driver-related data included information on driver sobriety at the time of accident, and driver ages and gender.

Accident data for the five-year period between 1988 and 1993 was used to estimate accident severities. A total of 1,505 individual vehicular accidents[2] reported during this period were used in this study, with 1,020 of those accidents resulting in property damage only.[3] Out of the remaining 485 accidents, 10 were fatality collisions, 63 evident injury and 208 disabling injury collisions. Table 3.1 provides additional information on the distribution of severity by important variables such as daytime/night, sobriety, accident location (horizontal curve as opposed to a straight section), and number of vehicles involved in the collision.

3.5 Model estimation

To estimate the nested logit model specified in equations (3.6-8), we use a sequential estimation procedure. In this procedure, the lower conditional level of the nest (equation (3.7)) is estimated as a simple multinomial logit (MNL) model using standard maximum likelihood methods and the estimated coefficients are used to compute the inclusive value of that level (i.e. L_{in} in equation (3.8)). The next step involves estimating the higher level nest treating it as a simple MNL form but conditioning it on the estimated coefficients of the lower nest. This is done by introducing the computed value of L_{in} for the lower nest as an explanatory variable. All possible nested structures (which examine possible correlation among the unobserved effects of various severity levels) were considered. Statistically, as measured by likelihood ratio tests, the

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1 Although this information is subject to bias based on when the reporting officer arrives at the scene, uncertainty about restraint system use significantly diminishes in the case of injury-related accidents in which subjects are incapacitated to the extent of being unable to remove their restraint systems. In the case of property damage and possible injury accidents, the significance of restraint system use is minimal. In this context, it must be noted that uncertainty about restraint system use generally results in information on restraint system use being coded “restraint system use not known”.

2 A total of 2,225 individual accidents were reported for the 65-month period between January 1988 and May 1993. However, weather data corresponding to 720 accidents was not available because of equipment failure or faulty operation. Also, it is important to note that our data were obtained only from reported accidents. It is likely that many accidents (particularly those that are minor in severity) may go unreported. This means that our accident sample is not a random sample of all accidents. Fortunately this will have a minimal impact on model estimation results. In fact, all coefficients will be correctly estimated with the exception of the constant terms. If the number and severity of unreported accidents were known, the three constant terms reported in this paper could be adjusted by a simple calculation and no additional estimation would be necessary (see Ben-Akiva and Lerman (1985) for details on such stratified-sample adjustments).

3 As mentioned previously, accident classification is based on the most severe consequence of the accident.

structure shown in Figure 3.1 proved to be the correct model form.[1] This nesting indicates that the property damage only and possible injury severity levels shared unobserved terms that would have caused a serious model specification error had a simple multinomial logit model been estimated (as shown in equation (3.5)).

Table 3.1: Accident severity distribution by key variables.

Accident Conditioning Variable	Severity frequencies				
	Property Damage	Possible Injury	Evident Injury	Disabling Injury	Fatality
Daylight (excluding dawn and dusk)	609	135	31	126	6
Night	353	53	27	64	3
Drunk-Driving	31	1	2	9	2
Sober Driving	989	203	61	199	8
Horizontal Curve	410	76	25	88	8
Straight Section	610	128	38	120	2
Single-vehicle collision	587	99	44	128	5
Two-vehicle Collision	377	91	16	67	4
Multi-vehicle Collision (greater than two vehicles)	56	14	3	13	1

Maximum likelihood estimation results are presented in Tables 3.2 and 3.3. Table 3.2 presents the estimation of the lower nest (property damage only and possible injury)[2] and Table

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1 We also tested this specification for possible correlation among unobservables using the specification test developed by Small and Hsiao (1985). The tests showed that this specification does not have statistically significant specification error.

2 Possible injury accidents (which may seem a somewhat vague category) are determined at the scene by Washington State troopers using well-defined, uniformly taught identification procedures. Our testing of various model structures suggests that this is a unique severity category and must be considered separately (i.e., even though the accident will eventually be classified as an injury or property damage only accident).

3.3 shows the estimation of the overall model of accident severity (upper nest). The inclusive value coefficient of 0.4153 with its t-statistic of 2.6391 suggests that shared unobservables significantly present between property damage only and possible injury alternatives.[1] Both models resulted in good statistical fits,[2] with the lower level of the nest showing a ρ^2 of 0.39 and the overall model a ρ^2 of 0.52.

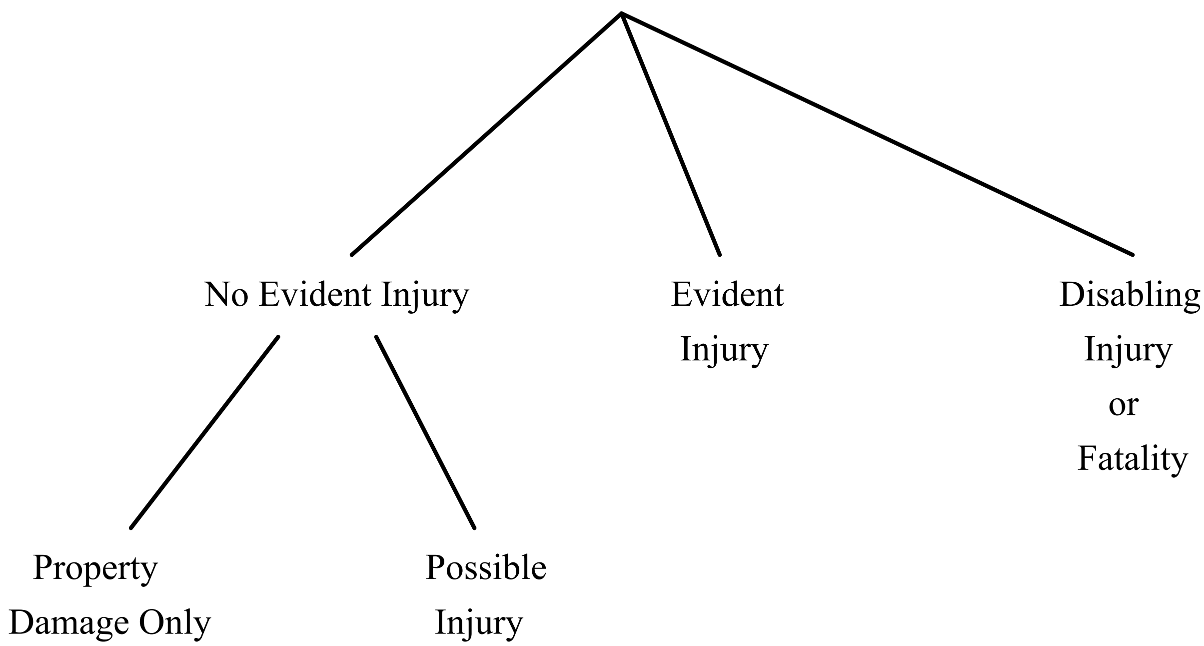

Figure 3.1: Nested structure of accident severities.

[1] If no correlation between these unobserved terms was present, the coefficient value would not be significantly different from one. When the coefficient value of the inclusive value term is equal to one, the nested logit structure reduces to the simple multinomial structure as shown in equation 3.5.

[2] ρ^2 is defined as 1-[L(β)-L(0)] where L(β) is log-likelihood at convergence and L(0) is initial log-likelihood when all parameters are set to zero. A modified form of ρ^2 is the adjusted ρ^2 that takes into account the number of parameters included and is given by 1-[(L(β)-K)/L(0)], where K is the number of parameters. The adjusted ρ^2 for the two models were determined to be 0.38 and 0.50 respectively.

Table 3.2: Estimation of property damage and possible injury probabilities conditioned on the occurrence of a non-injury accident.

Variable	Estimated coefficient	t-statistic
Constant (specific to property damage alone)	3.1950	5.19
Overturn accident indicator (1 if accident type was "single-vehicle overturn", 0 otherwise; specific to possible injury)	1.3993	3.49
Rear-end accident indicator 1 (1 if accident type was "rear-end" accident and occurred on wet pavement, 0 otherwise; specific to possible injury)	0.4351	1.00
Rear-end accident indicator 2 (1 if accident type was "rear-end" accident and involved exactly two vehicles, 0 otherwise; specific to possible injury)	1.3415	5.00
Percentage of horizontal curve length per kilometer of roadway (specific to possible injury)	0.0141	1.37
Number of horizontal curves per kilometer of roadway (specific to possible injury)	0.4931	1.94
Illumination indicator (1 if surroundings were dark with no street lights present, 0 otherwise; specific to property damage)	0.3271	1.72
Sideswipe accident indicator (1 if accident type was "sideswipe" involving more than two vehicles, 0 otherwise; specific to possible injury)	1.2686	1.74
Same-direction accident indicator (1 if accident type was "same-direction" involving more than two vehicles, 0 otherwise; specific to possible injury)	1.0640	2.07
Fixed object accident indicator (1 if accident type was "fixed object", 0 otherwise; specific to possible injury)	1.0597	3.14
Icy pavement indicator (1 if accident occurred on icy pavement and involved only one vehicle, 0 otherwise; specific to property damage alone)	0.5323	2.11
Single-vehicle collision indicator (1 if accident involved one vehicle, 0 otherwise; specific to property damage)	0.6490	1.91
Number of observations	1224	
Log-likelihood at zero	-848.41	
Log-likelihood at convergence	-518.40	
ρ^2	0.39	

Table 3.3: Estimation of overall nested logit model of accident severity probabilities

Variable	Estimated coefficient	t-statistic
Constant (specific to evident injury)	-2.8468	-3.53
Constant (specific to disabling injury/fatality)	-2.4882	-4.78
Angle accident type indicator (1 if accident type is “angle”, 0 otherwise; specific to evident injury and disabling injury/fatality)	1.5813	1.97
Overturn accident type indicator (1 if accident type is “overturn”, 0 otherwise; specific to disabling injury/fatality)	0.5192	2.24
Speeding indicator 1 (1 if “exceeding posted speed” was primary cause, 0 otherwise; specific to evident injury)	0.9640	1.72
Speeding indicator 2 (1 if “exceeding reasonable safe speed for conditions” was primary cause, 0 otherwise; specific to evident injury)	-0.8855	-2.57
Speeding indicator 3 (1 if “exceeding reasonable safe speed for conditions” was primary cause, 0 otherwise; specific to disabling injury/fatality)	-0.3160	-1.69
Restraint system use indicator (1 if a restraint system was not in use by at least one driver involved in collision, 0 otherwise; specific to evident injury and disabling injury/fatality)	0.6376	2.72
Occupant ejection indicator (1 if any occupant was partially or totally ejected, 0 otherwise; specific to evident injury)	2.0070	3.78
Gender of driver (1 if all drivers involved in collision were male; 0 otherwise; specific to disabling injury/fatality)	1.0008	2.12
Percentage of horizontal curves per kilometer of roadway (specific to evident injury and disabling injury/fatality)	0.0302	3.39
Number of horizontal curves per kilometer of roadway (specific to no evident injury and disabling injury/fatality)	0.7204	1.93
Curve-sobriety interaction (1 if accident occurred on a horizontal curve and at least one driver involved was identified as “had been drinking and alcohol-impaired,” 0 otherwise; specific to disabling injury/fatality)	1.2755	2.31
Snow-covered pavement indicator 1 (1 if accident occurred on snow-covered pavement, 0 otherwise; specific to evident injury)	-0.9450	-2.51
Snow-covered pavement indicator 2 (1 if accident occurred on snow-covered pavement, 0 otherwise; specific to disabling injury/fatality)	-0.5310	-2.86
Vehicle-mass difference indicator (1 if accident involved collision of a single truck and a single passenger car, 0 otherwise; specific to evident injury and disabling injury/fatality)	0.5214	1.83

(Continued)

Table 3.3: Estimation of overall nested logit model of accident severity probabilities. (Continued)

Variable	Estimated coefficient	t-statistic
Accident location indicator 1 (1 if accident occurred off the road, 0 otherwise; specific to evident injury)	1.2054	3.81
Accident location indicator 2 (1 if accident occurred off the road, 0 otherwise; specific to disabling injury/fatality)	0.5118	2.54
Age-sobriety interaction (1 if all drivers involved in accident were older than 55 years and at least one driver involved was identified as "had been drinking and alcohol-impaired," 0 otherwise; specific to evident injury)	1.6541	1.34
Night-time-pavement interaction (1 if accident occurred at night and on icy pavement, 0 otherwise; specific to evident injury and disabling injury/fatality)	0.2475	1.00
Fixed-object-horizontal curve interaction (1 if accident type was "fixed-object" and occurred on a horizontal curve, 0 otherwise; specific to disabling injury/fatality)	0.4580	1.99
Fixed-object-icy pavement interaction (1 if accident type was "fixed object" and occurred on icy pavement, 0 otherwise; specific to no evident injury)	0.5606	2.21
Inclusive value of property damage and possible injury (L_{in}, specific to no evident injury)	0.4153	2.64
Number of observations	1505	
Log-likelihood at zero	-1653.4	
Log-likelihood at convergence	-802.3	
ρ^2	0.52	

Turning first to the coefficient estimates of the lower nest (i.e. property damage only and possible injury conditioned on the accident having no evident injuries) we find that all variable coefficients included in the specification are statistically significant and have plausible signs. The implications of each of the coefficient estimates is discussed below.

Variable: Overturn accident indicator

Finding: Greater probability of possible injury relative to property damage only

The "single-vehicle" overturn accident indicator's positive coefficient indicates a greater likelihood of possible injury than property damage only. This shows that single-vehicle accidents with no evident injury tend to be more severe in nature.

Variable: Wet-pavement rear-end accident indicator

Finding: Greater probability of possible injury relative to property damage only

This variable captures the effect of rear-end accidents occurring in rainy weather. Such weather conditions make vehicles in front more difficult to see and increase the distance required to stop. It may also be argued that inclement weather may lower driver speeds and reduce risk of possible injury to a statistically insignificant level. However, intermittent and light rainfall, in spite of making the pavement wet and slippery, may not be dense enough to significantly lower driver speeds. The rear-end accident indicator may be capturing the effect of higher-than-expected vehicle speeds at the time of impact.

Variable: Two-vehicle rear-end accident indicator

Finding: Greater probability of possible injury relative to property damage only

While the previous finding reflects rear-end accidents in general, this variable captures the effect of two-vehicle collisions only. This coefficient is highly significant, statistically, indicating that injury, though not evident such as disabling, may be internalized to a greater extent than previously thought in such collisions. It is speculated that one important factor relating to the high significance of this variable could be the dissipation of kinetic energy and momentum per vehicle. The lower the number of vehicles involved, the greater the impact on each vehicle, thus increasing the likelihood of internal injuries, such as whiplash, which would be coded at the scene of the accident as a possible injury . The significantly higher coefficient (1.415 versus 0.4351 for the previous variable) corroborates the effect of inclement weather on driver speeds.

Variable: Percentage of horizontal curve length per kilometer of roadway

Finding: Greater probability of possible injury relative to property damage only

This variable captures the effect of terrain on the severity of an accident with no evident injuries. The high proportion of horizontal curves was found to increase the likelihood of a possible injury accident.

Variable: Number of horizontal curves per kilometer of roadway

Finding: Greater probability of possible injury relative to property damage only

This variable further confirms the finding offered by the curve-length variable. A greater number of curves on a particular section of roadway, although in some cases a speeding-deterrent, will affect steering control and reduce sight distance and thus be more likely to result in a possible injury collision.

Variable: Illumination indicator

Finding: Night-time conditions with no street lights present increase the probability of property damage only

This variable is likely an artifact of roadway design practices. Since the most dangerous portion of the road are the likely to be illuminated, we would expect a positive correlation between the absence of illumination and the likelihood of a property damage only accident.

Variable: Sideswipe accident indicator

Finding: Greater probability of possible injury relative to property damage only in multi-vehicle accidents

This variable (sideswipes involving more than two vehicles) primarily captures the exposure to possible injury. If the number of vehicles involved in a sideswipe accident exceeds two, the exposure increases in terms of number of occupants involved in the accident. Thus the greater likelihood of a possible injury. This variable may also be capturing the level of severity generally associated with this type of accident.

Variable: Same-direction accident indicator

Finding: Greater probability of possible injury relative to property damage only in multi-vehicle accidents

This variable (same direction accidents involving more than two vehicles) further illustrates the exposure, in terms of the number of occupants likely to be involved in the accident, that was also attributed to the sideswipe accident indicator. The finding is consistent with previous findings on the relationship of possible injury to increased exposure.

Variable: Fixed-object accident indicator

Finding: Greater probability of possible injury relative to property damage only

This variable is consistent with intuition which suggests that given that an accident resulted in no evident injuries, there is a greater probability of suffering possible injury from collisions with fixed objects. It must be noted that this applies only to accidents resulting no evident injuries.

Variable: Icy pavement indicator

Finding: Greater probability of property damage only relative to possible injury

This finding suggests that for single-vehicle accidents that occur on icy pavements, property damage will occur with greater probability than possible injury. This finding is consistent with previous conclusions on exposure in terms of number of vehicles involved and illustrates the effect of icy conditions. While icy pavement conditions hinder braking and steering control, they also tend to lower vehicle speeds. This effect reduces the risk of possible injury and limits the severity of an accident to property damage only.

Variable: Single-vehicle collision indicator

Finding: Greater probability of property damage only relative to possible injury

This finding corroborates earlier observations that fewer involved-vehicles increase the likelihood of property damage only. It also provides an important severity measure for accidents involving only one vehicle.

We now turn our attention to the estimation results of the overall model as presented in Table 3.3. The interpretation of coefficient estimates is provided below.

Variable: Angle accident type indicator

Finding: Greater probability of evident injury or disabling injury/fatality than no evident injury[1]

In a freeway corridor, angle accidents can occur when a leading vehicle is turned sideways positioning it at angle to the flow of following traffic, thereby making severe collisions more

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1 As mentioned previously, no evident injury accidents include property damage only and possible injury where possible injury is typically a minor injury that is not evident at the scene of the accident.

likely. Angle accident indicators may also be acting as surrogates for factors such as black ice which are not strictly observed due to weather data limitations.

Variable: Overturn accident indicator

Finding: Greater probability of evident injury or disabling injury/fatality

This finding corroborates the finding documented for "single-vehicle" overturn effects in the lower level model. After correcting for single-vehicle effects which are incorporated in the no evident injury category, we observe that overturns result in a greater probability of evident injury or disabling injury/fatality.

Variable: Speeding indicator 1 (exceeding posted speed limit)

Finding: Greater probability of evident injury relative to no evident injury or disabling injury/fatality

This finding isolates the effect of speeding over posted speed limits on accident severity. Current knowledge and intuition suggest that speeding is a primary cause in severe accidents such as those resulting in disabling injury/fatality. However, there are associated factors such as number of curves in a section, sobriety and age which confound the effects of speed. Controlling for these factors may uncover specific effects of speed in isolation. In the present model, we control for all such factors (as discussed below) and isolate the effects of speed.

Variable: Speeding indicators 2 and 3 (exceeding safe speed for prevailing conditions)

Finding: Greater probability of no evident injury relative to evident injury or disabling injury/fatality

This finding illustrates an important distinction in the effects of high and low speeds in that it examines the impact of low speeds on severity. By examining speed-related effects in accidents where exceeding the posted limit was the primary cause, we essentially restrict the population of accidents related to speed to above the speed limit (104 kilometers per hour). The variable under discussion examines the effect of speeds over the range of possible speeds below the speed limit.[1] As mentioned previously, several factors interact in association with speed and aggravate

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[1] It must be noted that once speeds exceed the posted limit, speeding indicator 1 overrides speeding indicator 2 as the primary cause from a reporting perspective. Hence, speeding indicators 1 and 2 split the accident

its effect. For speeds under the posted limit but exceeding reasonable speeds for prevailing conditions, aggravating factors typically include weather-related variables such as pavement surface conditions, age, and grade or curve-related factors. As discussed in a later section, we control for these factors and isolate the effect of exceeding safe speeds for prevailing conditions. Isolating the effect of safe speeds indicates that at lower speeds, it is more likely that the accident will have no evident injury. This finding[1] illustrates the importance of a more comprehensive model specification for providing better insights into underlying processes.

Variable: Restraint system use indicator

Finding: Greater probability of evident injury or disabling injury/fatality relative to no evident injury if at least one driver did not use a restraint system at the time of the accident

This finding is in agreement with other studies (Evans, 1986b). An interesting observation was that separating the restraint system used by driver and passengers did not yield significantly different coefficients for passengers.[2]

Variable: Occupant ejection indicator

Finding: Greater probability of evident injury relative to no evident injury or disabling injury/fatality

This finding indicates that after controlling for factors such as overturn collisions or run-off-the road accidents, ejection of the occupant (partial or total) will result in a greater likelihood of evident bodily injury as opposed to death or disabling injury. This variable accounts, along with the restraint system use indicator, for factors such as structural integrity of the vehicle and door failures on impact.

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population into "above speed limit" and "below speed limit" sub-populations. This segmentation provides unique insights into the impacts of speeds because the effects of these two speed categories are quite different.

1 The parameters for safe speed were specified initially for the evident injury and disabling injury/fatality alternatives simultaneously. By so doing, we constrain the β's to be the same for both alternatives. We removed this constraint and specified the β's separately for the alternatives. Relaxing the constraint allowed us to conclude the impact of safe speed with respect with evident injury was statistically different from that associated with disabling injury/fatality.

2 The statistically insignificant parameter for passenger restraint possibly indicates very high collinearity between driver and passenger restraint system use. In addition, when accident types such as rear-ends, angle and sideswipes are explicitly accounted for in the specification, rear-seat passenger injury is largely accounted for.

Variable: Gender of driver

Finding: Greater probability of disabling injury/fatality relative to no evident injury or evident injury if the accident involved all male drivers

This finding suggests that male drivers may be inherently greater risk takers and that risk is compounded by the exposure factor in multi-vehicle collisions when all drivers are male.

Variable: Percentage of curve length per kilometer of roadway

Finding: Greater probability of evident injury or disabling injury/fatality than no evident injury

This finding is consistent with the earlier finding on the same variable in the no evident injury model (as shown in Table 3.2). The finding implies that curve-length percentage increases the likelihood of an injury on a roadway section by possibly affecting the driving task and driver behavior.

Variable: Number of horizontal curves per kilometer of roadway

Finding: Greater probability of no evident injury or disabling injury/fatality relative to evident injury

This variable illustrates that evident injury is a less likely consequence as the number of curves per kilometer increases. This may be because some drivers' natural reaction is to slow-down when faced with many curves in close proximity, thus decreasing the likelihood of injury accidents.

Variable: Curve-sobriety interaction

Finding: Greater probability of disabling injury/fatality relative to no evident injury or evident injury

This variable captures the aggravating impact of curves on drunk driving. From a design perspective, this is an important finding because it presents opportunities for highway engineers to mitigate circumstances that aggravate drunk driving effects. A drunk driver’s lack of control is particularly critical on horizontal curves resulting in lane violations and ensuing multi-vehicle collisions or severe run-off-the road impacts.

Variable: Snow-covered pavement indicators[1]

Finding: Greater probability of no evident injury relative to evident injury or disabling injury

This finding indicates the impact of seasonal[2] as well as location-specific effects on accident severity. The presence of snow on the pavement at the time of the accident may indicate a general caution observed by drivers. If an accident were to still occur, the greater caution exercised by drivers helps mitigate the severity of an accident by reducing the effect of aggravating factors such as speed. On the other hand, presence of snow may also capture the higher observed frequency of "parked vehicle" accidents (i.e. disabled vehicles or those vehicles parked to put chains on) which tend to be property damage only. Lane obliteration may cause lane violations and ensuing collisions such as sideswipe and same direction accidents which were observed to be milder in severity.

Variable: Vehicle-mass difference indicator

Finding: Greater probability of evident injury or disabling injury/fatality relative to no evident injury

This variable captures the effect of truck-passenger car collisions on accident severity in two-vehicle accidents. By isolating two-vehicle collisions, we truly capture vehicle-mass difference effects, as opposed to a combination of vehicle-mass and exposure-related effects that would be present in multivehicle collisions involving more than two vehicles.

Variable: Accident location indicators

Finding: Greater probability of evident injury or disabling injury/fatality relative to no evident if the accident occurred off the road

This variable captures the impacts of off the road accidents due to roadside features such as ditches and embankments. Such features tend to cause an injury. The findings indicate that the

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1 As Table 3.3 shows, the β's for the evident injury and disabling injury/fatality categories were estimated unconstrained (i.e. separate coefficients for each severity category) and found to give statistically superior results relative to the constrained case (as measured by a likelihood ratio test).

2 Seasonal effects capture, in addition to direct weather effects, factors such as traffic volume. Reduced traffic volumes during the months of November through March reduces the likelihood of multi-vehicle accidents. Indirectly, this accounts for exposure.

likelihood of evident injury is significantly greater than disabling injury/fatality in off-the-road collisions. Accounting explicitly in the specification for specific accident types such as overturns, which typically occur in off-the-road collisions, allows us to isolate the impact of the off-the-road coefficient for disabling injury/fatality severities.[1]

Variable: Age-sobriety interaction

Finding: Greater likelihood of evident injury relative to disabling injury/fatality or no evident injury

This variable provides insight into an important two-way interaction that has not been investigated prior to this study. Age and sobriety have long been identified to play separate but significant roles in accident occurrences and severities. Several studies (Jonah, 1986; Mayhew *et al.,* 1986) have shown that older drivers are less prone to risk taking than younger drivers. Coupled with this, the risk of crash involvement of older drivers is also reduced due to greater driving experience. In addition, it has also been noted that alcohol-related impairment in driving is greater among older drivers. Given that an accident occurs, the combination of these factors results in injury accidents that are not as severe as disabling/fatality collisions. Being less likely to take risk and having greater driving experience seems to offset the greater impairment in driving that alcohol causes in older drivers, at least in terms of severity. However, the effect that such factors have on overall accident frequency is an open question that is not addressed in this study.

Variable: Night-time-pavement condition interaction

Finding: Greater likelihood of evident injury or disabling injury/fatality relative to no evident injury

This variable models the effect of night-time conditions and icy pavements on accident severities. In the event an accident occurred under such conditions, the positive coefficient of this variable with respect to evident injury and disabling injury/fatality indicates the influence of temperature-related and seasonal factors on driving. The importance of this interaction term stems from the compounding effect that night-time conditions have on driver behavior under icy

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[1] Off-the-road coefficients for evident injury and disabling injury/fatality were estimated separately. By doing so, the parameter for disabling injury/fatality was determined to be significantly lower than that for evident injury indicating that run-off-the-road by themselves are more likely to cause evident injury than disabling injury/fatality. It is in the presence of collisions such as vehicle overturns that the likelihood of disabling injury/fatality is enhanced.

conditions. It may be argued that the propensity of accidents occurring in icy weather could be lower during night because of increased caution among drivers; however, given that an accident occurs, the severity is likely to be high. This higher severity may be impart caused by slower driver-reaction times which tend to be significantly slower at night.[1]

Variable: Fixed-object-horizontal curve interaction

Finding: Greater probability of disabling injury/fatality relative to evident injury or no evident injury

This interaction term accounts for the impact of roadside features on accident severities on horizontal curves. The finding underscores the importance of roadside design on horizontal curves.

Variable: Fixed-object-icy pavement interaction

Finding: Greater probability of no evident relative to evident injury or disabling injury/fatality

This variable further corroborates, as mentioned previously, the impact of speed on the severity of fixed-object collisions. Icy weather acts as a deterrent to speeding, and as a result the consequence of fixed-object collisions are likely to be less severe. Again, this finding does not relate to the frequency of such collisions which could be expected to be higher under such conditions.

In addition to examining the impact of key variables on accident severity, elasticities of important design variables were also examined. Elasticity is the measure of the percentage change in the probability of a specific severity level for a unit percentage change in an independent variable. It is generally computed as a point-measure for continuous variables.[2] An elasticity greater than unity in absolute value indicates that the dependent variable is elastic with respect to the subject independent variable. The elasticities of overall accident severity

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1 The element of surprise and emergency response are important factors affecting driver reaction times. Several studies (Triggs and Harris 1982; Olson 1989; Hooper and McGee 1983; Taoka 1982) have evaluated driver reaction times under varying conditions and for different age groups, and concluded that night-time reaction times could be significantly higher than daytime values. The significance of the night-time-pavement interaction term presents a surrogate factor for reaction time, and illustrates the importance of potentially challenging highway geometrics.

2 Elasticities over a larger range of independent variable values are misleading when computed using this formula. In addition, elasticities for indicator variables which have binary values of 0 or 1 are meaningless.

probability with respect to curve-length percentage and number of horizontal curves per kilometer of roadway were computed to be -0.2704 and -0.9017 respectively. Intuitively this says that a 1 percent increase in the percentage of horizontal curve length per kilometer will result in a 0.2704 percent increase in the likelihood of an accident being evident injury or disabling injury/fatality. Also, a 1 percent increase in the number of horizontal curves per kilometer will result in a 0.9017 percent increase in the probability of the accident resulting in no evident injury or disabling injury/fatality. While both elasticities are less than 1, the elasticity computation provides interesting insight into the comparative importance of these two variables in determining accident severity.

3.6 Conclusions

The study provides a framework for estimating accident severity likelihood conditioned on the occurrence of an accident. It was concluded that a nested logit model which accounted for shared unobservables between property damage and possible injury accidents provided the best structural fit for the observed distribution of accident severities. This represents an important step in the methodological evaluation of ITS with respect to accident safety. By developing a probabilistic model that contains several important variables representing geometric, weather, and human factors we have shown that ambiguity and bias stemming from confounding effects in a partially specified model can be eliminated. In addition, this research provides suggestive results by its use of variables such as curve-sobriety interaction and curve-pavement surface interaction. Specifically, it suggests that ITS may be an effective means of compensating for adverse design, human factors, and weather conditions. A well designed ITS could significantly improve the driving task in the presence of adverse factors such as alcohol, inclement weather, and complex roadway geometrics. A significant shift in the distribution of accident severities toward milder accidents in combination with lower accident frequencies (Shankar *et al.,* 1995) will provide a basis for ITS evaluation. Further research which links the severity model to models of accident severity cost is needed to assess the potential and extent of savings in accident cost.

Part II

Analysis of Speed Data

This Part presents analysis of speed and vehicle classification data that is available from the three loop detectors installed in the study area. These loop detectors are 16 ft dual loop detectors and are installed by lane. They collect data in 8 speed classifications (<15mph, 15-25, 26-35, 36-45, 46-55, 56-65, 66-75, >75mph) and in 4 vehicle classifications (based on the length of vehicles). The speed stations are located (see Figure 1.1) at mile markers 46, 52, and 63 (for reference the study area starts at mile marker 33 and ends at mile marker 71, increasing from west to east).

Variations in speed were studied by using standard multiple regression techniques and by developing speed models for different classes of vehicles. To be able to isolate the impact of *TravelAid* on vehicle speeds, we must control for the effect of traffic volumes, as well as climatic, and time-of-day effects (i.e. night and day). In addition, when the system is operational, we will have a complete record of VMS messages (type and time) and changes VSLs. This data will be used to assess the system's effect on speeds by vehicle class. The analysis of the before data, collected in Winter 1994-95, is presented in the following Chapter. With a before and after comparison, similar to the one discussed above for accident frequencies and severities, we will be able to isolate the exact impact of *TravelAid* on the observed distributions of speeds.

Chapter 4

Modeling lane-mean speeds and deviations

4.1 Introduction

Prior speed-flow relationship studies have focused on single-regime or multi-regime functional relationships that were generally univariate or bivariate in nature. Linkages between speed and flow were generally studied over different traffic density ranges. Engineering intuition suggests that such approaches offer only a limited understanding of the underlying processes governing speed-flow relationships. Particularly in the context of intelligent transportation systems (ITS) where the use of technological components will likely result in fundamental shifts of assumed speed-flow relationships. In the presence of ITS, it is important that the causality underlying the processes affecting traffic speed-flow relationships and consequently safety be uncovered, because systemic affects associated with such technologies are potentially wide-ranging and often simultaneous.

The Chapter begins by discussing previous research and by providing a description of the data-collection site. This is followed by an overview of the modeling approach, estimation technique and the presentation of model-estimation results. Finally, conclusions and recommendations are provided.

4.2 Previous research

Prior theories and empirical validations have established speed-flow relationships that are unidirectional and regime-based (see for example, Greenshields, 1935; Edie, 1961; May and Keller, 1968). Suggestions on structural modeling (i.e. a simultaneous equations approach), with its potential to provide an improved understanding of the interrelationships among the contemporaneous influences of lane-mean speeds, lane-speed deviations, environmental conditions, geometric elements, vehicle-types, and temporal and seasonal factors, have been conceptual for the most part. Instead, significant effort has been focused on the use of independent ordinary or non-linear least squares estimation (see for example Easa and May, 1980). Use of independent regression equations that separately estimate speed and flow-related parameters without accounting for the contemporaneous correlation of the disturbances will cause the respective estimated parameters to be biased and inconsistent (Greene, 1993). Apart from the specification aspects mentioned above relating to the causal modeling of traffic speed and flow, little evidence is available on modeling frameworks that simultaneously incorporate the influence of environmental, geometric, temporal and traffic-flow factors. Some efforts in this area have focused on the impact of weather (Ibrahim and Hall, 1994) and geometrics (Iwasaki, 1991), while others have focused on the temporal variations in traffic flow (see for example Brilon and Ponzlet, 1996).

The attempt of this research is to combine the need for a complete model that is comprehensive in factors identified in previous research with the need for an estimation framework that is structural in nature. It should be noted here that the focus of the research is on the structural relationship between lane-mean speeds (i.e. time-mean speeds) and related lane-speed deviations and the traffic characteristics, environmental conditions, and temporal and seasonal factors. As such, the investigation will focus on the contemporaneous inter-relationships at a given location in a given time period.

4.3 Empirical setting

The specific study area of this research is on I-90 in the Cascade mountains with an elevation 975 meters above sea level. The climate is harsh with an average of 215 centimeters of rainfall and 1140 centimeters of snowfall annually. In general, this portion of I-90 has significant variations in speeds (i.e. high lane-speed deviations), due to the combined impact of vehicle mix, inclement weather, seasonal effects (e.g., variations in traffic volume, precipitation, and ambient temperatures), and challenging roadway geometrics. These speed variations significantly contribute to the likelihood and severity of accidents on this portion of I-90 (see Shankar *et al.,* 1995, 1996).

4.4 Modeling approach

Our intent is to develop a model of mean speeds and speed deviations (measured over some time interval) for each lane of a multilane roadway. Turning first to lane-mean speeds, from a structural point of view, it is important to note that the mean speed in each lane will not only be a function of traffic characteristics in the lane, but also a function of the mean speeds in the adjacent lanes. This suggests an equation system in which lane-mean speeds are determined simultaneously across the roadway's lanes. In a similar fashion, speed deviations in each lane will be dependent on speed deviations in adjacent lanes. Lane-speed deviations will also be a function of the lane's mean speed and the mean speeds in adjacent lanes. Because of this interrelationship, lane-speed deviations must also be determined in a simultaneous equation system with mean speeds entering the equation system in a recursive fashion.

The structural equation system for lane-mean speeds and lane-speed deviations can be written as follows: For lane-mean speeds, over some time interval, the equation system is,

$$
\begin{aligned}
u_1 &= \alpha_1 + \beta_1 X_1 + \lambda_1 Z_1 + \theta_1 \overline{u_1} + \varepsilon_1 \\
u_2 &= \alpha_2 + \beta_2 X_2 + \lambda_2 Z_2 + \theta_2 \overline{u_2} + \varepsilon_2 \\
&\;\;\vdots \\
u_n &= \alpha_n + \beta_n X_n + \lambda_n Z_n + \theta_n \overline{u_n} + \varepsilon_n
\end{aligned} \tag{4.1}
$$

where u_n is the mean speed in lane n, X_n is a vector of exogenous variables influencing the mean speed in lane n, Z_n is a vector of endogenous variables influencing the mean speed in lane n (i.e. traffic flow characteristics that may be influenced by lane-mean speeds such as proportion of total roadway traffic in the lane), $\overline{u_n}$ is a vector of mean speeds in lanes adjacent to lane n, α_n, β_n, λ_n, and θ_n are vectors of estimable coefficients, ε_n is a disturbance term. Similarly, lane-speed deviations, over some time interval, can be written as,[1]

$$
\begin{aligned}
\sigma_1 &= \rho_1 + \eta_1 V_1 + \tau_1 Y_1 + \gamma_1 \overline{u_1} + \omega_1 \overline{\sigma_1} + \nu_1 \\
\sigma_2 &= \rho_2 + \eta_2 V_2 + \tau_2 Y_2 + \gamma_2 \overline{u_2} + \omega_2 \overline{\sigma_2} + \nu_2 \\
&\;\;\vdots \\
\sigma_n &= \rho_n + \eta_n V_n + \tau_n Y_n + \gamma_n \overline{u_n} + \omega_n \overline{\sigma_n} + \nu_n
\end{aligned} \tag{4.2}
$$

where σ_n is the standard deviation of speed in lane n, V_n is a vector of exogenous variables influencing the standard deviation of speed in lane n, Y_n is a vector of endogenous variables influencing the standard deviation of speed in lane n (i.e. traffic flow characteristics that may be influenced by lane-speed deviations such as proportion of total roadway traffic in the lane), $\overline{u_n}$ is a vector of mean speeds in lane n and in other lanes, $\overline{\sigma_n}$ is a vector of the standard deviation of speeds in lanes adjacent to lane n, ρ_n, η_n, τ_n, γ_n, and ω_n are vectors of estimable coefficients, ν_n is a disturbance term.

To estimate equations (4.1) and (4.2), three-stage least squares (3SLS) is appropriate. This approach allows for simultaneous estimation of coefficients using information from the equation

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[1] Note that our equations model lane-speed deviations as dependent variables which are functions of lane-mean speeds. The reverse relationships between lane-mean speeds and lane-speed deviations is not specified. This is there is no basis for assuming lane-mean speeds are influenced by speed deviations. This was borne out during some preliminary estimation runs that found lane-speed deviations to be statistically insignificant when included in Equation 4.1.

system. By so doing, it ensures that coefficient estimates are generally more efficient (asymptotically) than alternative simultaneous-equation estimation approaches such as the indirect least-squares (ILS), two-stage least squares (2SLS), and limited-information maximum likelihood (LIML).[1] An alternative estimation approach is full-information maximum likelihood (FIML), but because the asymptotic variance-covariance matrices of FIML and 3SLS can be shown to be equal, the choice of 3SLS is acceptable. The 3SLS estimation procedure is conducted by first getting two-stage least squares (2SLS) estimates of the equation system which are calculated using instruments (endogenous variables regressed against all exogenous variables). The 2SLS estimates are then used to estimate the equation system's disturbances which are subsequently used to estimate the contemporaneous variance-covariance matrix of disturbances. Finally, generalized least-squares (GLS) is applied to estimate model coefficients using the estimated contemporaneous variance-covariance matrix of disturbances as a basis. See Greene (1993) for a complete description of the procedure.

To model lane-mean speeds and lane-speed deviations at this location, data were collected using magnetic loop detectors. Interstate 90, at this location, is a three-lane divided freeway in each direction with the eastbound alignment on a 1.5 percent upgrade and the westbound alignment on a 2.5 percent downgrade. Eastbound and westbound traffic data were collected by lane. Data on spot speeds by lane, vehicle classification by lane, were gathered in the fall of 1994 and the winter, spring and summer months of 1995. Speed data were collected in speed bins of 10 miles per hour, aggregated over one hour.[2] Classification of vehicle types was based on four wheelbase classes of up to 26, 26 to 39, 39 to 65, and 65 to 114 feet. Lane-by-lane data were collected for spot speeds and vehicle classifications in both eastbound and westbound

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1 The 3SLS procedure is more efficient than single-equation methods such as ILS, 2SLS, and LIML, when the variance-covariance matrix is not diagonal. This will be the case when there is contemporaneous correlation among disturbance (i.e., the unobserved factors affecting mean speed in one lane are correlated with those unobserved factors that affect mean speed in other lanes). If these unobserved factors are not correlated (i.e., the case of a diagonal variance-covariance matrix), it can be readily shown that 3SLS reduces to 2SLS.

2 Aggregation of speed data over one hour is likely to mask some underlying variation in the speed distribution; however, the level of detail that is afforded at micro-speed data such as 5-second or 20-second data is not likely to significantly alter the structure of the cause-effect relationship between speed and speed deviation. Any additional insight into the cause-effect relationship could stem from the stochasticity of peak hour flows. As will be demonstrated later, the stochasticity of peak hour flows and its impact on speed-speed deviation relationships will be captured adequately by indicator variables acting as surrogates for peak hour phenomena thus eliminating potential omitted variable biases. The authors do acknowledge that micro-speed data does provide insight into merge and weave phenomena and shock-wave-related incremental impacts on traffic flow continuums, but point out that the use of such data is different, namely to investigate "resulting conditions" stemming from inconsistencies in traffic flow.

directions. Table 4.1 shows computed lane-mean speeds and lane-speed deviations by lane using one hour time periods.

Table 4.1: Summary of lane-mean speeds and lane-speed deviations.

	Hourly Grouped Speeds					
	Grouped Lane-Mean Speed (miles per hour)			Grouped Lane-Speed Deviation (miles per hour)		
Eastbound						
Location	Mean	Minimum	Maximum	Mean	Minimum	Maximum
Right Lane	70.193	31.250	76.760	7.164	4.440	16.150
Middle Lane	75.612	32.580	79.820	5.548	3.780	13.860
Left Lane	78.012	34.880	90.000	4.858	0.000	21.680
Westbound						
Location	Mean	Minimum	Maximum	Mean	Minimum	Maximum
Right Lane	72.986	40.470	79.430	7.000	4.580	15.640
Middle Lane	76.441	43.570	81.940	5.756	3.000	14.210
Left Lane	78.830	40.000	86.670	5.310	0.000	28.720

Tables 4.2 and 4.3 show the results of the 3SLS estimation of grouped lane-mean speeds at the study location. Tables 4.4 and 4.5 show the results of the 3SLS estimation of grouped lane-speed deviations. For estimation purposes, the logarithm of the lane-mean speed was used as the dependent variable in the lane-mean speed model system. As seen in the tables, exogenous variables significantly determining lane-mean speed and lane-speed deviation include time-of-day, time-of-week, and seasonal, indicators. Vehicle mix and the distribution of traffic across the lanes were also found to be significant determinants of lane-mean speed and lane-speed deviation.[1] All estimated coefficients were found to be of plausible sign. For the eastbound direction, the system R^2 for the lane-mean speed model was 0.8629 and 0.3288 for the lane-speed deviation model. For the westbound direction, system R^2 was 0.9232 and 0.3087 for the

[1] For estimation purposes these variables were instrumented (see description in Tables 4.2-5) because of possible endogeneity. This is because changes in lane-mean speeds and/or lane-speed deviations can affect the distribution of traffic flow over the lanes. Thus changing values in the dependent variable could change values in the independent variable, which is violation of least-squares assumptions. Not correcting for this will result in biased and inconsistent coefficient estimates.

lane-mean speed and lane-speed deviation models, respectively. The interpretation of the estimation results is provided below.

4.5 Estimation of mean speeds

The models of mean speed in the eastbound and westbound directions can be seen in Tables 4.2 and 4.3, respectively.

Table 4.2: Three-stage least squares estimation of grouped lane-mean speeds for eastbound I-90.

Variable*	Estimated coefficient	t-statistic
Equation 1: Logarithm of Right-Lane Mean Speed (Dependent Variable)		
Constant	-0.1106	-2.6503
Lane traffic flow indicator (1 if traffic flow in right lane is less than 75 vehicles per hour, 0 otherwise)	0.0021	2.7372
Truck percentage in right lane	-0.0292	-15.2267
High truck flow in right lane (1 if hourly truck flow is greater than 100 vehicles per hour, 0 otherwise)	0.0030	6.8196
Relative truck flow indicator 1 (1 if truck percentage in right lane exceeds 60% and total traffic flow in right lane is less than 50 vehicles per hour, 0 otherwise)	0.0047	5.8343
Relative truck flow indicator 2 (1 if truck percentage in right lane is less than or equal to 20% and total traffic flow in right lane exceeds 200 vehicles per hour, 0 otherwise)	0.0034	5.3791
Logarithm of middle-lane mean speed	1.0107	104.7271
Time-of-day indicator 1 (1 if hour of observation is between midnight and 6:00 AM, 0 otherwise)	-0.0030	-3.3621
Seasonal indicator 1 (1 if it is winter, 0 otherwise)	-0.0021	-3.5543
Seasonal indicator 2 (1 if it is spring, 0 otherwise)	-0.0010	-2.7644
Time-of-week indicator (1 if it is weekend, 0 otherwise)	0.0104	8.7886
Time-of-day indicator 2 (1 if it is PM peak hour, 0 otherwise)	0.0018	3.7352
Time-of-day indicator 3 (1 if it is AM peak hour, 0 otherwise)	-0.0014	-2.7911
Number of observations	2233	
R-squared	0.9072	
Corrected R-squared	0.9067	

(Continued)

Table 4.2: Three-stage least squares estimation of grouped lane-mean speeds for eastbound I-90. (Continued)

Variable*	Estimated coefficient	t-statistic
Equation 2: Logarithm of Middle-Lane Mean Speed (Dependent Variable)		
Constant	0.3628	12.0474
Logarithm of right-lane mean speed	0.4257	59.2642
Logarithm of left-lane mean speed	0.4960	80.9855
Hourly traffic flow in middle lane	-0.000014	-10.2548
Lane use distribution between middle lane and right lane (ratio of flows in middle lane to right lane)	-0.0010	-4.2564
Time-of-day indicator 4 (1 if it is night-time, 0 otherwise)	-0.0030	-3.5560
Time-of-week indicator (1 if it is weekend, 0 otherwise)	-0.0072	-13.2349
Number of observations	2233	
R-squared	0.9022	
Corrected R-squared	0.9019	
Equation 3: Logarithm of Left-Lane Mean Speed (Dependent Variable)		
Constant	-0.6949	-12.0579
Truck percentage in left lane	0.0057	2.1422
Lane distribution between left lane and middle lane (ratio of flows in middle lane to right lane)	0.0050	3.1882
Logarithm of middle-lane mean speed	1.1671	87.7616
Time-of-day indicator 4 (1 if it is night-time, 0 otherwise)	0.0050	3.0050
Number of observations	2233	
R-squared	0.7961	
Corrected R-squared	0.7958	
System R-squared	0.8629	

* Variables in italics are instrumented because of possible endogeneity. This is done by regressing the variable against exogenous variables and using the regression-predicted values for the 3SLS estimation. Variables in bold are endogenous and part of the simultaneous equation estimation. Finally, trucks are defined as vehicles with wheelbases exceeding 65 feet.

Table 4.3: Three-stage least squares estimation of grouped lane-mean speeds for westbound I-90.

Variable*	Estimated coefficient	t-statistic
Equation 1: Logarithm of Right-Lane Mean Speed (Dependent Variable)		
Constant	-0.4308	-14.3947
Truck percentage in right lane	-0.0144	-9.2982
High truck flow in right lane (1 if hourly truck flow is greater than 100 vehicles per hour, 0 otherwise)	0.0017	2.7649
Logarithm of middle-lane speed	1.0895	157.8630
Seasonal indicator 1 (1 if it is winter, 0 otherwise)	0.0012	2.5684
Time-of-week indicator 1 (1 if it is weekend, 0 otherwise)	0.0046	4.8303
Time-of-day indicator 3 (1 if it is AM peak hour, 0 otherwise)	-0.0013	-2.5191
Number of observations	2230	
R-squared	0.9472	
Corrected R-squared	0.9470	
Equation 2: Logarithm of Middle-Lane Mean Speed (Dependent Variable)		
Constant	0.1919	7.7056
Logarithm of right-lane mean speed	0.4539	62.1349
Logarithm of left-lane mean speed	0.5047	66.5657
Hourly traffic flow in middle lane	-0.000015	-9.5357
Lane use distribution between middle lane and right lane (ratio of flows in middle lane to right lane)	-0.0012	-4.4492
Time-of-day indicator 4 (1 if it is night-time, 0 otherwise)	-0.0036	-5.1740
Time-of-week indicator (1 if it is weekend, 0 otherwise)	-0.0030	-6.6528
Number of observations	2230	
R-squared	0.9454	
Corrected R-squared	0.9452	

* Variables in italics are instrumented because of possible endogeneity. This is done by regressing the variable against exogenous variables and using the regression-predicted values for the 3SLS estimation. Variables in bold are endogenous and part of the simultaneous equation estimation. Finally, trucks are defined as vehicles with wheelbases exceeding 65 feet.

(Continued)

Table 4.3: Three-stage least squares estimation of grouped lane-mean speeds for westbound I-90. (Continued).

Variable*	Estimated coefficient	t-statistic
Equation 3: Logarithm of Left-Lane Mean Speed (Dependent Variable)		
Constant	-0.1134	-2.6376
Hourly traffic flow in left lane	0.000035	6.3908
Lane distribution between left lane and middle lane (ratio of flows in middle lane to right lane)	0.0040	2.6966
Logarithm of middle-lane mean speed	1.0321	104.1540
Time-of-day indicator 4 (1 if it is night-time, 0 otherwise)	0.0067	4.6959
Number of observations	2230	
R-squared	0.8797	
Corrected R-squared	0.8795	
System R-squared	0.9232	

* Variables in italics are instrumented because of possible endogeneity. This is done by regressing the variable against exogenous variables and using the regression-predicted values for the 3SLS estimation. Variables in bold are endogenous and part of the simultaneous equation estimation. Finally, trucks are defined as vehicles with wheelbases exceeding 65 feet.

a) Equation 1 (right lane)[1]

Variable: Lane traffic-flow indicator (flows less than 75 veh/h)

Finding: Positively affects lane-mean speeds in the eastbound direction

This finding is intuitive in that it illustrates driver tendency to drive the allowable safe speed under near free-flow conditions. Under near free-flow conditions, the visual constraints posed by the presence of adjacent vehicles are removed thereby allowing lane-mean speeds to increase significantly beyond normal operating speeds (around the speed limit.) The effect appears to be significant in the eastbound direction only and it is likely that the downgrade effect for the

[1] The lanes are defined as right, middle, and left relative to the direction of travel.

westbound direction annuls the significance of low volumes on lane-mean speeds in the right lane.

Variable: Truck percentage in right lane[1]

Finding: Negatively affects lane-mean speeds in both directions

This finding reflects the impact of truck percentage on speed-flow distributions. Under general conditions, with no constraints on flow levels and accounting for the effect of all other factors, increasing truck percentage will tend to decrease lane-mean speeds. However, as will be illustrated in the following discussions, certain truck percentage-flow combinations will create desirable conditions for traffic flow.

Variable: High truck flow in right lane

Finding: Increases right-lane mean speeds in both directions

This finding suggests that when truck flow in the right lane exceeds a threshold of flow, lane-mean speeds will increase as a result of a combination of factors. Truck drivers driving in high truck volumes tend to "draft" taking advantage of the relatively greater uniformity of vehicle type in the lane. This finding is consistent with the truck equivalency factors presented in the U.S. Highway Capacity Manual (Transportation Research Board 1994).

Variable: Relative truck flow indicators (truck percentage exceeding 60% and total traffic flow less than 50 veh/h or truck percentage less than or equal to 20% and total lane flow exceeding 200 veh/h)

Finding: Increases lane-mean speeds in the eastbound direction

This finding is illustrative of the significance of the impact of vehicle mix on traffic flow distribution. Under low or near free-flow conditions but with a high percentage of trucks, or under higher volume conditions but with a relatively low percentage of trucks, lane-mean speeds are found to increase because of the uniformity of vehicle type. The non-uniform range that consists of flow-mix combinations of 50-150 veh/h and truck percentages of 20% to 60% is likely to cause the most detrimental impact on lane-mean speeds, as evidenced by the general finding on truck percentage. This finding is based on flows observed in the "flat portion" (i.e.

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1 Trucks are defined as vehicles with wheelbases exceeding 65 feet.

the low-flow portion) of the classic speed-flow curve. As congestion increases, it is likely that the effect of vehicle mix by lane might cause a redistribution of lane use by vehicle type. The effect appears to be significant in the eastbound direction only and it is likely that the downgrade effect for the westbound direction annuls the significance of these effects on lane-mean speeds in the right lane.

Variable: Adjacent lane-mean speed (middle lane)

Finding: Increasing middle-lane speeds increases right-lane mean speeds in both directions

This variable captures the endogenous lateral cause-effect relationships between adjacent lane speeds.[1] As will be evidenced in subsequent discussions, adjacent lanes tend to positively affect traffic speeds. The underlying process this factor captures is the need to drive faster to merge into adjacent lanes and also the psychological impact faster traffic in the adjacent lane has on drivers.

Variable: Time-of-day indicator (midnight to early morning)

Finding: Negatively impacts right-lane mean speeds

This finding represents selection effects of drivers choosing the right lane for travel in the morning. Drivers who tend to use the right lane under free-flow conditions, as expected in the midnight to early morning hours, usually consist of slower passenger-car drivers or truck drivers. This portion of the population tends to have lower travel speeds.

Variable: Seasonal indicators (winter, spring)

Finding: Tend to decrease right-lane mean speeds in the eastbound direction and increase right-lane mean speeds in the westbound direction

These variables capture the effect of weather on right-lane operations. Particularly in this area of I-90 where snow and associated inclement conditions occur in winter and early spring, right lanes tend to operate at lower speeds due to vehicle chaining requirements and the deterrence of adverse driving conditions in the eastbound direction. The westbound direction seems to experience anomalous effects, however, but this is likely an artifact of the data,

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1 Note that only the immediately adjacent lane has a statistically significant impact on lane speeds (i.e., the left-lane speeds were not fount to affect right-lane speeds).

especially the positive effect of winter coupled with no significant effect for Spring. The artifact of the data potentially arises from the location of the speed detectors. The westbound direction detectors are situated in the end portion of the "chain-up" zone for crossing the Cascade mountain range. Therefore speed data collected at the location represent a self-selected sample of vehicles whose speed distributions remain relatively unaffected by "chain-up zone" requirements.

Variable: Time-of-week indicator (weekend)

Finding: Tends to increase right-lane mean speeds in both directions

This variable represents the near free-flow conditions that exist on weekends, in addition to capturing the effect of uniformity of traffic mixes. Truck traffic in weekend periods is minimal and as evidenced before, with greater vehicle type uniformity, right-lane mean speeds are expected to increase.

Variable: Time-of-day indicators (PM and AM peak hours)

Finding: Right-lane speeds increase during the PM peak hour in the eastbound direction and decrease during the AM peak hour in the eastbound and westbound directions

This peak hour variable captures the effect of several factors such as commute direction and vehicle mix uniformity. Westbound I-90 carries commuter traffic in the morning peak hour, and little or no commuter traffic occurs in the eastbound direction. In addition, freight movement is greater during the morning peak hour than in the evening peak hour. The combination of these factors leads to greater uniformity of vehicle mix in the evening peak hour and more mixed flow in the morning peak hour. The lack of a significant PM peak hour effect in the westbound direction is likely an artifact of the data, and in generic situations likely will play a significant role in both directions.

b) Equation 2 (middle lane)

Variable: Adjacent lane-mean speeds (left and right lanes)

Finding: Increasing adjacent lane speeds increase middle-lane mean speeds in both directions

This variable corroborates the finding on endogenous lateral cause-effect relationships between adjacent lane speeds. The finding on the greater impact of left lane operations further affirms our conclusion that differential lane speeds are critical to the analysis of the overall speed distribution.

Variable: Hourly traffic flow in middle lane

Finding: Tends to negatively impact middle-lane speeds in both directions

This finding is consistent with flow-speed relationships observed in other empirical studies. Given that truck-related factors were not found to significantly affect middle-lane speeds, this finding indicates that as flow in the middle lane (as opposed to the right lane) increases it represents the gradual approach to congestion, and the consequent decrease in speeds.

Variable: Lane use distribution between middle and right lanes (ratio of middle- to right-lane flows)

Finding: Increase in ratio decreases middle-lane speeds in both directions

This finding illustrates the effect of congestion and the declining choice of the middle lane as a passing lane as a result of increasing congestion. As congestion levels are approached, the use of the middle lane changes from a passing lane to a capacity lane. Consequently, driver behavior appropriately reflects a tendency to slow down under increasing flows.

Variable: Time-of-day indicator (night-time)

Finding: Tends to decrease middle-lane speeds in both directions

This finding is consistent with the intuitive expectation that night-time conditions present more challenges to the driving task, and hence cause drivers to slow down.

Variable: Time-of-week indicator (weekend)

Finding: Tends to decrease middle-lane speeds in both directions

As opposed to a positive impact on right-lane speeds, weekend effects tend to decrease middle-lane speeds. Although this finding appears counter-intuitive, when viewed within a free-flow regime context, it appears tenable. During weekends, when near free-flow conditions exist, lane usage is not governed by the need to pass, but by arbitrary choice. Vehicles that use the middle lanes in weekend periods therefore in general are not speeding to pass, as opposed to a weekday situation. As a result, it is not unusual to expect slower moving vehicles in the middle lane.

c) Equation 3 (left lane)

Variable: Truck percentage in left lane

Finding: Increasing truck percentage increases left-lane speeds in eastbound direction

This finding illustrates the primary effect of a passing lane on cross-sectional flow-speed relationships when from a capacity standpoint. A higher truck percentage in the left lane reflects truck drivers' tendencies to pass slower traffic in order to accelerate up the steeper grade that is immediately upstream of the eastbound direction. The geometric constraints oncoming terrain poses to truck drivers causes this phenomenon. The westbound direction experiences no significant effect due to the significant downgrade that exists.

Variable: Lane use distribution between left and middle lanes (ratio of left to middle lane flows)

Finding: Increase in ratio increases left-lane speeds in both directions

This finding illustrates that as traffic flows in the middle and right lanes approach thresholds where lane speeds have to decrease to maintain safe operations, the use of the left lane as a passing lane increases thereby attracting faster drivers.

Variable: Adjacent lane-mean speeds (middle lane)

Finding: Increasing adjacent lane speeds increase left-lane mean speeds in both directions

This variable corroborates the finding on endogenous lateral cause-effect relationships between adjacent lane speeds. The finding on the isolated impact of middle lane operations is consistent with our findings on the impact of middle lane operations on right-lane mean speeds.

Variable: Time-of-day indicator (night-time)

Finding: Increases left-lane speeds in both directions

This finding appears counter-intuitive, but provides interesting insight into drivers' perception of lane usage by time-of-day. Under night-time conditions, the use of the middle lane as a passing lane declines in favor of the left lane for drivers who tend to drive significantly faster than the average driver. Thus the night-time factor captures aggressive driving behavior and the locational occurrence of such behavior in a cross-sectional context.

4.6 Estimation of speed deviations

The models of speed deviations in the eastbound and westbound directions can be seen in Tables 4.4 and 4.5, respectively.

Table 4.4: Three-stage least squares estimation of grouped lane-speed deviations for eastbound I-90.

Variable*	Estimated coefficient	t-statistic
Equation 1: Right-Lane Speed Deviation (Dependent Variable)		
Constant	34.5707	7.6989
Speed Deviation in middle lane	0.1996	2.5356
*Logarithm of right-lane mean speed***	3.6272	2.6788
*Logarithm of middle-lane mean speed***	-10.1006	-10.0808
Time-of-day indicator 1 (1 if hour of observation is between midnight and 6:00 AM, 0 otherwise)	0.2384	3.4834
Time-of-day indicator 2 (1 if it is PM peak hour, 0 otherwise)	-0.0917	-1.4435
Seasonal indicator 1 (1 if it is winter, 0 otherwise)	-0.2234	-4.3246
Time-of-week indicator (1 if it is weekend, 0 otherwise)	-0.2969	-5.8715
Truck-to-passenger car flow ratio	-0.1238	-7.8162
Number of observations	2233	
R-squared	0.2959	
Corrected R-squared	0.2934	
Equation 2: Middle-Lane Speed Deviation (Dependent Variable)		
Constant	34.6818	10.6756
Speed Deviation in right lane	-0.0516	-1.3422
Speed Deviation in left lane	0.3791	13.6739
*Logarithm of right-lane mean speed***	-31.0753	-11.7211
*Logarithm of middle-lane mean speed***	11.2859	8.9724
*Logarithm of left-lane mean speed***	12.0551	5.0897
Time-of-week indicator (1 if it is weekend, 0 otherwise)	0.4592	8.0088

* Variables in italics are instrumented because of possible endogeneity. This is done by regressing the variable against exogenous variables and using the regression-predicted values for the 3SLS estimation. Variables in

bold are endogenous and part of the simultaneous equation estimation. Finally, trucks are defined as vehicles with wheelbases exceeding 65 feet.

** Lane-mean speeds are instrumented variables in the speed deviation system. Predicted values from the lane-mean speed system were used in this 3SLS estimation.

(Continued)

Table 4.4: Three-stage least squares estimation of grouped lane-speed deviations for eastbound I-90. (Continued).

Variable*	Estimated coefficient	t-statistic
Seasonal indicator 1 (1 if it is winter, 0 otherwise)	-0.1081	-2.3134
Time-of-day indicator 1 (1 if hour of observation is between midnight and 6:00 AM, 0 otherwise)	0.2430	6.1934
Time-of-day indicator 2 (1 if it is PM peak hour, 0 otherwise)	-0.1829	-3.5588
Number of observations	2233	
R-squared	0.3598	
Corrected R-squared	0.3572	
Equation 3: Left-Lane Speed Deviation (Dependent Variable)		
Constant	22.9298	3.5773
Speed Deviation in middle lane	1.0753	10.3436
*Logarithm of middle-lane mean speed***	-29.5472	-13.8764
*Logarithm of left-lane mean speed***	24.0178	11.6909
Passenger car percentage	-1.0800	-2.4323
Seasonal indicator 1 (1 if it is winter, 0 otherwise)	0.6884	6.5079
Time-of-day indicator 2 (1 if it is PM peak hour, 0 otherwise)	0.4557	3.3125
Number of observations	2233	
R-squared	0.3285	
Corrected R-squared	0.3267	
System R-squared	0.3288	

* Variables in italics are instrumented because of possible endogeneity. This is done by regressing the variable against exogenous variables and using the regression-predicted values for the 3SLS estimation. Variables in bold are endogenous and part of the simultaneous equation estimation. Finally, trucks are defined as vehicles with wheelbases exceeding 65 feet.

** Lane-mean speeds are instrumented variables in the speed deviation system. Predicted values from the lane-mean speed system were used in this 3SLS estimation.

Table 4.5: Three-stage least squares estimation of grouped lane-speed deviations for westbound I-90.

Variable*	Estimated coefficient	t-statistic
Equation 1: Right-Lane Speed Deviation (Dependent Variable)		
Constant	-0.5669	-0.3505
Speed Deviation in middle lane	0.8431	37.1615
*Logarithm of right-lane mean speed***	9.7616	9.7441
*Logarithm of middle-lane mean speed***	-9.0162	-8.7505
Time-of-day indicator 1 (1 if hour of observation is between midnight and 6:00 AM, 0 otherwise)	-0.1023	-2.0570
Time-of-week indicator (1 if it is weekend, 0 otherwise)	-0.1552	-3.8241
Number of observations	2230	
R-squared	0.3965	
Corrected R-squared	0.3951	
Equation 2: Middle-Lane Speed Deviation (Dependent Variable)		
Constant	2.1069	08975
Speed Deviation in right lane	1.1797	31.0057
Speed Deviation in left lane	-0.0332	-1.6305
*Logarithm of right- lane mean speed***	-12.3373	-3.6331
*Logarithm of middle-lane mean speed***	9.5426	7.1049
*Logarithm of left-lane mean speed***	1.6071	0.5003
Time-of-week indicator 1 (1 if it is weekend, 0 otherwise)	0.1856	3.5658
Seasonal indicator 1 (1 if it is winter, 0 otherwise)	0.0380	1.5280
Time-of-day indicator 1 (1 if hour of observation is between midnight and 6:00 AM, 0 otherwise)	0.1429	2.4480

* Variables in italics are instrumented because of possible endogeneity. This is done by regressing the variable against exogenous variables and using the regression-predicted values for the 3SLS estimation. Variables in bold are endogenous and part of the simultaneous equation estimation. Finally, trucks are defined as vehicles with wheelbases exceeding 65 feet.

** Lane-mean speeds are instrumented variables in the speed deviation system. Predicted values from the lane-mean speed system were used in this 3SLS estimation.

(Continued)

Table 4.5: Three-stage least squares estimation of grouped lane-speed deviations for westbound I-90. (Continued).

Equation 2 (continued)		
Number of observations	2230	
R-squared	0.3460	
Corrected R-squared	0.3436	
Equation 3: Left-Lane Speed Deviation (Dependent Variable)		
Constant	29.3353	5.8855
Speed Deviation in middle lane	0.3794	5.2335
*Logarithm of middle-lane mean speed***	-33.2354	-15.0579
*Logarithm of left-lane mean speed***	26.9555	11.1272
Seasonal indicator 1 (1 if it is winter, 0 otherwise)	0.4621	4.2952
Number of observations	2230	
R-squared	0.2682	
Corrected R-squared	0.2669	
System R-squared	0.3087	

* Variables in italics are instrumented because of possible endogeneity. This is done by regressing the variable against exogenous variables and using the regression-predicted values for the 3SLS estimation. Variables in bold are endogenous and part of the simultaneous equation estimation. Finally, trucks are defined as vehicles with wheelbases exceeding 65 feet.

** Lane-mean speeds are instrumented variables in the speed deviation system. Predicted values from the lane-mean speed system were used in this 3SLS estimation.

a) Equation 1 (right lane)

Variable: Speed deviations in middle lane

Finding: Middle-lane deviation positively affects speed deviation in right lane in both directions

This variable captures the lateral lane effects across the roadway. However the impact includes the car-following response effect (not expected in adjacent lane speed effects) due to lane changes that adjacent-lane deviations bring. Greater deviations in the middle lane indicate to drivers in the right lane more opportunities, although intermittent, for lane changing than a lower deviation would. Hence, the car-following driver response in the right lane is simultaneously being influenced by the opportunity for lane changing which causes the sub-conscious effect of higher fluctuation in in-lane speeds.

Variable: Lane-mean speeds[1]

Finding: Right-lane mean speeds positively affect right-lane speed deviations while middle-lane mean speeds negatively affect right-lane speed deviations

This finding is intuitive and consistent with the relationships drawn in previous studies between the coefficient of dispersion and mean speeds (see for example May, 1990). The negative impact of middle-lane speeds on right lane deviations indicates that drivers tend reduce their deviations as adjacent lane speeds go up in order to make their lane changing operations safer.

Variable: Time-of-day indicators (early morning and PM peak)

Finding: Early morning effects cause an increase in right-lane deviations in the eastbound direction while PM peak hour effects cause a decrease in right-lane speed deviations in the eastbound direction. In the westbound direction early morning effects cause a decrease in right-lane deviations while PM peak hour effects are insignificant.

The “midnight to early morning” variable, as discussed previously in its effects on lane speeds, captures driver response under near-free-flow conditions. Depending on whether it is an upgrade or a downgrade, driver response in car following is expected to change. In the eastbound direction, where a significant upgrade follows the loop detector locations, deviations tend to increase in the most-used lanes during that time of day, namely, the right and middle lanes. In contrast, the downgrade in the westbound direction collapses the speed distribution and has a downward effect on speed deviations in general.

In the PM peak hour, traffic flow increases to levels that warrant use of the middle and left lanes from a capacity standpoint, and coupled with the greater uniformity in vehicle mix, the net effect on speed deviations in the right lane is a decline. That this effect was not found to be

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[1] Lane-mean speeds are instrumented variables in the speed deviation system. Predicted values from the lane-mean speed system were used in this 3SLS estimation.

significant in the westbound direction is explained by lack of significant commuter traffic in that direction at the location being considered. In fact, any commute-related effects in the westbound direction is marginally captured by the "early morning" variable which, as mentioned previously, has a negative impact on right-lane speed deviations.

Variable: Seasonal indicator (winter)[1]

Finding: Winter effects tend to decrease speed deviations in the eastbound direction

Winter effects capture the effects of driver behavior under inclement conditions. Although speeds tend to decline under inclement conditions, driver behavior is altered to the extent that significantly more attention is paid to the driving task. Drivers tend to maintain constant headways, and minimize lane changing operations.[2] The net effect of such behavior is an associated decline in right-lane deviations. It is also important to note that the "chain-up" zone occurs upstream of the eastbound direction, causing additional constraints on traffic dispersion. In the westbound direction, due to the fact that the detectors are downstream of the "chain-up" zone, such constraints are minimal. Nevertheless, the finding on the westbound effects of the season variables may merely be artifacts of the data for other reasons.

Variable: Time-of-week indicator (weekend)

Finding: Decreases right-lane speed deviations in both directions

The finding on this variable illustrates selectivity in the driving population that chooses the right lane on weekends. As mentioned previously, perhaps, this class of drivers not only maintain lower speeds but also lower deviations because they are risk averse.

Variable: Truck-to-passenger car ratio

Finding: Decreases right-lane speed deviations in the eastbound direction with no significant effect in the westbound direction

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1 In the absence of microscopic weather data, lateral lane effects are captured by the seasonal indicator. While this does not cause an omitted variable bias, real-time microscopic weather information will provide interesting insights into the impacts of factors such as precipitation versus snow pileup, and rainfall versus pavement drainage on driver behavior.

2 Such behavior is more prevalent amongst drivers who choose to use the right and middle lanes. On the contrary, as will be evidenced later in the discussion of weather effects on left-lane speed deviations, the self-selection of riskier drivers in left lanes will likely cause an increase in speed deviations.

Increasing truck-to-passenger car ratio effects reiterate the impact of vehicle-mix uniformity and "truck drafting phenomena" on reduction of speed deviations. In the presence of significant upgrades, there is self-selection of the right lane by heavier traffic. In the presence of a downgrade, as evidenced in the westbound direction, this need is not compelling.

b) Equation 2 (middle lane)

Variable: Speed deviations in right and left lanes

Finding: Right-lane deviations negatively affect middle-lane speed deviations while left-lane speed deviations have a positive impact in the eastbound direction. In the westbound direction, the effects are opposite

The finding on these variables are consistent with the unobserved effects due to grades as presented in previous discussions.

Variable: Lane-mean speeds

Finding: Right-lane mean speeds have a negative impact on middle-lane speed deviations while middle- and left-lane mean speeds have positive impacts in both directions

Higher right-lane mean speeds indicate that the vehicle-to-vehicle interaction in the traffic flow continuum is smoother with drivers experiencing a decreased need for lane changing. Consequently speed deviation in the middle lane is affected inversely with the lane change need. The positive impact of middle- and left-lane speeds on in-lane deviations appears aberrational and inconsistent with previous findings However, it is likely capturing the flux in driver selectivity in the middle lane. Middle-lane users are arguably the most diverse in terms of their inherent driving natures, and hence may have a fundamental tendency to vary their speeds more. Consequently in situations where in-lane or left-lane speeds increase, drivers may be increasing their speeds in order to change to the left lane or that traffic volumes are quite below capacity.[1]

Variable: Time-of-week indicator (weekend)

Finding: Increase in on middle-lane speed deviations in both directions

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[1] In the westbound direction, the effect of left-lane speed is statistically insignificant (t-statistic = 0.50). However as mentioned previously, this could be an artifact of the data and it is likely that when grade-related effects are quantified as continuous variables and interactions by lane, such anomalies will diminish. The intent of this paper to present as general a specification that offers comparable insights into the effects of endogenous variables on speed and speed deviation relationships.

This finding corroborates previous inferences given that traffic volumes in the middle lane during weekends are expected to be minimal.

Variable: Seasonal indicator (winter)

Finding: Decrease in middle-lane speed deviation in the eastbound direction while increasing in the westbound direction

This finding is consistent with evidence on winter effects found in previous variables. However, it appears that westbound direction experiences adverse effects (positive) in the passing lanes, the effects most likely being downgrade-related.

Variable: Time-of-day indicator (midnight to early morning)

Finding: Increases middle-lane speed deviations in both directions

This finding indicates the effect of free-flow conditions on driver behavior when the population selection effect (as evidenced in right lane relationships) is absent. Coupled with the fact that the middle lane and left lanes serve as passing lanes under such conditions, causes an increase in speed deviations.

Variable: Time-of-day indicator (PM peak hour)

Finding: Decrease in middle-lane speed deviations in the eastbound direction and insignificant in the westbound direction

This finding indicates the effect of commute-related volume effects on speed deviations and is consistent with earlier inferences on traffic flow variable-related impacts.

c) Equation 3 (left lane)

Variable: Speed deviation in middle lane

Finding: Positively affects speed deviations in the left lane in both directions

The lateral "friction" effects caused by interaction between the middle and left lanes are captured by this variable. Given that this portion of I-90 is largely in the "flat" portion of the upper part of the speed flow curve, the middle and left lanes serve predominantly as passing lanes, thereby experiencing a self-selected sample of drivers who are more risk-prone and significantly influenced by variations in speed. The positive impact of the variable captures such lateral lane effect dynamics.

Variable: Middle- and left-lane speeds

Finding: Increasing middle-lane speeds decrease left lane deviations while increasing in-lane speeds increase in-lane deviations in both directions

This variable captures similar to the endogenous relationships between the middle and right lanes, the cascading effect of speed variation from the right lane to the left lane. With higher middle lane speeds the need to change to the left lane decreases, thereby minimizing friction in the left lane. On the other hand, when left-lane speeds increase, there is a consequent increase in speed deviation because the self-selection of the left lane to the most risk-prone drivers is greatest.

Variable: Passenger car percentage

Finding: Negatively affects eastbound speed deviations

This finding illustrates locale-specific effects related to grades. The eastbound direction which experiences significant upgrades consequently also experiences a greater distribution of truck traffic across the cross-section. The passenger car variable captures this effect and corroborates the impact of uniformity of vehicle mix on traffic flow dispersion.

Variable: Time-of-day indicator (PM peak hour)

Finding: Increases eastbound speed deviations

This finding is consistent with earlier discussions in that the middle and left lanes serve as passing lanes and commuter lanes in the PM peak hour in the eastbound direction. The positive effect may also be capturing the tendency of drivers in their home-bound commute to take greater risks, evidence that cannot be supported in the westbound direction because of its lack of commute effects.

Variable: Seasonal indicator (winter)

Finding: Increases left-lane speed deviations in both directions

This finding is consistent with those presented for middle-lane speed deviations.

4.7 Conclusions

Endogenous relationships within lane speeds and between lane speeds and speed deviations were found to be statistically valid. The westbound and eastbound directions of our study site experienced dissimilar effects related to grade, time-of-day and time-of-week characteristics. On the other hand, the endogenous relationships in large part are similar, with estimated coefficients of like sign, means and standard errors. Our findings show that in-lane speeds are affected only by adjacent-lane speeds and in-lane speed deviations are affected progressively by adjacent lane speed deviations and in addition, in-lane and adjacent-lane speeds. Coupled with findings on the contemporaneous impact of temporal and vehicle-mix factors, such inferences corroborate the need for a comprehensive investigation into lane-mean speed and lane-speed deviation relationships. To be sure, the data we used was limited (i.e. a single site) it that it did not allow us to explore variations in geometric characteristics, functional classifications, and other factors that might vary from site to site. Further insights could be gained from a more diverse data set that encompasses various regions and roadway functional classes.

The findings gathered from this research appear promising for further application of the structural equations methodology to macroscopic traffic-flow modeling. It is quite possible that dynamic effects could be uncovered to a greater extent with more microscopic data by incorporating pre-determined lane-mean speed and lane-speed deviation variables in the specifications. Such a study could have objectives relating to the unraveling of incremental dynamics in traffic flow under smaller time windows and greater seasonal, vehicle-mix constraints. While the present research offers generic insights, understanding the cause-effect relationships between lane-mean speed and lane-speed deviations under such constraints could enrich our knowledge of driver response under specific conditions. Such knowledge will be beneficial to the design and planning of advanced traffic management systems intended for the improving traffic flow and safety.

Part III

Survey Studies

It is important to study driver behavior before the implementation of the *TravelAid* advisory systems. This enables the comparison of before and after data to understand the actual effect of the *TravelAid* project. For this purpose, a survey was designed and data was collected from Snoqualmie Pass drivers during the winter of 1995.

The design of the survey and the data collection is described in the next Chapter. There is then a Chapter that describes the research of Morse (1995) on the reported speed reductions of drivers in adverse weather conditions. It is followed by a Chapter on the analysis of various other reported driver behavioral characteristics (Boyle, 1998). That research provides before data for a comparative driving simulator study described in the next Part.

Chapter 5

Methodology

A questionnaire was developed to collect motorist's opinions about safe speeds in dry, wet, and icy conditions, as well as the motorists' perception of an in-vehicle device that provides real-time information. As part of the evaluation of the *TravelAid* Project, the questionnaire was designed to collect data on the needs of the motorists and data for the evaluation project. The *TravelAid* Project includes the evaluation of the use of an in-vehicle display device. The questionnaire included questions about the use of the device and solicited volunteers to participate in simulation experiments and personal interviews regarding the use of the device. The questionnaire was mailed to 1,960 motorists to determine what information is most useful (important) to motorists and to safety. The results of the questionnaire are discussed later in this Chapter. License-plate numbers were collected from vehicles using Snoqualmie Pass in March 1995. These numbers were used to obtain the addresses for the mail-back survey.

5.1 License-plate numbers

License-plate numbers were collected from vehicles using Snoqualmie Pass and a questionnaire was mailed to the registered owner. Experience with mail-back surveys (Mannering and Koehne, 1994) has shown that a sample of 400 responses is adequate to create a statistically valid model of driver-behavior based on driver characteristics.

Other surveys conducted recently in the Seattle area experienced a 25 percent response rate (Mannering and Koehne, 1994). Therefore, about 1,600 addresses were needed to insure 400 responses. Based an a 25 percent collection-error rate, 2,000 license-plate numbers would be required to obtain 1,600 valid addresses.

Binoculars were used to read license-plate numbers from vehicles. Observers sat on a roadway structure over the freeway and read the numbers from the rear of vehicles driving away from the observers. Eight hundred numbers were collected on March 21, 1995: 400 from milepost 62 (the east end of the pass) and 400 from milepost 32 (the west end of the pass). Numbers were not collected from the summit because there is no structure from which to observe. One thousand license-plate numbers were collected from milepost 32 on March 22, 1995. Two observers each collected 500 numbers from different directions of the freeway. Since the ski areas were closed when the numbers were taken from the roadway, very few skiers were observed on the road as well as in the parking lot.

On Saturday, March 26, 500 additional numbers were collected from vehicles in the parking lots of the Snoqualmie Pass ski areas. Table 5.1 shows the date and count of license-plate numbers collected from each location.

The use of numbers collected from the parking lots of ski areas could bias the survey. However, because skiers are a significant portion of winter time users, it is important that skiers be included in the survey. Since 22 percent of the numbers came from skiers, but 38 percent of the respondents use the pass for recreational reasons, the sample may be biased toward non-skiers. This bias will only be significant if skiers have different information requirements than other motorists. Models developed for recreational users and non-recreational users showed no significant difference in information requirements.

All license-plate numbers were written on pre-printed tally sheets, which were marked to show the direction of travel (a special code was used for the numbers from the parking lot).

The numbers were entered into a text file and sorted. Collecting license-plate numbers on three different days could have caused a problem with duplicate numbers. Fifty duplicate numbers were found and removed, giving a total of 2250 numbers. The file was sent to the Department of Licensing, which returned a file containing 2,175 addresses. 75 numbers were not on file. It is possible that some numbers were misread or were transcribed incorrectly when entered into the data file.

There are many factors that could cause the number to be misread. In order to collect data, the research team had to sit on a six-foot shoulder of a busy arterial facing away from traffic — an uncomfortable situation. Passing motorists who shout, honk or drive too close are a strong distraction. Several letters in the alphabet are very similar in shape and easily confused. Many vehicle owners have decorative license-plate covers or borders. The borders partially obscure or blend into the letters and make them difficult to read.

Discussions with other survey takers in the Seattle area indicated that a significant number of plates would not be on file. However, if the observer misread one letter and created a ‘new’ number, the new number could be valid. There is no way to know how many of the license-plate numbers collected were misread. The misread numbers could affect the number of responses if the ‘new’ number matches a person who does not drive on Snoqualmie Pass or matches a vehicle that is inoperable. Because all drivers’ opinions are equally important, responses to misread numbers will not adversely affect the outcome of the survey.

Business addresses and rental car addresses were removed, leaving 1,960 personal addresses. The target respondents were drivers. If the survey were sent to businesses or rental car agencies, there would be no way to know who would answer it.

Table 5.1: The count of license-plate numbers collected on three dates from three locations.

Date	Milepost 32		Milepost 62		Ski area
March	Eastbound	Westbound	Eastbound	Westbound	
21 - Tu.	200	200	200	200	0
22 - We	500	500	0	0	0
26 - Sa.	0	0	0	0	500

5.2 Questionnaire

The format of the questionnaire was driven by the cost of postage and ease of use by the respondent. A three-page questionnaire was designed and printed on a single sheet and folded to open like a book (with no loose pages to be lost). The three-page design was not long enough to intimidate the recipient and the single sheet made the questionnaire easier to follow, preventing confusion and incomplete sections.

The questionnaire was broken into three sections: information about the respondent's trip, the respondent's opinions about the pass, and demographic information about the respondent. See the appendix for a copy of the questionnaire.

In the trip section of the questionnaire, the respondent answered questions about a typical trip on Snoqualmie Pass. The frequency of trips, the driving speed, the purpose of the trip, seatbelt usage, accident information, and the source and importance of weather and roadway information were all topics addressed by this section of the questionnaire.

The opinion section asked the respondent to give opinions about safe driving speeds and general safety aspects of the pass. The respondent was also asked to give opinions about the use of an in-vehicle display device.

The last section asked questions about age, income, sex, marital status, family size and the number of vehicles owned by the family. The respondent was also asked if they are interested in participating further in the project — either as a tester of an in-vehicle device, or in an interview or simulation experiment. The questionnaire also contained space for the respondent to put contact information for further participation and to make comments.

When finished with the questionnaire, the respondent was asked to mail it back with return postage paid by the project. The results of the survey are discussed in the next section.

5.3 Descriptive statistics

Of the 1,960 questionnaires distributed, 23 percent were returned, providing 444 observations for analysis. The responses to the survey are superimposed on the questionnaire in Appendix A.

Based on the questionnaire responses, 39 percent of the respondents use Snoqualmie Pass for recreational purposes, 28 percent for family visits, 21 percent for business, 3 percent for errands and 9 percent for other reasons (such as trips to the doctor). The large number of trips using the pass for recreation and family visits and the infrequency of the trips (usually less than 2 per month) points to the need for an efficient and reliable motorist information system on the pass. Infrequent users cannot rely on experience to know what to expect in terms of weather and roadway conditions. Infrequent users also have difficulty in judging the proper speed in adverse weather conditions, as shown in the statistical analyses later in this Chapter.

Figure 5.1 shows the number of trips made during the months of December, January and February. The number of trips made in the winter months was used in the models to measure winter driving experience. The plots of trips made in spring, summer, and fall closely resemble those shown in Figure 5.1.

The results of this questionnaire showed that 52 percent of the respondents drive at or above the posted speed limit (65 mph) on dry roadway conditions. In wet conditions, 61 percent drove between 55 and 65 mph. Ninety-three percent indicated that they drove less than 55 mph in icy conditions. The large number of motorists driving at or near 65 mph in wet conditions suggests that motorists may be over-driving their capabilities as well as a safe speed.

Most respondents (95%) indicated that increasing safety is moderately to very important, while 85 percent indicated that saving trip time is moderately to very important. The tendency to speed is corroborated by the respondents that indicated that saving trip time is important. This finding is of particular interest when compared to the number of respondents that reported safety to be moderately to very important. More than three quarters of the respondents indicated that the 65 mph speed limit is unsafe in wintry conditions. In winter, the need for safety and lower speeds is in conflict with the desire to reduce trip time and higher speeds. With the implementation of variable speed-limit signs, the *TravelAid* Project will enhance safety and encourage lower speeds during adverse conditions.

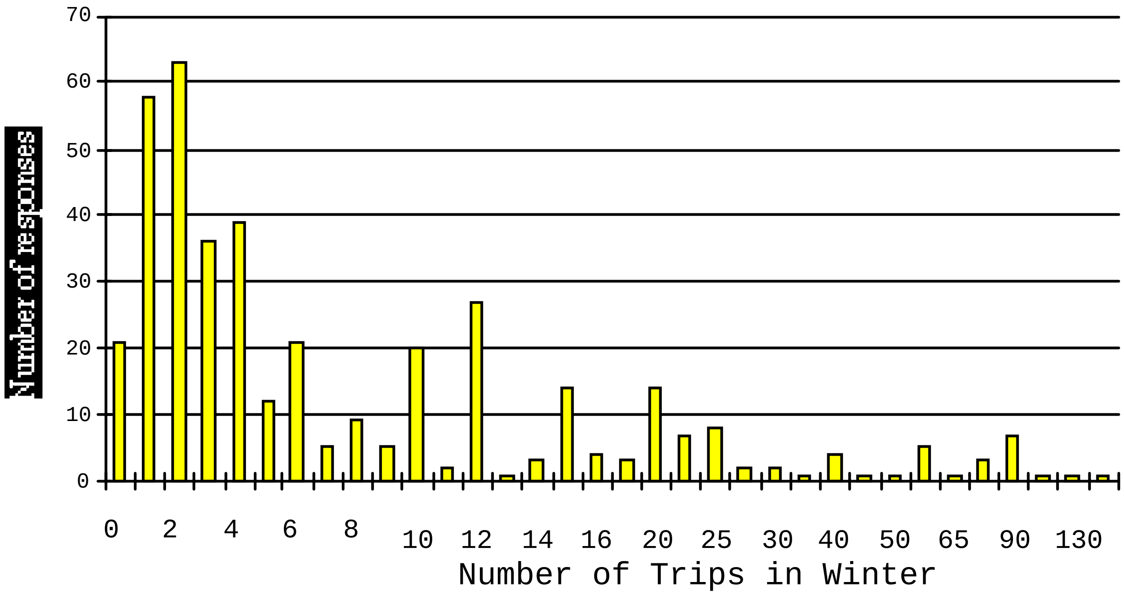

Figure 5.1: The number of trips made in winter (Dec. through Feb.).

A small number of respondents (14%) admitted they drive at or above the speed limit in wet or icy conditions, and 85 percent agree that trip safety is important. Seventy-seven percent of the respondents disagreed that 65 mph is a safe speed limit for wintry conditions. These results are not contradictory. If the majority of drivers know that it is unsafe to drive 65 mph on the pass in winter and agree that safety is important, why is the speed limit 65 mph? Until the *TravelAid* Project, law enforcement agencies had no economical means to change the speed limit during the winter. With the variable speed-limit signs, the Washington State Patrol will be able to enforce a speed limit that is appropriate for prevailing conditions. The final report on the Evaluation of the *TravelAid* Project will discuss the impact of the variable speed limits on the accident rate.

Respondents indicated that current weather conditions were very important (66%). Roadway conditions were considered very important to 74 percent of respondents. Forty-four percent of respondents consider weather forecasts very important. Motorists are most interested in roadway conditions because these conditions have the largest impact on trip time and safety. Current weather conditions are considered important because their influence on roadway conditions. Weather forecasts are of least interest because they have the least impact on current conditions, but may be useful to predict the roadway conditions that the motorist may encounter on the next trip or return trip.

Fifty-seven percent of the respondents indicated that the presence of an incident was very important information. The number of lanes blocked was very important to fewer respondents (50%). The type of incident and the level of congestion were very important to 35 percent of respondents. This finding suggests that motorists are more interested in the presence of a problem than the specific details or nature of the problem. If this is true, then information providers must concentrate on distributing information on the existence of a problem and do not need to worry about the details of the problem. When the amount of information is restricted, such as on a variable message sign or in-vehicle display device, the details of a problem can be omitted; the presence of the problem is the essential information.

Highway advisory radio was the preferred source of road and weather information, chosen by 44 percent of the respondents, followed by commercial radio stations with 23 percent. Table 5.2 shows the number of responses for each information source.

Between half and three quarters of the respondents consider accident, lane blockage information, current weather, or road information to be very important. These types of information all directly influence trip time and safety. Highway advisory radio was the most common source of road and weather information. This means that the most desired information is available in very limited locales. The use of an in-vehicle display device will significantly increase the availability of road and weather information — the driver will receive information as it becomes available in the I-90 corridor between North Bend and Cle Elum, not just at the highway advisory radio transmission sites.

Many respondents (86%) agreed or strongly agreed that the 65 mph speed limit is safe for dry road conditions. Most respondents (77%) disagreed or strongly disagreed that the 65 mph speed limit is safe for wintry conditions. Two-thirds of the respondents (68%) agreed or strongly agreed that other sections of Interstate 90 are less dangerous in rain or snow.

Many respondents (92%) indicated that they would use an in-vehicle information device if one was provided (at no cost to the user). However, 60 percent of those respondents indicated that they would obey the device only if conditions warranted if told to put on chains. Thirty-seven percent would obey immediately. Fifty-six percent would obey immediately if told to slow down — 42 percent would slow down only if conditions warranted. Seventy-three percent of the respondents are interested in using an in-vehicle display device, but respondents were split on their perceived obedience of the device. Most respondents indicated that they would reduce speed when commanded by the device. However, most respondents would not put on chains unless conditions warranted chains. Figure 5.2 shows the relationship between the number of respondents willing to use a display device and their perceived obedience of the device.

Table 5.2: The number of responses for each source of driver information.

Source	Number of responses	Percentage
CB Radio	7	2
Cellular Phone	6	2
Commercial Radio Station	87	23
Highway Advisory Radio	165	44
Commercial TV Station	30	8
Variable Message Signs	25	7
Observation of Traffic Conditions	12	3
Talking to Other Drivers	2	0.5
Other Sources	44	12

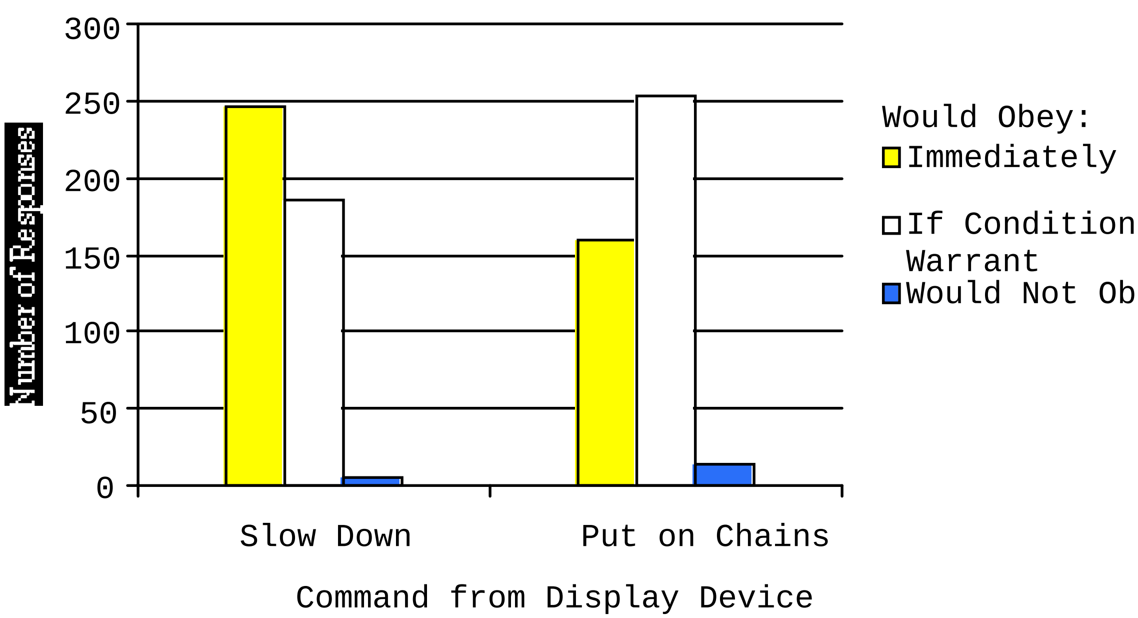

Figure 5.2: The perceived obedience of an in-vehicle display device.

Speed reduction is easily accomplished from the driver's compartment — little effort is required. However, putting on chains is disruptive — someone must spend the time and energy to install the chains. These findings suggest that the interest in the device must stem from the information that it provides (or we live in a gadget-happy society.) Since space in which to safely chain-up is limited and motorists are reluctant to chain-up until absolutely necessary, the greatest benefit of the display device (from the driver's point of view) may be the timely road and weather information, while highway officials may see the speed control aspect to be most beneficial. The final report on the Evaluation of the *TravelAid* Project will discuss the results of the simulation experiments using the in-vehicle display devices.

Nearly all of the respondents (91%) wear their seatbelts all of the time. Seatbelts are never worn by 4 (0.90%) of the respondents. These results are significantly higher than the state and national average seatbelt usage rates. Nationally, the average seatbelt use rate in passenger vehicles is 58 percent, compared to 83 percent in Washington State. The higher than average conformance to the seatbelt regulation may indicate a willingness to also obey the variable speed-limit signs, if they are seen as necessary safety measures. However, the survey results may not accurately reflect seatbelt usage in Washington. Respondents may have answered optimistically or been influenced by the desire to "give the right answer" and reported higher than actual seatbelt usage.

Summary statistics for the surveyed data is provided in Table 5.3 for those variables that were used in the forthcoming data analyses. As we can see from the table, 64.2% were male and 73.1% were married.

The average driving speed was highest for driving on dry roads, and lowest for icy roads. This is also anticipated since most drivers tend to drive slower in more hazardous road conditions. Further, no one in this surveyed sample reported that they drove over 75 mph on icy roads.

In terms of utilization of an in-vehicle device, 91.6% (n=404), said they would use the system, and 8.4% (n=37) said they would not. Therefore, a large proportion of the drivers sampled saw a need for such an in-vehicle system while driving over the pass. In addition, 42.8% said they would "slow down" only if conditions warranted it, and 57.2% said they would "slow down" immediately. When we compare this with the ratio of those who would obey only if conditions warranted for "putting on chains", to those who would obey immediately (61.6/38.4), we find a greater proportion unwilling to obey immediately. This suggests that if the system requires the driver to conduct an activity outside their vehicle, drivers will question the validity of performing the extra task.

Table 5.3: Summary statistics of survey data.

Gender (sample size and percentage)	
Males	280 (64.2%)
Females	156 (35.8%)
Age of drivers	
Marital Status (sample size and percentage)	
Married	269 (73.1%)
Single	99 (26.9%)
Number of people in vehicle (average)	2.21
Amount of time driving over pass during:(average)	
Winter	11.2 times
Spring	8.6 times
Summer	8.4 times
Autumn	7.9 times
Average speed on: (average)	
Dry roads	65.0 mph
Wet roads	58.8 mph
Icy roads	43.3 mph
Primary trip purpose (number of respondents/percentage)	
Recreation	163 (38.9 %)
Business	86 (20.5 %)
Family	118 (28.2 %)
Errands	14 (3.3 %)
Other	38 (9.1 %)
Utilization of in-vehicle system (sample size of yes/no responses)	404/37
Would “slow down”	
Immediately if system told them to do so	247 (57.2%)
Only if conditions warranted	185 (42.8%)
Would “put on chains”:	
Immediately if system told them to do so	159 (38.4%)
Only if conditions warranted	255 (61.6%)

Chapter 6

Speed reductions in adverse conditions

6.1 Introduction

The variable message signs and the variable speed-limit signs provided by the *TravelAid* Project will address two issues on Snoqualmie Pass: motorist speeds in adverse conditions and road and weather information for motorists. In order to evaluate the *TravelAid* Project, data was required regarding the information needs and driving characteristics of the motorist. A survey was conceived to gather data about the motorists: their use of the pass, driving habits and characteristics, opinions and perceptions, preferences and uses of road and weather information. In this Chapter a brief background on information distribution systems will be given. Then the development of the survey questionnaire will be described. Following that the results of the survey will be analyzed and then discussed.

a) Information distribution systems

Currently, road and weather information for Snoqualmie Pass is available from the following sources:

- Commercial radio and television broadcasts
- Highway Advisory Radio broadcasts
- Pay-per-use telephone numbers
- Manually controlled message signs (e.g., “chains required”)

According to Bosely *et al.,* (1993), the most popular (traditional) methods of information distribution include those on Snoqualmie Pass and:

- Rest-area broadcasts
- Commercial local-area advisory broadcasts
- NOAA Weather Radio broadcasts
- American Automobile Association (AAA) telephone services
- Variable Message Signs remotely controlled

- Variable Message Signs remotely controlled by sensors
- Visible indicators, wind socks, etc.

While these methods are widely used, all but the last two have one thing in common: one or more humans in the communication chain. Human interaction tends to delay the information and may allow for different interpretations among system operators. One noteworthy omission from this list is a vehicle-borne information system. Since the driver is the ultimate recipient of the information, in-vehicle systems have the advantage of continuously receiving information and presenting it to the driver.

Bosely *et al.,* (1993) studied the collection and distribution of road and weather information, from the point of view of the agency responsible for snow and ice removal. However, the needs of the driver were not addressed or discussed by Bosely *et al.,* (1993). This research attempts to answer these questions: What information is needed? When and where is the information needed? What are safe speeds for different road and weather conditions? How much do motorists slow down in wet conditions? in icy conditions?

Ground-mounted systems have limited distribution areas and may not be available when the driver needs to make a decision. According to Bosely *et al.,* (1993), the primary requirement of an information system is to provide information in near real-time. Real-time is ambiguous in this case — does the term refer to the information or to the driver's need? For the driver, real-time means that the information is available when needed — during the decision-making process. Conversely, real-time can mean that the information reaches the user while it is still "fresh" and meaningful. If either of these conditions are not met, the driver will find the information not useful, or misleading.

Information distribution systems have many important functional requirements. Leidschendam (1984) provides a list of the most important requirements, which includes flexibility, prioritization, validity, and presentation.

Flexibility is the most important aspect of an information system. The system needs to be compatible with future developments in technology. Any particular system must not preclude the introduction of any other system (Leidschendam, 1984).

Information with the highest priority needs to be distributed first, although this priority is usually determined at the source of the information and may differ from the priority defined by the driver. The information must also be relevant to the driver — if it is not, the driver will waste resources to evaluate the information and discard it.

Information validity is also a concern. Information from different sources must be analyzed to ensure consistency and eliminate contradictory information. Leidschendam (1984) indicates that information that is not reliable and accurate will lose effectiveness and credibility. Drivers quickly dismiss information that is perceived to be inaccurate or contradictory. This phenomenon is also alluded to by Bosely *et al.,* (1993).

Leidschendam (1984) also states that it is important to present the information in a format that is understandable and unambiguous. Driver interpretation is the ultimate test of the information distribution system. After a system is in place, it must be evaluated to measure its effectiveness (Leidschendam, 1984).

The *TravelAid* Project will address the issue of driver information through the use of variable message signs and the in-vehicle display devices. The signs and display devices will provide current road and weather information. The second issue addressed by the *TravelAid* Project is speed control and, ultimately, accident reduction.

b) Accidents and speed control

The annual number of injury accidents in the United States remains relatively constant in light of advances in technology in the automotive industry, such as anti-lock brakes and air bags. Kaub and Rawls (1993) contend that the additional safety provided by new technology is off-set by the increasing use of the highway system. Air bags and anti-lock brakes are saving lives, but more accidents occur as more people drive more miles each year.

According to Kaub and Rawls' (1993) interpretation of *Accident Facts—1989*, speed is a contributing factor in more than one-third of the fatal accidents that occur each year. With the exception of the introduction of the radar gun, speed enforcement technology and techniques have changed little since the 1930's and 1940's (Kaub and Rawls, 1993). Law enforcement authorities rely primarily on ghosting (following the suspected speeder), radar, and direct observation for speed enforcement. However, Kaub and Rawls (1993) suggest an alternative method of speed enforcement.

The speed control system presented by Kaub and Rawls (1993) relies on computer technology. In their plan, magnets will be permanently mounted in the pavement. A sensor on the automobile will detect the magnets and measure the time required to drive from one magnet to the next. Given a constant distance between magnets and the time required to travel between them, an in-vehicle computer system can calculate the speed of the automobile. If the vehicle exceeds the posted speed limit, the computer would alert the driver to the situation. Kaub and

Rawls (1993) suggest that repeated warnings from the computer could result in the issuance of speeding tickets to the registered owner when the vehicle is sold.

While “automatic” speed enforcement and “blind” speeding tickets (blind because you never see the law enforcement officer) may sound appealing to law enforcement officials, there are several implementation problems.

First, the Constitution guarantees a timely redress of grievances, and offenders should not be expected to wait any length of time to settle the speeding ticket. Kaub and Rawls (1993) recommend settling the tickets when the vehicle ownership is transferred (could be many years and many tickets from now) or when the vehicle is next tested for emissions (many states do not require emissions tests). A better time to settle any outstanding speeding tickets (or any other infraction) is at the time of vehicle-registration renewal. Secondly, implementation may be inhibited by resistance to law enforcement by something other than a police officer. The third obstacle that may hinder the implementation of automatic speed enforcement is the inability to identify the offender — only the registered owner (not the driver) is identified. The owner can claim that another person was driving the vehicle on the day in question; therefore, that person is responsible for the infraction.

The method described by Kaub and Rawls (1993) has a final hurdle: the requirement that all vehicles be modified to calculate speed based on magnets in the roadway. Drivers may not choose to have their vehicles modified, or they may disable the system.

Another approach to speed enforcement is the “photo cop” — an automated system that measures the speed of vehicles, photographs violators, and mails the registered owner a ticket. This system receives the same criticism as Kaub and Rawls’ magnetic system — blind enforcement and the identification of the guilty driver.

The system installed by WSDOT does not have these obstacles to overcome. WSDOT will change the variable-speed-limit signs to match current weather and road conditions, based on information from the weather stations along the highway. Rather than make modifications to an extensive array of vehicles that use Snoqualmie Pass, the WSDOT will modify the motorist information system. In this way, all motorists will have access to motorist information, not just motorists with specially equipped vehicles.

The Washington State Patrol will enforce the speed displayed by the signs. Enforcement will not be blind — citations will be issued by a patrol officer. Currently, motorists can be cited for traveling “too fast for conditions”, which provides a gray area in the determination of the proper speed for existing conditions. The variable speed-limit signs will indicate the proper speed for existing conditions, eliminating the need for judgment calls by the driver and the law enforcement officer. The offender will be identified as the driver of the vehicle and cited at once. After the signs are in place, no other modifications will be necessary. Using the existing law-enforcement infrastructure and variable speed-limit signs, the *TravelAid* Project will address the second issue — speed control in adverse conditions.

Weather stations located along Interstate 90 on Snoqualmie Pass will provide information to a system operator, who will use the information to determine the appropriate speed and message to be displayed on the signs and display device.

6.2 Statistical analysis

This section describes the development and results of the statistical models used to analyze the survey data concerning speeds driven in different conditions. A model was created to compare each of two adverse conditions to dry roadway conditions.

a) Model estimation

The questionnaire asked respondents to indicate the speed driven on Snoqualmie Pass in different weather conditions. Respondents chose speed categories (i.e. 55-64 mph, 65-74 mph, etc.) for dry, wet and icy roadway conditions (see survey question three in Appendix A). The models in this Chapter will predict changes in category selection. For example, if a respondent chose 65-74 mph in dry conditions and then 45-54 mph in icy conditions, the model will show a 20-mph reduction (which is an average) because the average difference between two adjacent categories is 10 mph. Throughout this Chapter, a 10-mph speed reduction is used to indicate a speed reduction of one category. In reality, the actual speed reduction could be slightly more or less. For example, if a person that drives 67 mph in dry conditions and 60 mph in wet conditions, the model will indicate a one-category reduction in speed, even though the actual speed reduction is seven mph. Conversely, a person that drives 60 mph in dry conditions and 55 mph in wet conditions will indicate no speed reduction (i.e. both responses will be in the 55-64 mph category), when the driver actually reduces speed by five mph. To be truly correct, the reader must keep in mind that a 10-mph reduction is really a one-category reduction, a 20-mph reduction is really a two-category reduction and so forth.

Responses to the questionnaire were entered into a text file and analyzed using Statistical Software Tools (SST), version 1.1, developed at the University of California at Berkeley. Two Multinomial Logit models were estimated. The first model determined the likelihood of speed reduction in wet conditions. In wet conditions, responses to the survey indicated that drivers chose one of three alternatives (compared to dry conditions): no speed reduction, an average 10 mph speed reduction (one category), or an average 20 mph speed reduction (two categories). A sketch of the speed reduction alternatives for wet conditions is shown in Figure 6.1.

None	10 MPH	20 MPH

Speed Reduction in Wet Conditions

Figure 6.1: Speed reduction alternatives for wet conditions.

The second model determined the likelihood of speed reduction in icy conditions. In icy conditions, responses to the survey indicated that drivers chose one of five alternatives (compared to dry conditions): no speed reduction, 10 mph speed reduction, 20 mph speed reduction, 30 mph speed reduction, or 40 mph speed reduction. A sketch of the speed reduction alternatives for icy conditions is shown in Figure 6.2.

None	10 MPH	20 MPH	30 MPH	40 MPH

Speed Reduction in Icy Conditions

Figure 6.2: Speed reduction alternatives for icy conditions.

Estimation of the multinomial logit specification was carried out using standard maximum-likelihood methods. The results of the two models are discussed below.

b) Model of speed reduction for wet conditions

Table 6.1 shows that the signs of the model coefficients are plausible and that the model has good overall convergence. The log-likelihood for the model of wet conditions converges from -459.2 to -316.9, with a ρ^2 of 0.302. The number of respondents that chose each alternative is shown in Figure 6.3. Interpretations of the model findings are provided below.

Table 6.1: Multinomial logit model of speed reduction for wet conditions.

Variable	Estimated coefficient	t-statistic
Constant 1, (specific to zero speed reduction)	1.96	5.74
Constant 2, (specific to a 10 mph speed reduction)	1.55	3.14
Winter driving experience, (1 if less than 21 trips were made in Dec. - Feb., 0 if more than 21 trips were made. Specific to a 10 mph speed reduction)	0.68	2.49
Number of accidents driver has had on Snoqualmie Pass, (specific to zero speed reduction)	-0.66	-1.42
Seatbelts, (1 if seatbelts are always worn, 0 otherwise. Specific to 10 mph speed reduction)	0.69	1.86
Gender of the driver, (1 if male, 0 if female. Specific to zero speed reduction)	0.51	2.30
Purpose of the trip, (1 if the purpose is visit family, 0 otherwise. Specific to a 10 mph speed reduction)	0.58	2.39
Immaturity of the driver, (1 if the driver's age is less than 33 years. Specific to zero speed reduction)	0.56	2.03
Household income, (1 if annual income is $40 - 75,000. Specific to zero speed reduction)	0.54	2.53
Number of observations	418	
Log-likelihood at zero	-459.2	
Log-likelihood at convergence	-316.9	
ρ^2	0.30	

Alternatives: No speed reduction, 10 mph reduction, 20 mph reduction

Figure 6.3: Number of responses for each alternative in model of wet conditions.

Variable: Winter driving inexperience

Finding: Increases the likelihood of 10 mph speed reduction

This variable indicates that drivers are more likely to reduce their speed by 10 miles per hour if they make fewer than 21 trips across the pass in the months of December, January and February. Conversely, drivers that make more than 21 trips in the months of December, January and February are likely to reduce their speed by 20 miles per hour or maintain the same speed. Frequent users will be very familiar with the roadway on the pass and therefore, more comfortable driving at higher speeds. It is possible that drivers with more winter driving experience become over-confident and do not slow down for wet conditions. On the other hand, some experienced drivers may have had close calls in the past and have become aware of their capabilities and understand what can happen when speed is combined with wet conditions.

Variable: Number of accidents driver has had on Snoqualmie Pass

Finding: Decreases the likelihood of zero speed reduction

This variable indicates that drivers are more likely to reduce their speed while driving on the pass in wet conditions if they have had an accident on the pass. It is possible that these drivers have learned from previous experiences and are more cautious. The respondents indicated that most of the accidents resulted from the loss of control of the vehicle in adverse weather conditions.

Variable: Seatbelt usage

Finding: Increases the likelihood of 10 mph speed reduction

This variable shows that drivers who always wear seatbelts are more likely to reduce their speed by 10 mph when driving in wet conditions. Conversely, drivers who do not always wear a seatbelt are likely to maintain speed or reduce their speed by 20 miles per hour. It is possible that drivers that do not always wear seatbelts are more naturally prone to take risks and are willing to drive faster in adverse conditions. The questionnaire did not investigate the age of vehicles owned by the respondents. It is also possible that drivers do not always wear a seatbelt because they drive vehicles that are not equipped with seatbelts. In this case, unbelted drivers may reduce their speed by 20 miles per hour to compensate for the lack of a seatbelt. Drivers that always wear seatbelts are willing to make the extra effort to reduce risks and therefore, reduce speed when driving in adverse conditions. Perhaps belted drivers feel protected by the seatbelt and feel a speed reduction of more than 10 miles per hour is not warranted.

Variable: Gender of the driver (male)

Finding: Increases the likelihood of zero speed reduction

This variable indicates that males are less likely to slow down in wet conditions than female drivers. As studies in the insurance industry have shown, female drivers pose a smaller risk to the insurance company than do males. Generally, males are willing to take more chances (such as driving fast on wet roadways) than their female counterparts.

Variable: Purpose of the trip

Finding: Family visits increase the likelihood 10 mph of speed reduction

This variable shows the tendency of the driver to slow down by 10 mph in wet conditions while traveling to visit family. Family visits are of an informal nature, without strict deadlines. Recreation on Snoqualmie Pass usually involves a business or government-controlled enterprise (such as a ski area or a campground) with access limited to certain hours of the day. Business travel also carries time constraints. This variable shows that drivers are not willing to take unnecessary risks when traveling to visit other family members.

Variable: Immaturity of the driver

Finding: Increases the likelihood of zero speed reduction

This variable indicates that young drivers (less than 33 years old) are more likely to maintain their speed when driving in wet conditions. With age and experience, drivers tend to take fewer risks and drive more responsibly. Increasing age brings increasing responsibilities — spouse, family, income, house, etc. — and drivers become reluctant to put these responsibilities at risk.

Variable: Household income

Finding: Increases the likelihood zero of speed reduction

Drivers in households with average income ($40,000 to $75,000) are less likely to reduce speed in wet conditions than are drivers from other income levels. Conversely, high- and low-income drivers are more likely to reduce speed in wet conditions. Drivers with average incomes may feel driven to "get ahead", and always push to accomplish more in less time to achieve their goals. Low-income drivers may feel that they would be financially strapped by a driving mishap and be more cautious to protect their resources. Perhaps high-income drivers understand that the time savings do not offset the potential loss due to an accident caused by driving too fast in wet conditions.

c) Model of speed reduction for icy conditions

Table 6.2 shows that the signs of the model coefficients are plausible and that the model has good overall convergence. In the model of icy conditions, the log-likelihood converges from -661.5 to -472.4, with a ρ^2 of 0.277. The number of respondents that chose each alternative is shown in Figure 6.4. Interpretations of the model are provided below.

Variable: Passengers in the vehicle

Finding: Increases the likelihood of 20 mph speed reduction

This variable shows that drivers with passengers in the vehicle with them are more likely to reduce speed by 20 miles per hour in icy conditions. Drivers are considerate of others and unwilling to put them at risk. With a possible critic at hand, drivers are more conscientious and drive more carefully. However, common courtesy and good sense may be tempered by impatience. Drivers with passengers are less likely to reduce speed by 30 miles per hour in icy conditions.

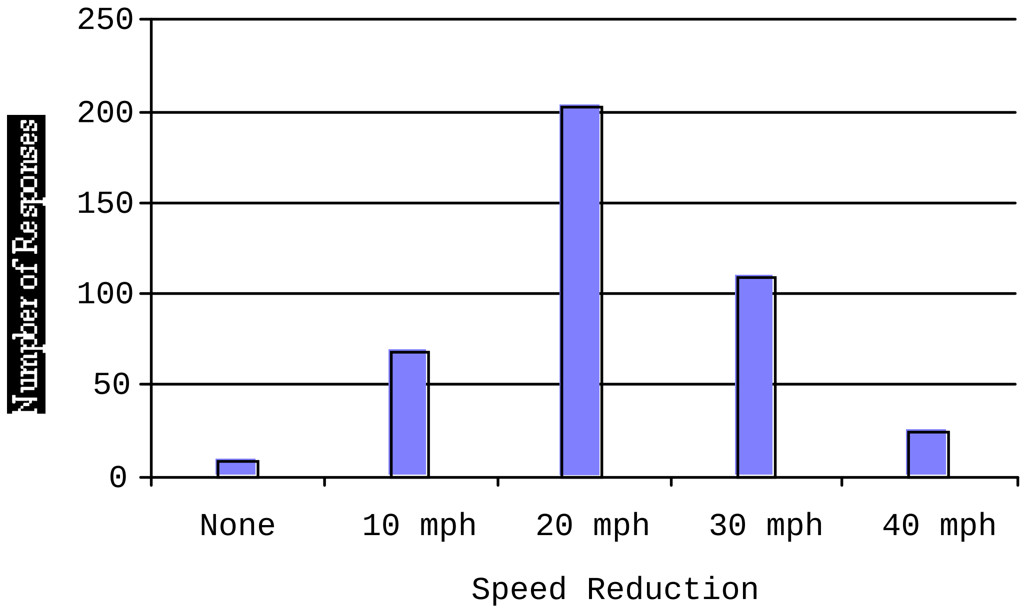

Figure 6.4: Number of responses for each alternative in model of icy conditions.

Table 6.2: Multinomial logit model of speed reduction for icy conditions.

Variable	Estimated coefficient	t-statistic
Constant 1, (specific to zero speed reduction)	-3.99	-2.53
Constant 2, (specific to a 10 mph speed reduction)	-0.22	-0.60
Constant 3, (specific to a 20 mph speed reduction)	0.61	1.72
Constant 4, (specific to a 30 mph speed reduction)	0.63	1.97
Passengers in the vehicle, (1 if there are passengers, 0 if not. Specific to a 20 mph speed reduction)	0.85	3.53
Winter driving experience, (1 if less than 10 trips are made in Dec. - Feb., 0 if more than 10 trips are made. Specific to a 20-30 mph speed reduction)	0.72	2.77
Purpose of the trip, (1 if the purpose is visit family, 0 otherwise. Specific to a 10 mph speed reduction)	0.84	2.68
Seatbelt usage, (1 if seatbelts are always worn, 0 otherwise. Specific to zero speed reduction)	-2.12	-2.12
Gender of the driver, (1 if male, 0 if female. Specific to zero speed reduction)	3.18	2.59
Gender of the driver, (1 if male, 0 if female. Specific to 10-30 mph speed reduction)	1.16	2.65
Maturity of the driver, (1 if the driver's age is greater than 60 years. Specific to a 10 mph speed reduction)	0.84	2.57
Household income, (1 if annual income is $40 - 75,000. Specific to zero speed reduction)	2.08	2.35
Household income, (1 if annual income is $40 - 75,000. Specific to 10 mph speed reduction)	0.85	3.98
Family size, (1 if the driver lives alone, 0 otherwise. Specific to zero speed reduction)	3.93	3.96
Number of people working outside the home, (1 if more than 2 people work, 0 otherwise. Specific to a 20-30 mph speed reduction)	-0.84	-2.25
Single-car family, (1 if the family owns 1 car, 0 otherwise. Specific to a 10 mph speed reduction)	-1.00	-1.98
Number of observations	411	
Log-likelihood at zero	-661.5	
Log-likelihood at convergence	-472.4	
ρ^2	0.28	

Alternatives: zero speed reduction, 10 mph, 20 mph, 30 mph, 40 mph reduction

Variable: Winter driving inexperience

Finding: Increases the likelihood of 20 to 30 mph speed reduction

This variable shows that drivers who make fewer than ten trips across the pass in December, January and February are more likely to slow down by 20 or 30 mph in icy conditions. Drivers with little winter driving experience are more cautious and slow down in icy conditions. Drivers become more comfortable and bold with experience and more aware of their capabilities. These experienced drivers are less likely to slow down in icy conditions.

Variable: Purpose of the trip

Finding: Increases the likelihood of 10 mph speed reduction

This variable shows the tendency of the driver to slow down by 10 mph in icy conditions while traveling to visit family. As in the model of wet conditions, family visits are of an informal nature, without strict deadlines. Recreation on Snoqualmie Pass usually involves a business or government-controlled enterprise (such as a ski area or a campground) with access limited to certain hours of the day. Business travel also carries time constraints. This variable shows that drivers are not willing to take unnecessary risks when traveling to visit other family members. However, impatience may overcome prudence. Drivers on family visits are not willing to reduce speed by more than 10 miles per hour.

Variable: Seatbelt usage

Finding: Decreases the likelihood of zero speed reduction

This variable shows that drivers that always wear seatbelts are less likely to maintain their speed when driving in icy conditions. Again, as in the model of wet conditions, it is possible that drivers that do not always wear seatbelts are more naturally prone to take risks and are willing to drive faster in adverse conditions. The questionnaire did not investigate the age of vehicles owned by the respondents. It is possible that drivers do not always wear a seatbelt because they drive vehicles that are not equipped with seatbelts. In this case, unbelted drivers may reduce their speed to compensate for the lack of a seatbelt. Drivers that always wear seatbelts are willing to make the extra effort to reduce risks and therefore, reduce speed when driving in adverse conditions.

Variable: Gender of the driver (male)

Finding: Increases the likelihood of zero speed reduction

This variable indicates that males are more likely to maintain speed in icy conditions than female drivers. Again, as in the model of wet conditions, female drivers pose a smaller risk to the insurance company than do males. Generally, males are willing to take more chances than their female counterparts.

Variable: Gender of the driver (male)

Finding: Increases the likelihood of 10, 20, or 30 mph speed reduction

This variable indicates that males are more likely to reduce speed by 10, 20, or 30 mph in icy conditions than female drivers. Conversely, this variable and the previous variable show that female drivers are more likely than male drivers to reduce speed by 40 miles per hour and less likely to maintain speed in icy conditions. As noted above, females are generally less willing to take risks than their male counterparts.

Variable: Maturity of the driver

Finding: Increases the likelihood of 10 mph speed reduction

This variable indicates that mature drivers (older than 60 years) are more likely to reduce speed by 10 mph when driving in icy conditions. With age and experience, drivers tend to take fewer risks and drive more responsibly. Increasing age brings increasing responsibilities — spouse, family, income, house, etc. — and drivers become reluctant to put these responsibilities at risk.

Variable: Household income

Finding: Increases the likelihood of zero or 10 mph speed reduction

Drivers in households with average income ($40,000 to $75,000) are more likely to maintain speed or reduce speed by 10 mph in icy conditions than drivers from other income levels. This variable indicates that drivers from very high or low income brackets are more likely to reduce speed by more than 10 miles per hour than are drivers in the average income bracket. Drivers with high income have learned to use their resources wisely and do not take unnecessary risks. Drivers from the lower income brackets have also learned to use resources wisely and cannot afford unnecessary risks. Drivers in the average income bracket are able to budget insurance premiums and are less fearful of submitting a claim to the insurance company.

Variable: Family size

Finding: Increases the likelihood of zero speed reduction

This variable shows that drivers that live alone are more likely to maintain their speed in icy conditions. Drivers that live alone have fewer responsibilities and therefore may be willing to take more risks, such as driving fast on ice. Drivers who live alone do not have someone "checking up" on them — no one to question them if they arrive earlier than expected.

Variable: Number of people working outside the home

Finding: Decreases the likelihood of 20-30 mph speed reduction

This variable shows that if more than 2 family members work outside the home, drivers are less likely to reduce their speed by 20 to 30 mph in icy conditions. Perhaps with more than two family members working outside the home, there is no one at home to run errands and chauffeur children to extra-curricular activities, and drivers must maintain their speed in icy conditions to maintain a schedule. If more than two people work outside the home, the odds are that at least one is a teenager and parents are setting a good example by reducing speed by 40 mph when driving on ice. Drivers in families with more than two members working feel responsible for helping support of the family and take responsibility for their actions.

Variable: Single-car family

Finding: Decreases the likelihood of 10 mph speed reduction

This variable shows that drivers in households that own one car are less likely to reduce speed by 10 mph in icy conditions. If a household has two workers but only one car, the drivers may feel a need to maintain speed even in icy conditions so that they can maintain a schedule and not cause delay to the other worker. If the household has only one worker, the driver may reduce speed by more than 10 mph in icy conditions because the family cannot afford to lose their only means of transportation.

6.3 Model specification issues

The multinomial logit model used in this Chapter can potentially be afflicted with a serious specification error because the derivation of this model requires us to assume that the unobserved terms are independent from one alternative to another. Intuitively, it is possible that alternatives could share unobserved terms and have a correlation that violates the assumption made during the model estimation. For example, the 30 mph and 40 mph speed reductions may share unobservable terms related to cautious driving. In the presence of shared unobservable terms, the logit formulation will erroneously estimate the model coefficients. The problem of shared unobservable terms is referred to as an independence of irrelevant alternatives specification error. To test for the possibility of this error, alternate model structures were created (nested logit models). These alternate models showed that the simple multinomial logit model was appropriate and did not violate the independence of irrelevant alternatives. Therefore, the models used in this research are properly specified with regard to this important concern.

6.4 Conclusions

This research provides an important methodological framework (the use of a multinomial logit specification) for estimating the speed reduction likelihood in wet or icy conditions on Snoqualmie Pass. The findings of this study confirm previous conclusions (Bosely *et al.,* 1993; Kaub and Rawls, 1993) and point to a possible factor contributing to the number of accidents on Snoqualmie Pass during the winter months. By developing a probabilistic model that contains several important variables relating to driver characteristics and attributes, this study has shown that it is possible to avoid the ambiguity and bias stemming from confounding effects in a partially specified model (a model with omitted variable specification error). In addition, this study provides suggestive results by its investigation of speeds driven on Snoqualmie Pass under adverse conditions. The wide diversity of speeds driven in icy conditions may be an indication of the cause and severity of winter-time accidents on Snoqualmie Pass. The installation and use of variable speed-limit signs on the pass will narrow the speed differential between motorists and dampen the potential for larger numbers and reduce the severity of accidents on Snoqualmie Pass.

This research uncovered many important relationships between speeds driven in wet or icy conditions and the winter driving experience, accidents, seatbelt usage, gender, age, income, purpose of the trip, passengers in the vehicle, the size of the household, the number of working family members, and the number of cars in the household. The wide diversity of variables found to influence the speed driven in adverse conditions suggests that many factors play a role in a driver's choice of speeds when traveling on wet or icy roads. The use of variable speed-limit signs to control speeds in adverse conditions will eliminate the effect of many of the variables and overcome the wide discrepancy in speeds in wet or icy conditions.

The results of the survey indicate that motorists drive as fast as the law allows and pay too little attention to prevailing roadway conditions. Using variable speed limits on the pass will require motorists to drive at speeds commiserate with current conditions. The speed limits are legal and the Washington State Patrol will be able to enforce the speed limit portrayed on the signs. It is the recommendation of the author that WSDOT install variable speed-limit signs on all 11 mountain passes.

An interesting result is the number of respondents that would like to have an in-vehicle display device, but will not obey the device. At first glance, this seems like a waste of effort and resources. However, better informed motorists are safer travelers. If the drivers with display devices do not obey them, but do benefit from the information provided by the device, then the device has served a purpose.

People desire current information, but are on their own schedule. In these days of advancing technology, some drivers are willing to pay for timely information in the form of a display device. Future studies may show that people are being overrun by devices and wish for a universal information display system with a common communication format. For example, driver information display systems may merge with other information systems, such as the Seiko receptor watch and personal information managers (PIM).

The accident rates of users of the pass should be studied to verify that the variable speed limits are indeed safer and reducing the number of accidents. Without enforcement by the Washington State Patrol, the variable speed limits may lose their effectiveness.

Chapter 7

Reported driver behavior

7.1 Introduction

In examining driving behavior with the use of an in-vehicle system, several issues needed to be explored. One of the main issues is the true added benefits provided by additional traffic information. To answer the question, "Are variable messages presented on the road just as efficient if not better than in-vehicle information", data needed to be collected and analyzed.

There are essentially, two types of data which are typically used to model behavioral information: stated preference, and revealed preference (Koutsopoulos *et al.,* 1995). Stated preference data is used to identify how drivers would behave in hypothetical situations. Surveys provide one means of collecting stated preference data. However, since most surveys are answered while not on the road, data bias can exist. Drivers' responses may not reflect what they actually will do under the stated condition, but rather, what they hope they would do. Revealed preference data provides information on what drivers would actually do in a real world situation. Unfortunately, hazards may be imposed on the drivers for the data which is required. Therefore, an alternative collection technique, is to use an immersed driving simulator in an attempt to portray these real world situations. Thus, a comparison between this and revealed preference data can be obtain. The more realistic a hypothetical scene is portrayed to a participant, the more validity can be added to the responses.

In order to validate and compare the information from the in-laboratory studies to what drivers perceive in the real world, an analysis of previous stated preference data has been completed. This data is used to establish the drivers desires and use of an in-vehicle system on the Snoqualmie Pass. The findings of this survey as it pertains to preferential system usage is presented in this section.

7.2 Binary logit models

Logit models are appropriate choices for qualitative responses whose outcomes are inherently categorical. The logit model, a special form of the general loglinear model is based on the binomial distribution and provides an analysis of the odds of a response variable.

Given the discrete groups, mathematical models can be generated to determine the probability of a driver falling into one of these discrete groups. The model for the multinomial logit is of the form:

$$P_n(i) = \frac{\exp[\beta_i \mathbf{X}_n]}{\sum_I \exp[\beta_I \mathbf{X}_n]} \qquad (7.1)$$

where $P_n(i)$ denotes the probability of a driver n to fall into a specific group i, vector $\mathbf{X}_n$ is a vector of measurable characteristics of the driver (e.g., driver age, driver income, utilization of traffic information, marital status, trip planning techniques, and so on), and β_i is a vector of estimable coefficients. The derivation of this model is described in detail in Greene (1993).

The advantage of the logit analysis is that the model assumptions are not as stringent as those for regression or discriminant analysis. In addition, various tests are available which are not possible in standard cross tabulation approaches (Demaris, 1992). For example, the effects of a given predictor variable on the dependent variable, which has been adjusted for other effects in the model, is summarized by parameters (estimated coefficients) that translate into odds ratios.

In addition, a goodness of fit measure for these models can be calculated from:

$$1 - \frac{L(c) - k/2}{L(0)} \qquad (7.2)$$

where L(c) is the log-likelihood at convergence, L(0) is the initial log-likelihood, and *k* is the number of variables in the model.

In the analysis of three questions from the Morse (1995) survey, binary logit models were estimated because of the dichotomous responses for utilization of an in-vehicle system (yes or no), and for how they use the system in terms of “putting on chains”, and “slowing down” (1: obey immediately, or 2: obey only if conditions warranted). Essentially, the models estimated included predictions on:

(1) whether or not they would use an in-vehicle system on Snoqualmie Pass,

(2) whether they would obey the system immediately if it told them to slow down, or wait until they feel it is necessary.

(3) whether they would obey the system immediately if it told them to put on chains, or wait until they feel is necessary, and

A discussion of each model is presented in the following sections.

7.3 Utilization of in-vehicle device model

The first binomial logit model (shown in Table 7.1) estimated whether or not drivers would or would not use an in-vehicle system. Essentially, of the 441 people that responded to the question "Would they use an in-vehicle system", 91.6% (n=404), said they would use the system, and 8.4% (n=37) said they would not. This model has a corrected $\rho^2 = 0.6826$.

From this model, several effects in relations to driving characteristics, traffic information usage and socioeconomic characteristics can be observed, and are discussed in the next sections.

Table 7.1: Binomial logit model of whether or not drivers would use an in-vehicle system.

Variable	Estimated coefficient	t-statistic
Constant	-1.88	-1.99
Winter driving indicator (1 if drive more than 6 times in the winter months, 0 otherwise)	0.87	1.80
Speed on wet roads indicator (1 if drive 65 mph or more, 0 otherwise)	2.41	2.72
Trip safety indicator (1 if increasing trip safely was "important to very important", 0 otherwise.)	1.35	2.78
Snow/ice accumulation (1 if information was "important to very important", 0 otherwise)	1.40	2.06
Presence of a hazard/accident (1 if information was "moderate to very important", 0 otherwise)	2.19	3.30
Observe traffic conditions (1 if the preferred medium traffic information receival, 0 otherwise.)	-2.19	-2.82
Pass is more dangerous than other section in good weather (1 if "strongly agree", 0 otherwise)	-1.93	-2.05
Trucks are more dangerous on Pass (1 if "agree to strongly agree", 0 otherwise)	1.41	2.82
65 mph is safe driving on dry roads (1 if "strongly disagree", 0 otherwise.)	-1.36	-1.18
65 mph is safe driving on rainy/wet roads (1 if "strongly disagree", 0 otherwise.)	1.08	2.14
65 mph is safe driving on winter roads (1 if "strongly disagree", 0 otherwise.)	-1.51	-2.70
Age indicator (1 if between 41 to 50 years, 0 otherwise)	-0.88	-1.74

(Continued)

Table 7.1: Binomial logit model of whether or not drivers would use an in-vehicle system. (Continued).

Variable	Estimated coefficient	t-statistic
Age indicator (1 if 65 years and older, 0 otherwise)	-1.11	-1.93
Income indicator (1 if make over $75,000, 0 otherwise)	1.36	1.96
College Graduate indicator (1 if college graduate, 0 otherwise)	0.66	1.29
Married with children (1 if married with children, 0 otherwise)	1.13	1.63
Children indicator (1 if you have children between 6 and 16, 0 otherwise)	-1.41	-2.35
Car indicator (1 if have more than 2 cars, 0 otherwise)	0.86	1.15
Number of observations		441
Log-likelihood at zero		-305.68
Log-likelihood at convergence		-88.014

Note: Alternatives for dependent variable are (1)Yes, and (2)No. All dependent variables are set to (1) the YES response.

a) Driving characteristics

This model shows that the amount of winter driving and how fast they drive on wet roads significantly affects whether or not they would use an in-vehicle system. More specifically, if a driver uses the Snoqualmie Pass more than 6 times during the winter (or at least twice a month during the winter), then they were more likely to use an in-vehicle system. This shows that drivers who frequently use the mountain pass, understand the importance of a traffic system to provide important road condition information. In addition, if they drive 65 miles per hour (mph) or more on wet roads, the drivers were more likely to use this system. This implies that drivers who like to drive fast, would like to know when they could do so.

If they reported that increasing trip safety was “important to very important” they were more likely to use an in-vehicle system. This makes intuitive sense since drivers who want a safer trip would like the best information possible about the road conditions to ensure their safety.

b) Traffic information

It was anticipated that those drivers who value traffic information were more likely to use an in-vehicle system. Therefore, findings that drivers who placed importance on snow/ice accumulation information and those who placed information on the presence of accidents or hazards were more likely to use this system was not surprising. These drivers are obviously concerned about the impact of road conditions on their commute.

If the driver preferred to observe traffic conditions to receive road and weather information, he or she was less likely to use this system. Again, this is foreseeable since these individuals use a traffic medium which does not require any type of technological advances, so they would perceive no benefit in yet another system.

c) Opinion of Snoqualmie Pass

Drivers who strongly agreed that in good weather, the Snoqualmie Pass is more dangerous than other sections, were less likely to use this system. This suggests that drivers who perceive the Pass to be dangerous, no matter what the road condition is, find no added value in using a system, because the road will always be perceived as dangerous, regardless of what information is available.

If the driver believes that trucks are more dangerous on the Snoqualmie Pass than in other areas, then they were more likely to use this system. Thus, information on oncoming trucks could help drivers who are concerned about a possible collision to know when to move to a lane further from the incident. Interestingly, drivers who agreed or strongly agreed that snow or rain was more dangerous on Snoqualmie Pass than on other sections of Interstate 90 were less likely to use this system. This could indicate that drivers who are uncomfortable with traveling in severe road conditions, feel even less comfortable diverting their attention from the road to use a visual in-vehicle system.

Drivers who strongly disagreed that 65 mph is a safe driving speed on dry roads were less likely to use this system. In contrast, drivers who “disagreed or strongly disagreed” that 65 mph is a safe driving speed on wet roads, were more likely to use this system. Similar to those drivers, previously mentioned, who perceived the Pass to be more dangerous than any other section in good weather, drivers who see 65 mph as an unsafe speed on dry roads may see little benefit in using a system when the road will be dangerous regardless of the weather condition. In addition to these findings, we also see that drivers who agreed or strongly agreed that driving

65 mph is safe on wintry roads, were less likely to use this system. This is a plausible finding since these drivers are going to drive recklessly, no matter what the road conditions.

d) Socioeconomic characteristics

Age, income, education, and type of households had an effect on whether or not the surveyed drivers wanted to use an in-vehicle system. For example, if they were in their forties (41 to 50 years old), then they were less likely to use the system. This suggests that middle age drivers are confident enough in their driving ability that they would prefer not to use a system to dictate what driving maneuver they should make. Drivers 65 years old and older were also less likely to use this system indicating a similar finding. Older drivers may also be accustom to a set driving routine and feel that an in-vehicle system may be a hindrance instead of a help.

Drivers who made over $75,000, and drivers who have a college degree were more likely to use this system. It is speculated that these drivers place greater value on their personal safety and time on the road, and would like to explore every possible means of decreasing unnecessary road time.

Drivers who were married with children were more likely to use an in-vehicle system. However, drivers who had a child between the ages of 6 and 16 were less likely to use this system. This surprising result could be indicating the drivers perceived notion that an older child is a better navigational assistance, and observer of traffic than an in-vehicle system. Lastly, drivers with two cars were more likely to use an in-vehicle system.

7.4 Slowing down model

This model (see Table 7.2) provides insight on the characteristics associated with drivers who are willing to immediately obey an in-vehicle traffic system and compare them with those who are willing to obey only if conditions warrant it. Of the 432 people who responded to this question, 42.8% said they would slow down only if conditions warranted it, and 57.2% said they would slow down immediately. This model has a corrected $\rho^2 = 0.2078$.

In the following section, an explanation of variables used in predicting whether drivers would slow down immediately, or only if conditions warrant it so, is provided.

a) The driving trip

Driving trip characteristics that caused drivers to more likely slow down only if conditions warranted include, (1) being a single occupant driver, (2) being a frequent winter driver over the pass, (3) being a fast driver on dry roads, (4) those finding great importance in saving trip time, and (5) those finding little importance in increasing trip safety. These findings suggest that drivers who are more familiar with driving over the Snoqualmie Pass, and those concerned about how soon they can get to their destination, would like to be absolutely sure that slowing down is indeed necessary. In contrast, drivers who have had an accident on Snoqualmie Pass, were more likely to obey immediately, indicating that these drivers are not as confident in their ability to judge road conditions appropriately.

Table 7.2: Binomial logit model on whether drivers would obey a system immediately or only if conditions warranted if told to slow down.

Variable	Estimated coefficient	t-statistic
Constant	0.35	0.63
Single occupancy driver indicator (1 if a single occupant, 0 otherwise)	0.38	1.31
Winter driving indicator (1 if drive more than 6 times during the winter, 0 otherwise)	0.39	1.60
Driving speed on dry roads indicator (1 if average speed is 65 mph or more, 0 otherwise)	1.02	3.99
Accident indicator (1 if had an accident, 0 otherwise)	-0.72	-1.35
Saving trip time indicator (1 if saving trip time is “important to very important”, 0 otherwise)	0.44	1.75
Trip safety indicator (1 if increasing trip safety is “not important”, 0 otherwise)	1.66	2.21
Snow/ice accumulation (1 if information was “very important” for planning trip, 0 otherwise)	-0.87	-3.01
Presence of a hazard/accident (1 if information was “moderate to very important”, 0 otherwise)	-0.81	-1.62
Type of hazard/accident (1 if information was “very important”, 0 otherwise)	-0.66	-2.39
Lane blockage (1 if information was “very important”, 0 otherwise)	0.85	2.45
Traffic congestion (1 if information was “important to very important”, 0 otherwise)	-0.72	-2.38
Presence of snow/rain is more dangerous on Pass (1 if “agree to strongly agree”, 0 otherwise)	-0.50	-2.00
65 mph is safe on dry roads (1 if “agree”, 0 otherwise)	-0.39	-1.33
65 mph is safe on winter roads (1 if “agree”, 0 otherwise)	1.07	2.71

(Continued)

Table 7.2: Binomial logit model on whether drivers would obey a system immediately or only if conditions warranted if told to slow down. (Continued).

Variable	Estimated coefficient	t-statistic
Male indicator (1 if male, 0 if female)	0.50	1.95
Age indicator (1 if between 26 to 40 years old, 0 otherwise)	0.40	1.41
Income indicator (1 if household income is over $75,000, 0 otherwise)	-0.84	-2.56
Income indicator (1 if household made between $50,000 — $75,000, 0 otherwise.)	0.36	1.25
Education indicator (1 if some high school or high school diploma, 0 otherwise)	-0.60	-2.23
Children indicator (1 if have child, 0 if do not)	0.42	1.59
Car indicator (1 if they have two cars, 0 otherwise.)	-0.50	-2.07
Number of variables		432
Log likelihood at zero		-299.44
Log-likelihood at convergence		-226.73

Note: Dependent variable choices were (1) would obey only if conditions warranted, and (2) would obey immediately. All variables set for equation (7.1).

b) Traffic information

It was anticipated that those who value traffic information would immediately obey a system that provided them with this information. Therefore, it was not surprising to find that those who placed great importance on (1) information relating to snow and ice accumulation, (2) presence of a hazard, (3) type of accident/hazard, and (4) traffic congestion, were more likely to obey immediately. What was surprising was the finding, that those who placed importance on lane blockage information was more likely to slow down only if conditions warranted. This could suggest that drivers who are interested in lane blockage information may be interested to the extent of knowing whether the lane they are traveling on is being blocked. Thus, if the system told them to slow down because a lane is blocked, they may not feel the need to do so until they are sure that it is their affected travel lane.

c) Opinion of Snoqualmie Pass

Appropriately, drivers who “agreed or strongly agreed” that snow is more dangerous on Snoqualmie Pass than other section, were more likely to obey immediately. Also, drivers who “strongly agreed” that dry roads was safe on the Pass were more likely to obey immediately and, drivers who “agreed to strongly agreed” that wintry road is safe were more likely to observe traffic conditions before slowing down.

d) Socioeconomic characteristics

As was found in the previous model, age, income, education and type of household had an effect on whether or not the surveyed drivers were willing to slow down immediately, or only if conditions warranted. In addition, gender was a significant variable. Specifically, male drivers were more likely to slow down only if they believe conditions warranted it.

Regarding other socioeconomic characteristics, it was revealed that drivers between 31 and 40 years old were more likely to slow down only if conditions warrant it. In terms of income, those that made over $75,000 were more likely to obey immediately. while those who made between $50,000 to $75,000 were more likely to slow down only if they deemed conditions warrant it so. This shows that wealthier individuals are more willing to accept information from an in-vehicle system while middle income drivers would like to observe what is occurring. Drivers who had some high school or a high school diploma were more likely to obey immediately and drivers who had children were more likely to obey only if conditions warrant it. If they had two cars in their family, they were more likely to obey immediately.

7.5 Put on chains model

The third model (see Table 7.3) predicted whether or not drivers would put on chains immediately if the system told them to so, or only if they feel it is warranted. Of the 414 people who answered this question, 61.6% said they would do it only if conditions warrants, and 38.4% said they would do it immediately. This model has a corrected $\rho^2 = 0.2002$.

Table 7.3: Binomial logit estimation of whether drivers would put chains on immediately or only if conditions warranted.

Variable	Estimated coefficient	t-statistic
Constant	0.18	0.36
Winter driving indicator (1 if drive more than 6 times during the winter, 0 otherwise)	0.76	2.93
Driving speed on dry roads indicator (1 if average speed is 65 mph or more, 0 otherwise)	1.23	4.57
Driving speed on wet roads indicator (1 if average driving speed is between 55 and 64 mph, 0 otherwise)	0.53	1.62
Accident indicator (1 if had an accident, 0 otherwise)	-0.68	-1.19
Saving trip time indicator (1 if saving trip time was “very important”, 0 otherwise)	0.51	2.10
Trip safety indicator (1 if increasing trip safety is “not important”, 0 otherwise)	1.53	1.79
Snow/ice accumulation (1 if information was very important, 0 otherwise)	-1.03	-3.32
Lane blockage (1 if information was “important to very important”, 0 otherwise)	0.86	2.40
Type of hazard/accident (1 if information was “very important”, 0 otherwise)	-0.61	-2.21
Traffic congestion (1 if information was “very important”, 0 otherwise)	-0.78	-2.38
Pass is more dangerous than other section in good weather (1 if “strongly agree”, 0 otherwise)	1.18	1.59
Presence of snow or rain is more dangerous on Pass (1 if “agree to strongly agree”, 0 otherwise)	-0.65	-2.49
65 mph is safe driving on dry roads (1 if “strongly disagree”, 0 otherwise.)	-0.95	-3.02
65 mph is safe driving on rainy/wet roads (1 if “strongly disagree”, 0 otherwise.)	1.70	2.36
Marital status indicator (1 if single, 0 otherwise)	0.37	1.13
Age indicator (1 if 25 years old and younger, 0 otherwise)	-0.96	-1.86

(Continued)

Table 7.3: Binomial logit estimation of whether drivers would put chains on immediately or only if conditions warranted. (Continued).

Variable	Estimated coefficient	t-statistic
Income indicator (1 if income between $50,000 to $75,000, 0 otherwise)	0.56	2.21
Education indicator (1 if have some high school or high school diploma, 0 otherwise)	-0.49	-1.85
Children indicator (1 if have children, 0 otherwise)	0.57	2.19
Number of observations		414
Log likelihood at zero		-286.96
Log-likelihood at convergence		-220

Note: Dependent variable choices were (1) would obey only if conditions warranted, and (2) would obey immediately. All variables set for equation (7.1).

When we compare this model to the previous model on predicting whether a driver would slow down immediately or only if conditions warranted, we note many similar findings. The same sign convention was found for similar variables pertaining to driving characteristics, opinions of driving on Snoqualmie Pass, use of traffic information, and socioeconomic characteristics. This would be expected since the driver would view the system in a similar fashion and thus react similarly. There are, however, noted differences. Specifically, significant findings were found for the indicator variables of “drivers whose average speed between 45 and 65 mph” (more likely), “presence of snow/rain is more dangerous on Pass”, “Being single”, and if you were 25 years old or younger.

7.6 Summary

In this Chapter, a presentation of the initial analysis on drivers’ adherence to messages was shown. Specifically, data collected from a 1995 survey provided the means for three binary logit estimations. These models looked at stated preference data to predict whether or not a driver over the Snoqualmie Pass would or would not use an in-vehicle system, whether or not they would obey immediately or only if conditions warranted for “slowing down”, and “putting on chains”. The findings showed that traffic information, the driver’s perception of the Snoqualmie pass conditions, and socioeconomic characteristics had significant implications to using an in-vehicle system. These findings will then be compared with data collected after drivers view and use an in-vehicle system (see the Chapter on the analysis of traffic advisory systems on travel behavior).

Part IV

Simulation Studies

The research discussed in this Part focuses primarily on how well traffic messages will help drivers divert potentially hazardous road conditions. In-laboratory studies were conducted to isolate the effects of speed, braking and lane changes by drivers as they go through a graphical representation of the Snoqualmie pass while being provided with information from two different sources,

- (1) an in-vehicle unit located in the driver's car and,
- (2) variable message signs located on the road.

Essentially this research will focus on traffic advisory information rather than navigational guidance.

The techniques used for this research involves a driving simulator in a laboratory setting, to examine the effects of driving behavior while viewing traffic information. The motivation behind this study is driven by the need to understand whether or not an in-vehicle system will help reduce the number of accidents on the road, and to do so without unnecessary risks to the drivers. If drivers can be persuaded to modify their driving maneuver by information provided by a traffic system, then road hazards can potentially be avoided.

The objectives of this study is to show how various statistical methods can be used to model driving behavior given data collected using an in-laboratory driving simulator. The use of a simulator will allow us to control the driving environment and isolate the effects of speed variations, lane changes and, braking.

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The objectives of this study is to show how various statistical methods can be used to model driving behavior given data collected using an in-laboratory driving simulator. The use of a simulator will allow us to control the driving environment and isolate the effects of speed variations, lane changes and, braking.

In this Part we will describe studies using data collected in an experiment using the driving simulator. The first Chapter of this Part describes previous research that is common to both of the studies performed. The second Chapter gives a detailed description of the experiment. It is followed by two Chapters, that describe the individual studies. The former study is an analysis of mean speeds and speed deviation in presence of IVUs, VMSs, and VSLs (Ulfarsson, 1997). The latter study focuses on the effect of these systems on travel behavior (Boyle, 1998).

Chapter 8

Previous research

8.1 Variable message signs

Variable Message Signs (VMS) have been incorporated in many metropolitan cities in the world (Van Eeden *et al.,* 1996; Emmerink *et al.,* 1996) in the hopes that the information provided by these signs will alter drivers' behavior in a positive manner.

Variable Message Signs provide on-road information to traveler's for the route that they are currently using. However, to observe information further down the road or in more severe weather conditions, in-vehicle information is also proposed. There are several in-vehicle systems on the road today to provide drivers with information or advice that is relevant to the activities of driving but which are not an integral part of the driving task. These include Toyota's GPS Voice Navigation System, a touch screen display mounted in the dashboard and being used Japan, and a Portable Navigation System by Toshiba that can be moved from one vehicle to another (and also used in Japan) (Upchurch, 1993). These systems differ from Automated Vehicle Operations, another ITS service, because the driver is still an important part of operating the car. In addition to the systems being used in Japan, there have also been many prototypes tested in the United States and other parts of the world, e.g., TravTek, Pathfinder in the US (Wasielewski, 1988), Ali-Scout in Germany (Tokewitsch, 1991), and AMTICS in Japan (Okamoto, 1989). The major goal of all these systems, is to help you achieve a timely, safe and enjoyable trip. Some systems focus more on navigational guidance while others are geared more toward traffic advisory. The system being used in this study, the Trafficmaster, focuses on helping drivers arrive at their location safely. Since the test area for this research project has only one main route, the ability to navigate to other routes will not be tested. If the mountain pass is closed, drivers must wait until it is reopened again before traveling. However, many other on-road and in-laboratory studies have looked at this function and their findings are discussed in the next section.

8.2 On-road field studies

On-road studies provide information on what happens in an actual driving situation. Problems which may not be encountered in a laboratory setting can materialize and provide insight into necessary system modifications.

Many on-road studies pertaining to in-vehicle systems have focused on navigational route guidance information (e.g., TravTek). The conclusion of many of these road studies reveal that a significant improvement in travel time can be achieved when these systems are used in unfamiliar surroundings versus no system usage (Dingus *et al.,* 1994).

Graham and Mitchell (1997) did a study on how drivers process in-vehicle information while driving through winter conditions.

In familiar surroundings, the biggest benefits came from congested areas where information on traffic volumes, length of delays, and accidents can help drivers determine if an alternate route should be used. For example, Wenger *et al.,* (1990) reported that commuters, who are normally in rush hour traffic, based their first decision to take an alternate route based on information that was provided in their vehicles. This research proposes to examine the benefits of providing traffic congestion information also.

8.3 Simulation studies

Simulation studies allow researchers to examine parameters of interest in difficult and critical driving situations without subjecting drivers to unnecessary risks which may occur in a real world situation. In addition, researchers are able to control parameters and to repeat experiments multiple times. In other words, we can isolate the effects of desired variables by maintaining a consistent driving environment. Factors relating to weather and road conditions can be held constant from one subject to another. Since past studies have shown that road and weather related conditions do affect driving behaviors (Shankar *et al.,* 1995), this study will also look at the effects of varying these conditions in a simulator setting. Simulators are also closer to showing the revealed preference of the participants than surveys, which show the stated preference of the subjects. These two preferences need not be the same, i.e. what a subject does in reality (revealed preference) is not necessarily what the subject states on a survey.

Driving simulator studies have been used to study the driving performances of the elderly (Ward, 1996), those with dementia (Rizzo, 1997), and to examine performance due to the time of day of travel (Lenne *et al.,* 1997). However, the largest literary contributions on driving simulation work has been directed on the impact of innovative technology toward driving behavior. A discussion of some of the relevant work in this field is presented.

Vaughn *et al.,* (1992) conducted experiments used a PC-based simulation program to investigate route choice under the influence of ATIS (Advanced Traveler Information System). Their findings showed that males were more likely to follow advice provided by the system, and interestingly, that drivers were more willing to obey the system for a route change if the route included the freeway.

Adler and Kalsher (1994) investigated the effects of traffic advisory and route guidance information on enroute behavior and travel performance using a simulation program called FASTCARS (Adler *et al.,* 1993). Information on the simulated traffic speeds and route guidance information was provided and driver travel speeds were collected. Their findings showed that providing subjects with guidance information resulted in shorter travel times compared to having drivers go through a trial and error scenario. Thus, their conclusions support the field studies discussed in the previous section. Although, their simulated program, FASTCARS, uses a graphics based interface to simulate audio and visual effects, the user is limited to a birds-eye view of the network.

Levine and Mourant (1995) designed a simulator that allows a user to view the simulator in a 3 dimensional environment with the use of a heads-mounted display (HMD). This allows the user to become immersed in the virtual environment while driving through a graphical representation of the road. Although this simulator is quite impressive, research conducted using this system has been limited to the perception of realism of the simulation and the sense of immersion in the virtual environment (Levine, 1995) and has not focused on driving behavior using the simulator.

Srinivasan and Jovanis (1997) conducted a driving simulator experiment to analyze the effects of mean speeds in three types of roadway scenarios (2-lane roads, 4-lane roads, and parkways), and four types of route guidance systems (i.e. paper map, HUD and electronic map, electronic map, and voice and electronic map). Significant findings for scenario effects and route guidance effects were found. Specifically, their findings showed that highest speeds were associated with electronic maps and slowest speeds were associated with paper maps.

Kaptein *et al.,* (1996) present a large number of considerations on the validity of driving simulators as study tools. They found that simulators can, in principle, give the driver every type of information found in a real driving situation but most simulators are in some way simplified. They found that such simplification could give valid results if the simulator gave the information needed for the particular task tested. In this study, for example, the effect of upgrades and downgrades on speed among other things is sought. Therefore it is important that the simulator slow down as expected when going uphill and that it speed up when going downhill.

Kaptain *et al.,* (1996) also note that driving speed in driving simulators is not absolutely valid but relatively valid. This finding is also supported by Riemersma *et al.,* (1990). This result means that the absolute speed used by drivers in simulators is not necessarily the same as the speed they would select in reality but the relative changes in speed are the same. So if they see a sign giving a new speed limit and they change their speed, the relative speed change would remain the same. This is important to know before giving out any results based on the actual speed measured in the simulator. To combat this, the speedometer was directly in front of the subjects on the screen as can be seen in the scenes from the simulator in Appendix H. The subjects therefore had constant feedback concerning their speed and they could therefore more easily maintain the speed they remember normally using, even if for some reason they perceive their driving speed to be different by viewing the scenery. The subject was also instructed to drive at the speed they normally would in the circumstances found in the simulation.

There has been research into the effect of simulation sounds on the general behavior of subjects and on driving speed in particular. The results were that the presence or absence of speed related sounds such as engine noise or wind noise did not affect the speed as noted by Kaptain *et al.,* (1996).

Kaptain *et al.,* mention more examples were the validity of simulator experiments can become questionable. The resolution of the screen can be too coarse which makes it hard for subjects to see anything at a long distance. This has some significance in the present study as the resolution is indeed limited and the visible distance is short. The effect of this is however minimized because the particular road simulated is very curvy and is generally going up. It therefore seems to the drivers as if the road is going around a bend in the distance or over a hill when it really just disappears. The field of vision can have a big effect if the simulation must go around sharp curves for example. This is not a problem in this study as the field of view is ample for highway conditions. There is no rear view in this study but Kaptain *et al.,* note that to be insignificant if there are no other vehicles in the simulation which the driver must be aware of, before changing lanes for example. In this case, the drivers have the road to themselves except for stationary snow plows at selected locations. The simulator used in this study is also not on a moving base nor are there any centrifugal or acceleration forces experienced by the driver. This will have some effect, but probably small, because the simulation is of a highway which, in reality, offers a smooth ride at the legal speeds.

Koutsopoulos *et al.,* (1995) have examined possible causes for bias in simulation studies. The basic types of bias mentioned by them are:

Prominence hypothesis: This is when the subject obeys every order of an in-vehicle unit or other message devices without considering the quality of the information.

Policy response: This is when the subjects believe they benefit from a particular response.

Preference inertia: Subjects continue to follow their preference no matter what happens.

Justification: Subjects try to justify a previous response to appear consistent to the experimenter.

Context effects: It is hard for subjects to perceive differences between trip purposes.

Incentive effect: This happens if there is a prize for finishing first, for example, or a penalty for errors.

Technology bias: Simulators affect different people differently, depending on various factors such as age and previous simulator experience.

To minimize these biases in the present study, a number of things were done. To minimize the prominence hypothesis and the preference inertia, each subject was told to specifically use or ignore the messages given depending on what they think they would do in reality. The policy response was not a major factor in this study because the subjects realized and were told that this was a theoretical analysis with no direct effect on the subjects. The justification bias can affect the results of the surveys and it can also affect the simulation if the subjects want to appear as being safe drivers to the experimenters. To minimize this effect the subjects were specifically told that the experimenters did not care in the least how safe or unsafe they drove or if they broke speed limits. The present study did not specifically check differences between trip purposes and the subjects were not told anything about the reason for why they were driving the simulated road so the context bias is not relevant. There was no prize or penalty during the simulation so the incentive bias is irrelevant. The technology bias could affect the subjects because it is hard to remove when a breadth of subjects from different socioeconomic groups is gathered. To minimize its effect each subject was given a five minute practice session in the simulator. After the initial practice session the subjects were asked if they felt comfortable driving the simulator. In the case they were not comfortable the subjects were given the opportunity to continue the practice session to better familiarize themselves with the simulator.

Kiefer and Angell (1993) have examined the differences between digital and analog speedometers and they found some differences between the two types. These differences are mainly related to the time it takes the driver to see the speed where the analog speedometer appears to be better, and also when the driver attempts to maintain a constant speed where the analog speedometer also appeared to be better. However, they could not conclude with statistical validity that one type was better than the other. For the purposes of this study it will not make a difference because the purpose of the simulation is not to analyze how well subjects maintain constant speed but rather have them drive as they normally would. The speed will also be averaged over sections of the road to remove the effects of minor speed fluctuations. Also, one of the main advantages of the analog speedometer found by Kiefer and Angell (1993) is that drivers glanced less often at analog speedometers and for a shorter time. As the digital speedometer is on the screen the driver will see the speed at all times and therefore this limitation of the digital speedometer is removed.

8.4 Trafficmaster

The in-vehicle system being evaluated for this study is called Trafficmaster (see Figure 9.2 and 9.5). Trafficmaster is an in-vehicle congestion warning device that has previously been tested and evaluated in the London area by Stevens and Martell (1993). The differences between the Snoqualmie Pass study area and the London study area, is road configuration and usage. The Snoqualmie Pass is a moutainous terrain with no other viable alternate routes. The Trafficmaster in-vehicle unit provides traffic information on speeds, traffic congestion and type of incident. Stevens and Martell (1993) focused their research on the safety implications of the Trafficmaster in relation to all other information sources which may be available. Their findings showed that safety was not significantly impaired with the Trafficmaster. However, no reported mathematical modeling of their data was done.

8.5 Summary

In this section, background information relating to the research, including a description of the in-vehicle unit which will be used in the study (the Trafficmaster) is presented. In addition, related research work is presented and compared with the focus of this research.

In general, there has been a great deal of field and laboratory work done on how effective in-vehicle systems can work for diverting to alternate routes, and providing drivers with navigational information. However, little has been done on modeling the behavior of drivers while provided in-vehicle traffic advisory information in a laboratory setting. This could be due to the complexity of gathering and analyzing this information in a laboratory. Typically, to understand driving behavior, one needs to observe the driver as they are maneuvering around severe weather and road conditions. It is, therefore, the goal of this study to be able to find a way to model these parameters and study their effects.

Chapter 9

Methodology

Preparation for the driving simulator experiment required several design criterias to be established. This section presents information on the subject pool, the type of equipment needed for the experiment, and the procedures undertaken to collect the appropriate data. Other research facilities have set up similar experimental conditions (e.g., Liu and Chang, 1995).

9.1 Subjects

There were 48 subjects needed for the experiment. A total of 51 subjects varying in age and gender were obtained. Particpants must have driven over Snoqualmie Pass to qualify for the driving experiment since questions on one of the survey related to driving over the Pass.

9.2 Equipment

A fixed based driving simulator was used for the experiments since the emphasis of this research was on the visual sensory feedback rather than the tactile sensory feedback. For that reason, all equipment listed focuses on effectively using the visual and auditory information. The following equipment list describes all the major hardware components required for the interface between the driving simulator, computer workstation, and screen projections of the driving scenes.

- A General Electric IMAGER610PJ RGB (Red Green Blue) Graphics Projector (ceiling mounted), is used to project color graphics to a screen projector.

- A 104” x 76” screen projector is used to display a life-size graphical representation of the driving scene.

- A Silicon Graphics Image (SGI) Workstation with 64 MB (SGI Indigo II Extreme Workstation with IRIX 5.3 operating system) and a 19 inch diagonal monitor (color resolution 1280 x 1024 refresh rate: 60 Hz non interlaced display).

- General Electric AVDU490 Control Unit: A data unit that connects the GE Imager to the SGI Workstation. This enables the Imager to receive the images displayed on the SGI Workstation.

- Ford Escort car frame equipped with seats, steering wheel, windshield, dashboard, brake and gas pedals. A computer mouse is attached to the steering wheel and provides feedback to the SGI workstation regarding where the car is located with respect to the road.

- A Motorola 68HC11 microcontroller is used to relay information on whether or not the car is on/off, and identifies when participants are braking and accelerating. The simulator simulates a vehicle with automatic transmission, so the driver uses accelerator and brake pedals along with the steering wheel but there is no gear shifting required.

- TRAFFICMASTER In-vehicle unit: This unit provides various scenes which include a map of the area being driven, variable speed information, and variable messages on road conditions (e.g., fog ahead). It is mounted on the center of the windshield, directly above the dashboard (see Figure 9.2). In general the unit can be used to display messages to the driver while on the road and more extensive pre-trip information. The pre-trip information can be about such things as congestion, the need for chains, weather conditions or speed limits. The on road messages, used in this experiment, give short messages with information about the road ahead with a new speed limit.

- A portable beacon transmitter capable of sending messages to the IVU via a program written for the IBM PC. This transmitter is connected to the IBM Hard Drive via a 9 pin (COM1) connection.

The images projected on the screen encompass a 2.46 m by 1.47 m (97” x 58”) rectangle. The images are not in 3-dimensions (3D), nor is the simulator able to detect motion. Nonetheless, the simulator is quite adequate for portraying real-world situations by providing life-size images of the driving scenes, the use of a real car frame with real car parts, and the drivers ability to drive with a steering wheel while utilizing the brake and gas pedals. The car which is situated in front of a large screen projector, enables the driver to feel immersed in the driving environment with a 60° field of view (see Figure 9.1). The reason for using 60° field of vision is that this is the human binocular field of vision which is the field that can be seen with both eyes at the same time when they are both fixed at a central position (NHTSA, 1987). The distances set for the driver to obtain a 60° field of view is calculated as:

$$Tan\theta = \frac{\frac{1}{2}(\text{width of projector})}{\text{driver's viewing distance from eye to projector}} \tag{9.1}$$

and therefore the distance from a subject's head to the screen is set at 2.13 m. Also, this field of vision is approximate since the vehicle simulator will not be moved from its position during the course of the experiment and the exact seating position of the subjects vary. The exact 60° field of vision would be reached if the subject sat in the middle of the car.

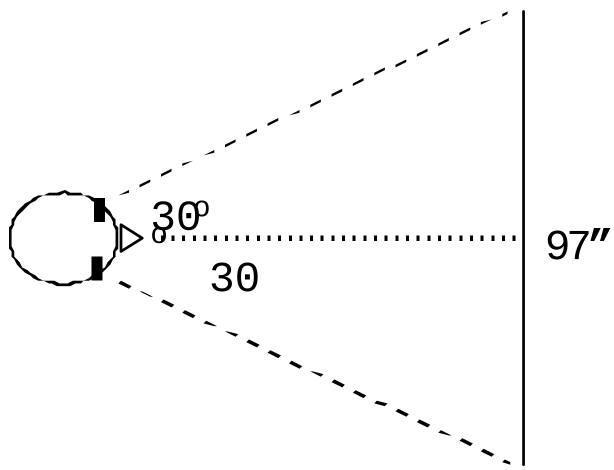

Figure 9.1: Subject's field of view (top view).

The operating components of the car are shown in Figure 9.3, and the lab setup for the simulator experiments is shown in Figure 9.4.

9.3 Software

There were three software programs that were needed to enable the simulator to function properly with the SGI workstation and the Trafficmaster in-vehicle unit.

1. MAXTALK. A communication package supplied with the 68HC11 Microcontroller. It was installed on an IBM Personal Computer (PC) and allows the PC to establish communication at 96 baud from a COM1 port to the Microcontroller. This enables activation of the stepper motor for the car, so that information on ignition, gear, acceleration, and braking can be recorded.

Figure 9.2: View of Trafficmaster mounted in car.

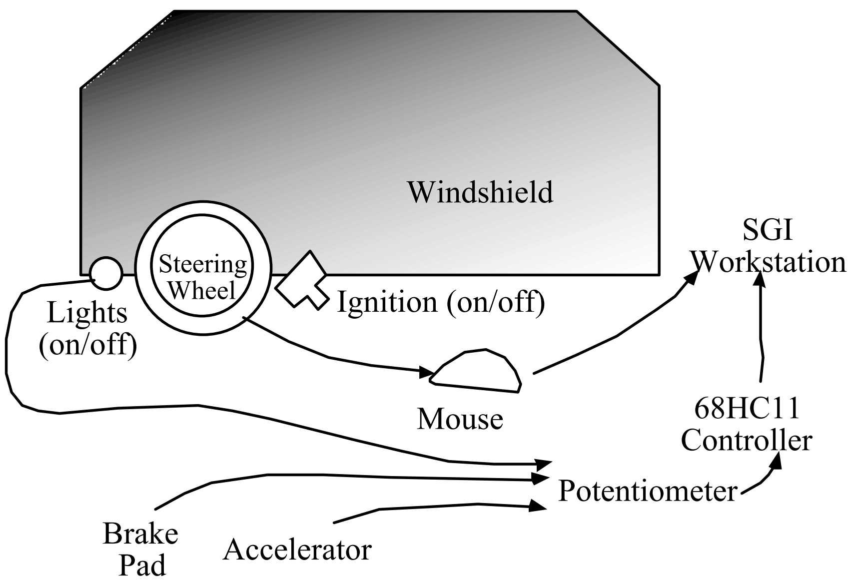

Figure 9.3: Components of the car used for the simulator.

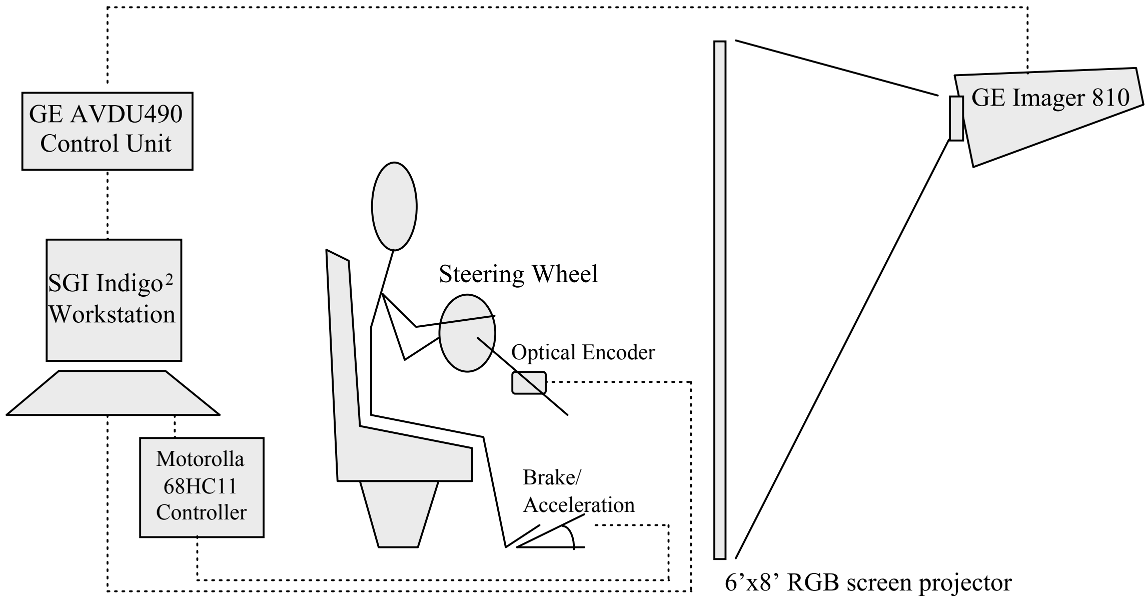

Figure 9.4: Driving simulator setup.

2. A modified version of the SGI DRIVE program written in the C++ programming language. The mean update rate of new images in this program was 20.6 Hz for files with VMS, and 23.2 Hz for files without VMS[1]. This program runs the actual simulation and presents the driver with a geometry contained in a data file. The program has been enhanced to give more realism on up- and downgrades by decreasing or increasing the acceleration respectively.

3. An in-house PC based program, written in the C programming language, relays the messages (on-road, pre-trip and speed information) to the Trafficmaster in-vehicle unit.

9.4 Procedure

At the onset, each subjects was given a list of instructions to read that relate to their particular driving conditions (see Appendix B). After reading the instructions, each subject then drove through two simulation sessions. The first session encompassed a 5 mile loop and was

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1 The update rate is the rate at which new images are presented to the user. This differs from the refresh rate, which affects the projector/screen. Given a 60Hz refresh rate, and an update rate of ~20 Hz, the system will present 3 consecutive images of a scene before the elements in the scene changes (i.e., 20 new images per second are shown to the user). An update rate beyond 10 to 15 Hz produces the illusion of smooth motion in the scene (cite reference).

used to familiarize the subjects with the simulator configurations (i.e. braking, steering, and accelerating), the use of the in-vehicle unit, and if necessary, answer any questions they may have.

The second session was the main part of the experiment and encompassed a 12 mile (or 19.31 kilometer) graphical representation of Snoqualmie Pass. Essentially, each person goes eastbound on Interstate 90 starting around milepost 35 (North Bend, WA) and ending at milepost 47, the top of the Snoqualmie summit.

One of four sign conditions was randomly assigned to each subject. Thus, the effects of signage was tested at four levels:

1. Presence of on-road variable message signs.
2. Presence of in-vehicle message signs.
3. Presence of both on-road and in-vehicle message signs.
4. Absence of messages (control condition).

The driving scenes viewed by each subject are described in the following section.

9.5 Driving scenes

The configurations for grade and horizontal curvatures were derived from WSDOT geometric configurations of Interstate 90 (see Appendix J) and is portrayed for the eastbound section of the interstate. Slight changes had to be made to some of the horizontal curves to fit the requirements of the simulation software. These changes increased the degrees of curvature of some curves.

The simulator creates the vertical curves by using the change in grade between two stretches to calculate the radius of curvature. The simulator uses the simple formula for a circle as opposed to the more realistic parabolic formula actually used in road design (Mannering and Kilareski, 1990). This should not pose a problem as the grade changes are typically slight. The actual length of the vertical curves is taken from the real geometric configuration. The configuration of the highway in the simulation can bee seen in Appendix F gives the computer data file representing the terrain.

The scenes represent a three lane highway with 11 feet shoulders on the right and left of the road. The lanes were designed to be viewed as 12 feet wide. Views of trees and mountains provide the surroundings as well as road signs posting the interstate route (i.e. 90), mile indicator, and speed limit information. In all sign conditions, fog and snowplows are observed at varying locations. There are no other vehicles in the simulation and the speeds observed should therefore be the free-flow speeds chosen by the respective subjects.

There were two levels of weather effects (“fog” and “no fog”) and two levels of snowplow effects (“snowplow” and “no snowplow”). The order of presentation of the road/weather conditions were counterbalanced across a 4x4 Latin Square to reduce order effects (see Appendix E for the ordering of messages and conditions). The four by four square gives rise to 16 different run scenarios. Therefore the number of subjects should be a multiple of 16. The number 48 was chosen as it is large enough to give statistical significance in the light of each subject yielding a large number of observations and it was practical in light of the time available to run the simulation experiments. As three of these runs were suspected to be faulty an additional three subjects were run using the same conditions giving a total of 51 subject. Tables 9.1 and 9.2 give an overview of the scenery conditions and the simulation run types. The order of the runs was randomized to make sure that a specific type of a run was not all done on the same day because it would include spurious effects as people may drive differently on a Saturday than on a Monday.

Table 9.1: The four scenery conditions.

- clear weather conditions
- clear weather conditions and a snow plow blocking 1—2 lanes
- foggy weather conditions
- foggy weather conditions and a snow plow blocking 1—2 lanes

Table 9.2: The four simulation run types.

Control run	No in-vehicle unit	/	No variable message signs
IVU run	In-vehicle unit	/	No variable message signs
VMS run	No in-vehicle unit	/	Variable message signs
IVU/VMS run	In-vehicle unit	/	Variable message signs

According to the National Oceanic and Atmospheric Administration (NOAA), fog is designated when the visibility is less than one km (3,300 feet) (NOAA, 1997). Using this guide, the density of the fog, for the “fog conditions”, in the simulator was designed so that a driver could not see past 805 m (0.5 miles). As shown in Table 9.1 some sections of the simulation contain fog. The fog is designed to limit the length of view to 805 m (half a mile). By definition fog is any mist that limits the length of view to 1 km or less. However the visible road in the simulation is only 229 m (750 ft) because the resolution of the image makes the road hard to see at longer distances. This does not pose a problem because the road is perceived as going up the mountain or around a bend in the distance. Due to this limitation, the fog does not make a real difference in the viewable length of road but it makes a perceived difference because the view to the mountains is blocked. Some participants actually noted that they perceived the fog as being of variable thickness but in reality it quickly achieves its thickness in the beginning and quickly disappears at the end, staying constant throughout the majority of the fog section.

The snowplows are not moving and they occupy two lanes. The driver’s task is to successfully go around them. Appendix H contains a number of figures showing different scenes from the simulator.

The speed, in mph, is shown on the screen in front of the driver with a digital speedometer. The differences between analog and digital speedometers are negligible for the purposes of this study (Kiefer and Angell, 1993). There is no sound emitted from the vehicle and it has been found that speed related noises do not affect the driving speed in driving simulators (Kaptein *et al.,* 1996).

9.6 VMS condition

For some road conditions, variable messages are also observed. The information displayed are similar to those used by the Washington State Department of Transportation on Interstate 90. There were three main messages viewed by the participants at various times for the VMS and IVU condition. The complete list of messages used can be seen in Appendix E.

1. Fog Ahead, Slow Down 45 MPH
2. Curvy Road, Drive Slowly
3. Snow Plow Ahead, 35 MPH

9.7 IVU condition

Participants using the in-vehicle unit were given additional instructions on the use of the Trafficmaster. The system shows them a map of the Snoqualmie Pass in four quadrants (see Figure 9.5). The in-vehicle messages are identical to the ones provided in the VMS condition (see Appendix E). The only difference was in message 2. Since the IVU was not limited by the characters and spacing and had a designated field for the speed limit, this additional information was provided. Therefore, for "Curvy Roads", the recommended speed limit was posted at 88.5 km/h (55 mph). There were also four different order of sign presentation over the 12 mile terrain and the exact orders for the VMS and IVU conditions are presented in Appendix E.

The messages for the IVU were relayed manually by the experimenter. Yellow signs were designed in the simulator scenes to prompt the experimenter to send a message. Once sent, 20 seconds would elapse before the message was actually displayed on the in-vehicle unit. This is consistent with the proposed usage on the Snoqualmie Pass.

Pictures of various scenes observed by the drivers can be viewed in Appendix H.

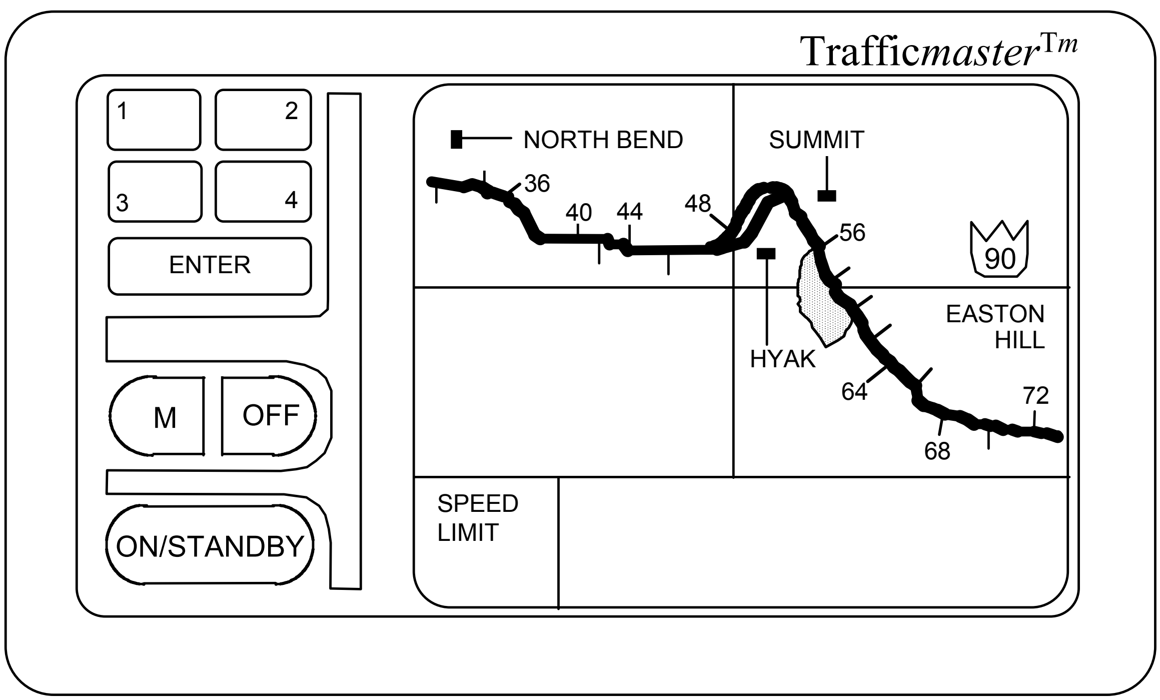

Figure 9.5: The Trafficmaster in-vehicle display.

9.8 Survey

At the end of the experiment, all subjects were asked to evaluate the in-vehicle unit whether they used it in the experiment or not. They were given more detailed information on the unit including the use of the pre-trip information, use of traffic congestion information, and any other necessary components. To allow the users to practice using the system, two messages were sent to them. A survey asking them to evaluate the TrafficMaster in-vehicle unit (see Appendix C) was then completed. A second survey, similar to the one distributed by Morse (1995) (see Appendix A), is also filled out (see Appendix D). The difference between this and Morse's survey is the inclusion of "fog" questions. Since the simulator tested drivers under foggy conditions, their opinion of driving in the fog was also collected. This information will enable a comparison to be made between data collected from this study with the information collected from the on-road study.

9.9 Information collected

Driving performance measures collected from the simulator experiment included lane changes, speeds, braking, position, time and the presence of fog. This information will be recorded onto a log file in ASCII format. A sample of the data is shown in Appendix G. In addition, data will be collected from the surveys completed by the participants of this same study.

9.10 Summary

In this Chapter, the methodology for the driving simulator work has been described. This included the subject pool, the equipment used, the different driving environment for the four sign conditions (i.e. IVU, VMS, Both, and none). The procedure for collecting the data via surveys and through the SGI was also discussed. The analysis performed with this data is described in the next two Chapters.

Chapter 10

Descriptive statistics

The data were collected from 51 subjects and each should give 18 observations (there are only 17 observations from one subject which due to a software error ended the simulation early) of speed and standard deviation data along with the surveys.

There were 15 females and 36 males. They ranged in age from 16 to 70 years (mean = 33.49, SD=14.08). Approximately 60% were single, 30% were married, and 8% were divorced. The other 2% said checked "other". The survey on the use of the Trafficmaster in-vehicle unit collected information on the participants opinion of the system. The socioeconomic characteristics of the drivers are summarized in Table 10.1.

Table 10.1: Socioeconomic characteristics of surveyed drivers.

Variable	Information
Age	33.49 years
Income	\$34,799.80 (SD=\$24,317.10)
Gender	Male 70.6% (n=36) Female 29.4% (n=15)
Marital Status	Married 29.4% (n=15) Single 60.8% (n=31) Divorced 7.8% (n=4) Other 2.0% (n=1)
Number of people typically in vehicle while driving Snoqualmie Pass	2.08 (SD=0.88)
Seat belt usage	All the time 82.3% (n=42) Most of the time 15.7% (n=8) Some of the time 2.0% (n=1)
Average driving speed on dry roads	69.00 mph (SD=9.13)
Average driving speed on wet roads	59.80 mph (SD=9.40)
Average driving speed on icy roads	41.41 mph (SD=10.20)

The overall average speeds driven by participants was 85.63 kilometers per hour. Subjects willing to use the Trafficmaster were willing to pay \$136.78 on average (SD=88.75) for the unit.

In addition, those who were willing to pay for a monthly service said they felt $13.80 on average was good.

Table 10.2: Frequency of responses to the usefulness of Trafficmaster features.

Trafficmaster feature	Extremely Useful	Of Considerable Use	Of Use	Not very useful	Of no use	Did not notice
Beep	21 (42)	15 (30)	10 (20)	1 (2)	3 (6)	0 (0)
On-road messages	20 (40)	21 (42)	7 (14)	2 (4)	0 (0)	0 (0)
Map Display	7 (13.7)	13 (25.5)	14 (27.5)	14 (27.5)	3 (5.9)	0 (0)
Pre-Trip	25 (50)	10 (20)	13 (26)	1 (2)	0 (0)	1 (2)
Speed Limit	8 (15.7)	14 (27.5)	19 (37.3)	8 (15.7)	2 (3.9)	0 (0)

Percentages are identified in parenthesis.

The statistics of the geometric, environmental and driver based variables are to be found in Tables 10.3–10.8. The statistics of the survey questions appropriate for this study, i.e. questions 1-5,7,14–24 on the Snoqualmie Pass survey in Appendix D, can be found in Tables 10.9 and 10.10.

Table 10.3: The number of horizontal and vertical curves in sections.

Horizontal curves	0	1	2	3	4	Total
Observations	31	223	259	301	103	917
Percentage	3.38	24.32	28.24	32.82	11.23	100
Vertical curves	0	1	2	3	4	Total
Observations	3	415	346	153	0	917
Percentage	0.33	45.26	37.73	16.68	0	100

Table 10.4: Distances within curves averaged over sections, and grade information.

Mean distance in a horizontal curve: $d_h = 290$ m, $\sigma = 170$ m
Mean distance in a vertical curve: $d_v = 290$ m, $\sigma = 120$ m

Maximum grades in a section	Observations
less than 2%	204
between 2% and 4%	155
greater than 4%	558
Total	917

Table 10.5: Maximum speed limits and maximum speed limit difference in a section as set by road signs, the IVU and/or the VMSs. The number of observations of each value are given. All speed values are in km/h

Max. speed limit	56.32	72.42	88.51	96.56		Total
Road signs	0	0	0	234		234
IVU	48	99	104	0		251
VMS	42	84	0	90		216
IVU/VMS	42	84	90	0		216
Total	132	267	194	324		917
Max. speed limit diff.	0	16.09	24.14	32.19	40.23	Total
Road signs	234	0	0	0	0	234
IVU	196	30	0	25	0	251
VMS	168	21	6	0	21	216
IVU/VMS	168	27	0	21	0	216
Total	766	78	6	46	21	917

Table 10.6: Number of sections with fog and number of sections with snow plows.

	No fog	Fog		Total
Observations	421	496		917
Percentage	45.91	54.09		100
No. of snow plows	0	1	2	Total
Observations	790	51	76	917
Percentage	86.15	5.56	8.29	100

Table 10.7: The number of particular VMS and IVU messages and the message they are trailing.

VMS message type	Observations
Curvy Road after Curvy Road:	36
Curvy Road after Fog Ahead:	6
Curvy Road after Snow Plow Ahead:	18
Fog Ahead after Fog Ahead:	36
Fog Ahead after Curvy Road:	6
Fog Ahead after Snow Plow Ahead:	18
Snow Plow Ahead after Curvy Road:	24
Snow Plow Ahead after Fog Ahead:	24

IVU message type	Observations
Curvy Road after Curvy Road:	39
Curvy Road after Fog Ahead:	6
Curvy Road after Snow Plow Ahead:	20
Fog Ahead after Fog Ahead:	40
Fog Ahead after Curvy Road:	6
Fog Ahead after Snow Plow Ahead:	19
Snow Plow Ahead after Curvy Road:	25
Snow Plow Ahead after Fog Ahead:	26

Table 10.8: The mean and standard deviation of the observed mean speeds, and the mean and standard deviation of the observed deviations.

$\bar{\bar{v}} = 88, \qquad \sigma_{\bar{\bar{v}}} = 20 \text{ km/h}$

$\bar{\sigma} = 8.8, \qquad \sigma_{\bar{\sigma}} = 5.9 \text{ km/h}$

Table 10.9: The statistics of the survey results used. Trip specific information.

Question 1

Occupants	1	2	3	4	5	Total
Observations	197	522	144	36	18	917
Percentage	21.48	56.92	15.70	3.93	1.96	100

Question 2

	Winter	Spring	Summer	Autumn
Mean trips	3.63	2.91	2.98	2.02
St. dev.	7.70	5.93	3.92	4.27
Range	0—50	0—30	0—24	0—24

Question 3

Speed (km/h):	<56	56—71	72—87	89—103	105—119	>=121	Total
Dry							
Observations	0	0	36	324	252	305	917
Percentage	0	0	3.93	35.33	27.48	33.26	100
Wet							
Observations	0	54	234	323	288	18	917
Percentage	0	5.89	25.52	35.22	31.41	1.96	100
Icy							
Observations	269	378	108	144	0	0	899
Percentage	29.92	42.05	12.01	16.02	0	0	100

(Continued)

Table 10.9: The statistics of the survey results used. Trip specific information. (Continued).

Question 4

Purpose	Observations	Percent
Recreation	684	76.08
Business	36	4.00
Visit family	143	15.91
Errands	18	2.00
Other	18	2.00
Total	899	100

Question 5

No. of accidents	Observations
0	899
1	18
Total	917

Question 7

Frequency	Observations	Percentage
all the time	755	82.33
most of the time	144	15.70
some of the time	18	1.96
rarely	0	0
never	0	0
Total	917	100

Table 10.11: The statistics of the survey results used, socioeconomic variables.

Question 14

Sex	Observations
Male	648
Female	269
Total	917

Question 15

Marital Status:	Married	Single	Divorced	Separated	Other	Total
Observations:	270	558	71	0	18	917

Question 16

Mean age:	33 years,	σ_{age} = 14 years	
Minimum age:	16 years,	Maximum age:	70
Observations:	917		

Question 17

Mean income	\$35,000	σ_{income} = 24,000	
Minimum income:	under \$10,000	Maximum income:	\$75,000-\$100,000
Observations:	899		

Question 18

	Some high school	High school	Tech. College	College degree	Graduate degree	Total
Observations	72	126	90	396	233	917
Percentage	7.85	13.74	9.81	43.18	25.41	100

(Continued)

Table 10.10: The statistics of the survey results used, socioeconomic variables. (Continued).

Question 19

Household size	1	2	3	4	5	6	Total
Observations	197	414	126	108	18	54	917
Percentage	21.48	45.15	13.74	11.78	1.96	5.89	100
Mean household size	2.5						
Standard dev.	1.3						

Question 20

No. of children, age < 6	0	1	2	Total
Observations	863	18	18	899
Percentage	96.00	2.00	2.00	100

Question 21

No. of children, aged 6 to 16	0	1	2	4	Total
Observations	827	36	18	18	899
Percentage	91.99	4.00	2.00	2.00	100

Question 22

Work outside home	0	1	2	3	4	Total
Observations	144	233	288	180	72	917
Percentage	15.70	25.41	31.41	19.63	7.85	100

Question 23

No. of veh.	0	1	2	3	4	Total
Observations	36	395	270	108	108	917
Percent	3.93	43.08	29.44	11.78	11.78	100

Question 24	
	Live and work in same zip code
Observations	108

Chapter 11

Analysis of mean speed and deviation

11.1 Introduction

The present study aims to examine the mean driving speed on Snoqualmie Pass in a simulator study. By having a number of participants drive through a 19.3 km (12 miles) simulated section of a Snoqualmie Pass and by having them answer a survey also used by Morse (1995), the mean speed and deviation on a mountainous highway under free-flow conditions can be modeled as functions of geometric, environmental and socioeconomic variables. The simulation has some drivers viewing variable message signs containing the messages used by the *TravelAid* project. Some drivers have the help of an in-vehicle unit that gives information similar to the VMSs. Other participants have both systems and neither system while driving in the simulator. This makes it possible to analyze the effect of these different methods of giving information to the drivers in addition to the effect of the geometric, environmental and socioeconomic variables.

This study begins with a review of the current literature on speed and simulation studies. In this review the limitations of simulator studies is discussed. Then, the modeling approach and the estimation methods used are presented and, finally the results of the model are given and discussed.

11.2 Previous research

a) Speed studies

Speed has always been of major importance in transportation engineering, for example, in the study of flow analysis and when determining the level of service (see May, 1990; Highway Capacity Manual, 1994). Numerous studies on what factors affect speed have been performed. The earliest studies looked largely on the effects of geometric design on speed but later studies have examined other factors such as vehicle characteristics and the environment. Galin (1981) used multiple regression to model average speed as a function of driver population characteristics, traffic conditions, vehicle and road characteristics and environmental factors. He used empirical data gathered from a large number of subjects traveling a specific section of a rural two-lane road. He found, for example, that older drivers drove at lower speeds in light vehicles but that age was insignificant among heavy vehicles. He also found that female drivers drove at significantly lower speeds than males.

There has also been research performed on how to specifically analyze speed behavior in horizontal curves (see Kanellaidis *et al.,* 1990) and also on speed perception in curves (see Milosevic and Milic, 1990). As the perception of speed in a driving simulation poses specific problems a very visible speedometer is used to give the drivers constant feedback on speed. Kanellaidis *et al.,* (1990) found that speed in horizontal curves is a function of the curve radius and the desired speed which they defined as the speed on the straight section before the curve starts to have effect. In light of this result the radius of curves will be recorded in this study and used as a possible explanatory variable. However it may not be significant in this study because larger sections of road are used were each can contain a number of curves.

Brisbane (1994) examined the effect of variable message signs designed to modify the speed characteristics on a highway in Australia. These signs were different from the ones used in the present study as they measure vehicle speeds with radar and point at the lane with the worst speed offender and send him an appropriate message. The signs used in this study do set new speed limits but without the fanfare of these Australian signs. Brisbane found that the Australian signs were extremely effective in modifying speed, in some cases about 98% of speeding drivers lowered their speed when seeing the signs.

Holland and Conner (1996) examined the effect of police intervention on speed. They found police intervention to be effective even for a few weeks after heavy police patrol of a particular road section in England. They found that the effect of police were different for drivers based on their attitude towards speeding.

Kanellaidis *et al.,* (1995) performed a detailed study on driver's attitudes towards speed limit violations. They used a survey and asked questions about the driver himself and about others and they found interesting discrepancies. The drivers were shown to be generally egocentric and thought very differently of their own speeding and the speeding of others. Kanellaidis *et al.,* found that the biggest group of high speeders which had very strong intentions to speed were young, educated males which can be compared to the results of the present study.

b) Modeling methods

This study differs from previous speed studies in a variety of ways. It uses a driving simulator to track the speed characteristics of each subject over an approximately 19 km long section of road, gathering observations along the way. This gives many observations per subject which means fewer subjects are needed to get a statistically significant sample size. This method has been previously used by Mannering and Chu Te (1986) to analyze the impacts of manufacturer sourcing on vehicle demand and by Mannering (1987) to analyze the impact of interest rates on automobile demand. This method of using many observations from each subject leads to a correlation of the error terms because the observations from a particular subject share unobserved variables that affect that particular subject. It is difficult to correct for this effect and following Mannering (1987) this correlation is not taken into account in this study.

To model speed and deviation a three stage least squares regression is used to estimate both equations simultaneously as these are endogenous variables. Three stage least squares regression has previously been used to model speed and deviation by Shankar and Mannering (1997).

11.3 Modeling

a) Geographic setting

The road being modeled is a 19.312 km (12 miles) stretch of I-90 eastbound from mile marker 35 to 47. This is as I-90 heads up and into Snoqualmie Pass, WA. In this area the road generally has an upgrade, the highest being 7% (4°). The road is also curvy as it winds up the pass. Each lane is 3.66 m (12 ft) wide and the shoulders on both sides are 1.22 m (4 ft).

b) Modeling issues

The goal is to create a mathematical model describing mean speed and speed deviation as a function of geometric, socioeconomic and other variables being measured by the driving simulator and by the surveys in Appendices C and D.

The speed data collected every second is subject to uninteresting fluctuations so it is more reliable to divide the road into sections and calculate the mean speed and standard deviation in each. These can then be regressed against the independent variables. There is a choice in deciding whether the sections should be of even length or if they should be designed to capture a constant geometric feature such as a whole horizontal curve. Following the logic of Shankar *et al.,* (1995) who divided Snoqualmie Pass to examine accident frequencies, sections of even length will be used. Sections of even lengths are more likely to have a similar number of observations and the error terms are therefore more likely to be more identically distributed. This helps to lessen heteroskedasticity. Shankar *et al.,* also found that this method gives an accurate representation of the road if the geometry of the sections are well known.

The minimum horizontal and vertical curvatures in each section were therefore recorded,along with the maximum up- and downgrades, the number of horizontal and vertical curves and the maximum length of horizontal and vertical curves in the section. The maximum and minimum speed limits in each section were also recorded because they are changed by the IVU in some simulation runs and by the VMSs in some runs. This gives all the necessary geometric information for the whole section. All this information will be included in the model but the coefficients are not expected to be significantly different from zero for all these variables.

Kaptain *et al.,* (1996) found that driving speed in driving simulators is not absolutely valid but relatively valid. Care must therefore be taken before any statements are made based on the actual speed measured in the simulator.

c) Data processing

The data collected by the driving simulator program needs to be processed before it is usable for the purposes of this study. The driving simulator monitors and writes out the following variables every second:

- the time since the start of the current run
- the position of the vehicle in simulator units
- the current lane
- the current position of the gas pedal
- the current gear
- the current position of the brake pedal
- the level of fog

A sample data file can be seen in Appendix G.

Because this study aims to model mean speed over a specific section length of the road this data must be used to calculate the current distance traveled since the start. The simulator units cannot be used for this purpose as they do not contain enough accuracy. They show the position with a margin of error of 10% of the current stretch length which is a variable length unit in the simulation. The stretch lengths used are shown in Appendix F in the length column.The distance is therefore calculated by using the mean speed of the previous second. This method also leads to an error, especially if the speed changes dramatically within the second. As the road simulated is a highway with few obstacles this is not expected to pose a problem.

Having calculated the distance traveled at each point the road can now be divided into sections of even length based on the calculated distances. A section length of 1 km is selected. The simulation is 19.3 km and the last 300 meters are dropped along with the first 1 km as in that first section the vehicle is typically accelerating as it starts at virtual standstill. There are therefore 18 equally long sections, each typically having 10—30 observations depending on speed. Due to a software malfunction the dataset from one subject contained only 17 sections resulting in a total of 917 sections for all 51 subjects. These sections become the observations used in the model.

d) Econometric methods

To create a model of mean speeds and deviation a system of two equations is set up where the mean speed and the deviation appear endogenously:

$$v_{ni} = \alpha + \beta \mathbf{X}_{ni} + \phi \sigma_{ni} + \varepsilon_{ni} \tag{11.1}$$

$$\sigma_{ni} = \zeta + \eta \mathbf{Z}_{ni} + \psi v_{ni} + \delta_{ni} \tag{11.2}$$

where v_{ni} is the mean speed of driver n in section i, σ_{ni} is the standard deviation of the mean speed, α, ζ, ϕ and ψ are estimable scalars, β and η, are estimable vectors, $\mathbf{X}_{ni}$ and $\mathbf{Z}_{ni}$ are vectors of exogenous variables, ε_{ni} and δ_{ni} are the error terms.

To estimate equations (11.1) and (11.2) simultaneously it is best to use the three stage least squares (3SLS) method. It has been previously used to model lane mean speeds and deviations by Shankar and Mannering (1997) with good results. As noted by them the 3SLS method is asymptotically more efficient than other possible regression techniques such as indirect least squares, two stage least squares and limited information maximum likelihood. The mathematical methods of 3SLS are described in Greene (1993) and various issues concerning the method are discussed in Kennedy (1992). The Statistical Software Tools version 2.0 (Quigley *et al.,* 1994) were used to perform the 3SLS regression.

The assumptions of ordinary least squares (OLS) regression apply to 3SLS too (see Kennedy, 1992). If they are not met the model will be erroneous. These issues were addressed in the following way:

Omission of relevant variables: Previous research on speed was consulted to help make sure all known relevant variables were included (see Galin, 1981; Kanellaidis *et al.,* 1990; Kanellaidis *et al.,* 1995; Shankar and Mannering, 1997).

Presence of irrelevant variables: The large base model used will have irrelevant variables but they will be weeded out by using the t-statistic as a measure of significance and by using engineering logic.

Nonlinearity: Previous research has shown speed to be largely a linear function (see Galin, 1981) however on a small scale the speed in curves appears to show nonlinear effects (see Kanellaidis *et al.,* 1990). This study works on a large scale and linearity can therefore be safely assumed.

Changing coefficients: The section length used is relatively short so effects such as the driver getting tired should not impact the study. Previous studies on speed have not indicated this to be a problem.

Non-zero disturbance mean: If the disturbance mean is non-zero it will result in a biased intercept. Previous research on speed have not been overly concerned with this problem. There will be a tendency for intercept bias as the speed in a driving simulator is only relatively valid (see Kaptein *et al.,* 1996).

Heteroskedasticity: Results if the variance of the error terms is different. It is lessened by the use of sections of even length.

Correlation of error terms: The 3SLS method corrects for the contemporaneous correlation of error terms and the problems associated with it. There will, however, be some correlation of error terms in this study because there are many observations from each subject. This problem was not addressed in the present models so some caution must be taken while interpreting the results (see Mannering, 1987).

Errors in variables: This study will suffer from this as the traveled distances are calculated from mean speed with one second intervals. This will introduce some error which should be small as the speed is not likely to change dramatically during the one second period.

Autoregression: This is if a time lagged variable of a dependent variable is used as an independent variable which is not done in this study.

Endogeneity: As speed and standard deviation are endogenous this issue is of concern and it is the reason for using the 3SLS simultaneous equation estimation technique as it solves this problem.

Multicollinearity: This happens if two ore more independent variables are linearly dependent. The 3SLS method as implemented by the SST software is sensitive to this and it will not function if a linear dependency is detected (see Quigley *et al.,* 1994).

There are 917 road sections with mean speed, standard deviation and detailed geometric information. There are also the 51 surveys filled out by the participants. To include the survey information the survey results for a particular subject are appended to each section driven by that subject. Therefore all vectors in equations (11.1) and (11.2) become 1 by 917. This is a statistically valid sample size even though the number of subjects was only 51, as each created 18 observations (except for one subject who created 17 observations). Typically each subject creates one observations such as the survey and then a large number of subjects are needed. Mannering and Chu Te (1986) have previously shown that a large number of observations can be made from one subject and thereby a relatively few subjects are needed to get a statistically valid sample size.

e) Designing the model

To design this model variables are first selected on the basis that they could be explanatory. To do that all the information that is endogenous and/or opinion based is excluded. The two interesting endogenous variables, average speed and standard deviation, are kept. This means the removal of all questions from the surveys which ask the participant to give his or her opinion. The appropriate data used will be factual only as opinions change and can be very different based on the wording of the questions. This removes the survey in Appendix C completely and questions 6 and 8–13 from the survey in Appendix D. The variables used to begin are therefore:

- Geometric variables:
    - number of horizontal and vertical curves,
    - lengths of horizontal and vertical curves,
    - radii of horizontal and vertical curves,
    - maximum up- and downgrades.
- Environmental variables:
    - maximum and minimum speed limits set by road signs, the IVU and/or the VMSs,
    - fog or clear weather,

- number of snow plows,
- the type of variable message received, if any,
- the type of in-vehicle message received, if any.

• Driver based variables:

- mean speed,
- standard deviation of mean speed,
- questions 1–5, 7, 14–24 from the survey in Appendix D.

This information has to be properly coded as either binary indicator variables, continuous variables or discrete ordered variables. The least restrictive coding for all variables is used at first. Therefore there is one binary indicator variable used for each number of curves for example.

The results are in Tables 10.3–10. Based on the results some variables may have to be left out of the analysis as they may have too few observations or may be constant. These issues will be addressed in the section on results.

To design the model all variables are used that possibly can be included without triggering a linear dependency. This means that some variables must be left out but after having designed the model there will be a check to see if one of these variables are more significant than the ones used. The 3SLS regression is run on this large base model and the methodology in Table 11.1 used to fine tune it.

In some instances it was found during the modeling process that the least restrictive coding as possible was not used for a variable as it had a high t-statistic and contained more than one logical piece of information. Then the coding was changed for that variable and all other possible variables were inserted again (i.e. reverted to the base model) and the model fine tuned according to the methodology in Table 11.1. This resulted in the final model shown in Tables 11.2–13.

By examining the number of observations for the different variables in Tables 10.4–10.11 it can be seen that in some cases they are very few. If the coefficient for one of these variables had significant t-statistics (i.e. the absolute value of the t-statistic was greater than one) a check was performed to see if the corrected R^2 value was improved by leaving that variable out. This was the case for the VMS and IVU messages that had less than 20 observations (see Table 10.7), also for the indicator variables for business, errands and other purposes in question 4 (see Table 10.9), for the number of accidents (see question 5 in Table 10.9), and for the indicator variable of other in the marital status question (see question 15 in Table 10.10). While performing the fine tuning of the model (as described in the section on the design of the model) it was found that the rest of the marital status indicator variables were not significantly different from each other. This means in effect that these variables were giving a constant contribution which belongs in the constant variable. These variables were therefore removed altogether.

Table 11.1: The modeling design methodology.

1. The t-statistic is used to determine if the coefficients of the variables are significantly different from zero. If the absolute value of the t-statistic is greater than one the variable is kept as it then has a coefficient significantly different from zero with at least a level of confidence of 85%. All variables which do not meet this criteria are deemed insignificant.

2. The least significant variable according to the t-statistic is picked and dropped from the model but noted on a list. The 3SLS regression is then run again and the process returns to step 1.

3. If all variables are significant the list of variables dropped from the model in step 2 is now inspected. They are inserted one at a time and the 3SLS regression is run. If a variable is shown to be insignificant it is dropped. If it becomes significant some other variable may become insignificant. If that happens the process returns to step 1 again.

4. If the list of variables that were dropped in step 2 becomes empty the variables that triggered a linear dependency are tried one at a time to see if any of them can improve the model.

5. Having tried all possible variables and removed all insignificant variables it is now examined if the binary indicator variables are significantly different from each other. One pair of indicator variables such as the ones for one and two horizontal curves in a section are taken and combined. The 3SLS regression is run and if the corrected R^2 has improved the combination is used. This is done for all possible pairs of related indicator variables.

11.4 Results

The final model can be seen in Tables 11.2–13. Interpretation of the results for equations (11.1) and (11.2) can be found in the following two sections. The corrected R^2 for the mean speed model was 0.54691 (see Table 11.2) and it was 0.39044 (see Table 11.3) for the standard deviation model. The system R^2 is 0.54709 with a total of 830 observations. All signs in the models were plausible.

Table 11.2: Three stage least squares estimation of mean speed in km/h.

Variable	Estimated coefficient	t-statistic
Standard deviation (km/h)	-1.40065	-10.76597
Constant (km/h)	74.20500	11.09307
Maximum speed limit set by road signs, (96.56 km/h if the driver had neither IVU nor VMSs, 0 otherwise)	$3.31811*10^{-2}$	2.48481
Maximum speed limit set by IVU only, (Speed limit in km/h if the driver had IVU only, 0 otherwise)	$8.33766*10^{-2}$	4.35987
Maximum speed limit set by VMS only, (Speed limit in km/h if the driver had VMS only, 0 otherwise)	$5.58700*10^{-2}$	3.36881
Horizontal curve indicator 3, (1 if there are three horizontal curves in a section, 0 otherwise)	-2.52385	-2.72206
Grade indicator 1, (1 if the maximum upgrade in a section is less than 2%, 0 otherwise)	2.73590	1.89721
Grade indicator 2, (1 if the maximum upgrade in a section is greater than 4%, 0 otherwise)	-3.34956	-2.68920
Vertical curve indicator 1, (1 if there are two vertical curves in a section, 0 otherwise)	1.74570	1.80096
Maximum distance in a vertical curve in a section (m)	$-8.43732*10^{-3}$	-2.27301
Fog indicator, (1 if there is fog somewhere in a section, 0 otherwise)	-11.33593	-12.28128
Usual number of occupants in driver's vehicle on Snoqualmie Pass trips	-1.39307	-1.91773
Driver's estimate of mean speed for Snoqualmie Pass trips under dry conditions (km/h)	0.32576	9.24832
Driver's estimate of mean speed for Snoqualmie Pass trips under icy conditions (km/h)	0.28867	10.15192
Primary purpose indicator, (1 if the primary purpose was to visit family, 0 otherwise)	-13.91232	-8.21165
Seat belt indicator, (1 if the driver reported using seat belts all the time, 0 otherwise)	-3.95983	-3.02806
Sex indicator, (1 if male, 0 if female)	9.09296	6.37411
Driver age (years)	-0.24544	-5.08766
Driver's household income ($)	$-1.15100*10^{-4}$	-5.33556

(Continued)

Table 11.2: Three stage least squares estimation of mean speed in km/h. (Continued)..

Variable	Estimated coefficient	t-statistic
Education indicator 1, (1 if the driver's highest level of education was high school or technical college, 0 otherwise	3.68538	2.78165
Education indicator 2, (1 if the driver's highest level of education was a college degree, 0 otherwise)	-15.75487	-11.87282
The number of people in driver's household	-2.75100	-4.85113
Number of children aged 6 to 16 in driver's household	2.37486	2.72239
Number of people in driver's household that work outside the home	-2.48350	-3.57331
Number of licensed and operable vehicles in driver's household	4.00188	5.90706
R^2	0.56002	
Corrected R^2	0.54691	

Table 11.3: Three stage least squares estimation of the standard deviation of mean speed in km/h.

Variable	Estimated coefficient	t-statistic
Mean speed (km/h)	-0.12816	-9.16855
Constant (km/h)	18.45278	13.94781
Maximum speed limit difference in a section, set by IVU only, (maximum difference in km/h if the driver had IVU only, 0 otherwise)	$7.79066*10^{-2}$	3.30098
Maximum speed limit difference in a section, set by VMS only, (maximum difference in km/h if the driver had VMS only, 0 otherwise)	0.15057	6.29182
Maximum speed limit difference in a section, set by IVU and VMSs, (maximum difference in km/h if the driver had both IVU and VMS, 0 otherwise)	0.16902	5.43059
Horizontal curve indicator 1, (1 if there is one horizontal curve in a section, 0 otherwise)	0.66029	1.71828
Horizontal curve indicator 2, (1 if there are two horizontal curves in a section, 0 otherwise)	1.27182	3.48832
Maximum distance in a horizontal curve in a section (m)	$-2.09485*10^{-3}$	-2.43596

(Continued)

Table 11.3: Three stage least squares estimation of the standard deviation of mean speed in km/h. (Continued).

Variable	Estimated coefficient	t-statistic
Grade indicator 2, (1 if the maximum upgrade in a section is greater than 4%, 0 otherwise)	-1.54436	-4.40456
Vertical curve indicator 2, (1 if there are two or three vertical curves in a section)	1.22853	3.67455
Fog indicator, (1 if there is fog somewhere in a section, 0 otherwise)	-1.56556	-4.26039
Number of snow plows in a section	4.24467	13.93509
Specific VMS indicator, (1 if a Curvy Road message follows a snow plow, 0 otherwise)	-3.80811	-3.49842
Experienced Snoqualmie Pass driver indicator, (1 if the driver reported traveling Snoqualmie Pass more than four times each season, on the average, 0 otherwise)	1.03135	1.46003
Driver's estimate of mean speed in km/h for Snoqualmie Pass trips under icy conditions	$4.83465*10^{-2}$	4.29633
Primary purpose indicator, (1 if the primary purpose was to visit family, 0 otherwise)	-1.70855	-3.57788
Driver's household income ($)	$-2.69305*10^{-5}$	-3.82674
Education indicator 2, (1 if the driver's highest level of education was a college degree, 0 otherwise)	-3.24076	-8.37843
Education indicator 3, (1 if the driver's highest level of education was a high school diploma, 0 otherwise)	1.33854	2.60246
Number of licensed and operable vehicles in driver's household	0.36368	2.35084
R^2	0.40441	
Corrected R^2	0.39044	

a) Interpretation of the estimation of the mean speed equation.

Variable: Standard deviation

Finding: Negative contribution

This result is in line with a priori expectations. The higher the standard deviation the lower the mean speed. This is logical since the only time drivers need to change their speed from their desired speed is when they slow down as presumably they are driving as fast as they want or dare. Therefore if a driver slows down he or she will want to speed up soon to regain the desired speed. This results in a higher standard deviation being associated with lower speeds.

Variable: Maximum speed limit set by road signs

Finding: Positive contribution

This result indicates that the mean speed of drivers without an IVU or VMSs get a constant positive contribution of 3.2 km/h. This means that these drivers drive faster than drivers with both IVU and VMSs as they do not receive a contribution to mean speed from the speed limits. A comparison between this and the following two variables can be seen in Figure 11.1.

Variable: Maximum speed limit set by IVU only

Finding: Positive contribution

This result is logical as a higher speed limit allows drivers to legally drive faster and that is generally desired by drivers. What is interesting about this result is that these drivers drove faster than all other drivers on the average.

Variable: Maximum speed limit set by VMS only

Finding: Positive contribution

This result is logical as the preceding result for the IVU set speed limits. Note that the coefficient a bit lower than the IVU coefficient indicating less impact on speed from the VMS signs. The VMS drivers drove at approximately the same speed as the drivers in the control run in sections with snow plows.

Variable: Horizontal curve indicator 3

Finding: Negative contribution

If a section contains three horizontal curves the average speed tends to be lower than if there are more or less curves in the section. This is logical as a high number of horizontal curves is expected to hinder speed. The reason the speed is lower for three curves than four can be explained when the typical lengths of curves are compared to the 1 km section length. If there are four curves in a section then the two curves at the edges are sure to be only partially within the section and therefore they cause less of an hindrance in that particular section.

Variable: Grade indicator 1

Finding: Positive contribution

If the maximum upgrade in a section is lower than 2% the average speed tends to be higher than for other sections. This is logical as the higher the upgrades the poorer the performance of the simulated vehicle which slows it down.

Variable: Grade indicator 2

Finding: Negative contribution

If the maximum upgrade in a section is greater than 4% the average speed tends to be lower than for other sections. This result is as expected and in harmony with the previous grade indicator.

Variable: Vertical curve indicator 1

Finding: Positive contribution

If there are two vertical curves in a section the average speed tends to be higher. This may at first seem to be counter intuitive but is really logical, especially in the light of the next variable. It may also be said that not all vertical curves bridge differences between upgrades, some connect to downgrades and thereby giving a tendency for higher speeds.

Variable: Maximum distance in a vertical curve in a section

Finding: Negative contribution

The longer distance spent traversing a vertical curve the lower the average speed. This variable works against the one for two vertical curves which gave a positive contribution. That contribution may be negated if the curve is long enough as the drivers tend to drive slower on long vertical curves.

Variable: Fog indicator

Finding: Negative contribution

The presence of fog in a section has a strong negative impact on average speed which is as expected.

Variable: Usual number of occupants in driver's vehicle on Snoqualmie Pass trips

Finding: Negative contribution

The drivers who generally have more people in the vehicle tend to drive slower. It seems drivers tend to drive more carefully when carrying passengers as they feel they are otherwise risking other people's lives. This result is supported by previous research (see Morse, 1995). This effect seems to carry into the simulator experiment as the drivers have gotten used to particular driving speeds which have been partially based on the number of passengers. It is interesting to see this effect in a simulation study where the risk to the driver's life is virtually zero. Galin (1981) did not find this variable to be significant in his study on speed.

Variable: Driver's estimate of mean speed for Snoqualmie Pass trips under dry conditions

Finding: Positive contribution

The faster the drivers estimated his or hers usual average speed the faster they drove in the simulation which fits with intuition.

Variable: Driver's estimate of mean speed for Snoqualmie Pass trips under icy conditions

Finding: Positive contribution

This variable shows the same effect as the previous variable as driver's who estimate going faster in reality went faster in the simulation than others.

Variable: Primary purpose indicator 1

Finding: Negative contribution

Drivers who reported their usual primary purpose for Snoqualmie Pass trips as visiting family drove slower than others. This is not surprising as such visits can be expected to be of a more leisurely nature than other types of trips and this has been found previously, for example by Morse (1995). It is interesting to see this effect carry into the simulation. The subjects were not instructed to behave as if they had a particular purpose while driving in the simulation but rather drive as they usually would. Previous research has shown that subjects generally have a hard time of driving according to specific trip purposes in simulators (see Koutsopoulos, 1995). In this study the subjects' usual purpose appears to manifest itself in their driving patterns.

Variable: Seat belt indicator

Finding: Negative contribution

Drivers that reported using seat belts all the time on Snoqualmie Pass have lower average speeds than do others. This is probably connected to the fact that those who do not use the seat belts all the time are not as safety conscious and therefore likely to have higher average speeds. As seat belt use is required by law in Washington state the drivers who do not use seat belts all the time are breaking the law. If they do not think much of breaking this law then they are probably also more likely to break the legal speed limit.

Variable: Sex indicator

Finding: Positive contribution

This is the expected result, that males drive faster than females. This is supported by previous research on attitudes towards speeding which shows that males have a more general tendency to speed (see Galin, 1981; Kanellaidis, 1995).

Variable: Driver age

Finding: Negative contribution

This result indicates that older people drive slower than younger people. This is as expected since previous research on the connection between age and speed has found this to be the case (see Galin, 1981; Kanellaidis, 1995). In a simulation study a further effect can be the technology bias, described by Koutsopoulos *et al.,* (1995). Older people may not be as used to computer simulations and may therefore have a more difficult time adjusting to the simulator.

Variable: Driver's household income

Finding: Negative contribution

The higher the household income of the driver the lower the average speed. This tendency of higher income drivers has been previously found by Morse (1995) where he found drivers from high income households to be more likely to reduce speed more than middle income drivers under adverse weather conditions. It seems drivers from higher income households are less willing to take risks with their life and therefore tend to drive safer than middle income groups.

Variable: Education indicator 1

Finding: Positive contribution

If the driver's highest level of education was high school or a technical college degree the average speed tends to be higher than for drivers of other levels of education. Kanellaidis *et al.,* (1995) found that the higher the educational level the more likely people were to have intentions to speed. This fits the result for technical college degrees but there were not significant differences between those drivers and those with a high school degree.

Variable: Education indicator 2

Finding: Negative contribution

Drivers with a college degree drive slower than others. This does not fit the results of Kanellaidis *et al.,* (1995) as they found higher education to be a positive contributor to drivers' intentions to speed. However, they do not mention if they split up their educational variable to allow each level of education to have their own coefficient. That can make a difference in the result.

Variable: Number of people in driver's household

Finding: Negative contribution

Drivers from bigger households drive slower. This variable is very much coupled with the following variables and must be analyzed in conjunction with them. This result is supported by the results of Morse (1995) which found drivers who live alone to be less likely to slow down under icy conditions. Drivers who live with families (or share a household with friends) are here found to drive slower than others. This may well be because drivers with families feel more responsibility than others but note the following variables.

Variable: Number of children aged 6 to 16 in driver's household

Finding: Positive contribution

Drivers who have older children and young teenagers drive faster. This couples with the household size which gives a negative contribution so the total contribution from these two variables together may still be negative. Drivers from larger households do therefore tend to drive slower but the more children aged 6 to 16 in the household the smaller the negative contribution. This study did not contain subjects from large enough families (see Table 10.10) to change the total contribution to positive values so the model cannot be easily extended into that region.

Variable: Number of people in driver's household that work outside the home

Finding: Negative contribution

The more people that work outside the home in the driver's household the slower the driver tended to be. This couples again with the previous two variables to give a total negative contribution for drivers from larger households.

Variable: Number of licensed and operable vehicles in the driver's household

Finding: Positive contribution

This variable adds further impact to the previous household variables. Driver's from households with more cars tend to drive faster than others. These households are likely to have higher incomes and thereby opposing the negative income based contribution. These households are also more likely to have more than one person working outside the home and therefore this variable opposes the negative contribution of the work outside of home variable.

b) Interpretation of the estimation of the standard deviation equation.

Variable: Mean speed

Finding: Negative contribution

This result fits the one found for the standard deviation of mean speed in the previous section as higher mean speeds are correlated with lower standard deviations.

Variable: Maximum speed limit difference in a section, set by IVU only

Finding: Positive contribution

This fits intuition as the greater the difference in speed limits within a section the larger the expected speed difference and therefore a larger standard deviation of mean speed. The IVU therefore contributes to the standard deviation by setting different speed limits depending on conditions and apparently the drivers took some note of the IVU set speed limits.

Variable: Maximum speed limit difference in a section, set by VMS only

Finding: Positive contribution

The VMSs had a similar effect as the IVU. They increase standard deviation by setting different speed limits depending on conditions and according to this, drivers followed the VMS suggestions.

Variable: Maximum speed limit difference in a section, set by IVU and VMSs

Finding: Positive contribution

As for the previous two variables for either IVU or VMS this variable is for drivers who had both. They, along with the drivers with IVU only or VMS only had higher standard deviations than drivers who saw road signs with a constant speed limit.

Variable: Horizontal curve indicator 1

Finding: Positive contribution

The standard deviation in a section with one horizontal curve was higher than for other sections. This is not surprising when comparing a section with a curve with a straight section. In such a case the standard deviation is expected to be higher as the speed is bound to change within the curve. For comparison with sections with more curves see the next variable.

Variable: Horizontal curve indicator 2

Finding: Positive contribution

The standard deviation in a section with two horizontal curves was also higher than for other curves, i.e. no curves or more than two as the case of one curve is covered by the previous variable. The standard deviation of one and two curves can be higher than for three or four curves in a section because if the section is so curvy then the driver may well adjust to a slower speed and maintain it while traveling through the section while if there are one or two only then the driver is more likely to slow down upon entering the curve and then regain speed when exiting. Therefore the standard deviation is higher for sections with one or two curves than for more or less curves.

Variable: Maximum distance in a horizontal curve in a section

Finding: Negative contribution

This result is not surprising and stems from similar reasons as noted to explain greater standard deviations in one or two curves than in three or four. If the curve is long the driver maintains the speed selected to traverse the curve longer and therefore the standard deviation is reduced for longer curves.

Variable: Grade indicator 2

Finding: Negative contribution

The standard deviation of sections with a maximum upgrade greater than 4% is less than for sections with lower grades. The mean speed in these sections is lower which means the standard deviation is higher than for other sections but this variable adjusts the effect of low speed on standard deviation as it is not as low on an upgrade as it is on a straight section or a downgrade with a similar mean speed.

Variable: Vertical curve indicator 2

Finding: Positive contribution

If there are two or three vertical curves in a section the standard deviation tends to be higher than for sections with fewer curves. There are no sections with more than three vertical curves as can be seen in Table 10.3. This is not surprising as vertical curves affect the speed, either by increasing it when going downhill or decreasing it when going uphill and thereby the standard deviation is increased.

Variable: Fog indicator

Finding: Negative contribution

The standard deviation tended to be less in sections with fog than in other sections. The mean speed in the fog tended to be lower than in other sections and the mean speed variable shows that higher speeds lead to lower standard deviation. The fog variable adjusts the effect of the lower speed on standard deviation as the fog lasts for a long time and within it the driver adjusts to the fog and maintains speed with less standard deviation than predicted by other variables. This result is therefore not as counter intuitive as it may seem at first.

Variable: Number of snow plows in a section

Finding: Positive contribution

This result was very much so expected as the snow plows block 1-2 lanes and require the driver to slow down and possibly change lanes and then pick up speed again. Therefore it is only normal that the number of snow plows in a section contribute to a higher standard deviation.

Variable: Specific VMS indicator

Finding: Negative contribution

When a VMS shows the "Curvy Road" message after the driver has encountered snow plows the driver typically assumed that there would be no more snow plows in the coming sections and picked up speed and held it relatively constant throughout the section with this sign. That leads to a lower standard deviation.

Variable: Experienced Snoqualmie Pass driver indicator

Finding: Positive contribution

Drivers who reported going on average more than four times across Snoqualmie Pass during each of the four seasons show a tendency to have higher standard deviations than others. It may be linked to the fact that these experienced drivers drove faster and upon encountering snow plows and fog they had to change their speed more than others and thereby generating a higher standard deviation of mean speed.

Variable: Driver's estimate of average speed for Snoqualmie Pass trips under icy conditions

Finding: Positive contribution

The higher the driver reported driving on average during icy conditions the higher the standard deviation. This may be due to similar reasons as for the previous variable. These drivers may drive faster than others and therefore have to change their speed more resulting in higher standard deviation.

Variable: Primary purpose indicator

Finding: Negative contribution

Driver's whose primary purpose for traveling across Snoqualmie Pass was to visit family had lower standard deviation than others. These drivers also drove slower as shown in the previous section and this variable is therefore correcting against the influence of speed on standard deviation. That is, even if these drivers drove at lower average speeds they maintained them better than others who drove at similar speeds and therefore have lower standard deviation.

Variable: Driver's household income

Finding: Negative contribution

The higher the driver's household income the lower the standard deviation. This couples with the result from the previous section which showed that these drivers drove slower. This result shows that driver's from higher income houses had lower standard deviation than other drivers even if they drove at similar speeds.

Variable: Education indicator 2

Finding: Negative contribution

This result works in much the same way as the previous result for income as it adjusts the standard deviation of drivers with college degrees who drove slower than others but had lower standard deviation than other drivers even if they drove at similar speeds.

Variable: Education indicator 3

Finding: Positive contribution

This result indicates that drivers with a high school diploma have higher standard deviation than other drivers. These drivers also drove faster as seen in the previous section. This therefore means these drivers have a tendency for higher standard deviations than other drivers who drove at similar speeds.

Variable: Number of licensed and operable vehicles in driver's household

Finding: Positive contribution

As seen in the previous section these drivers drove faster than others and they are by this shown to also have higher standard deviation than others and even higher than drivers who drove at similar speeds.

11.5 Conclusions

In this Chapter a model of mean driving speed and deviation under free-flow conditions on an highway has been created. The model can be used to explore the effects of the various explanatory variables on speed and deviation. However as the model is based on data from a driving simulation, care must be taken before the actual speed values predicted by the model are carried over to reality.

The findings of this study were mostly consistent with previous research on the variables that have previously been studied, such as the effects of sex and age (see Galin, 1981). Young drivers drove faster, male drivers drove faster and drivers with high school or technical college degrees drove faster than others. The only inconsistent result was that drivers with a college degree drove slower than others in this study while previous research found that the higher the education the higher the intent to speed (see Kanellaidis *et al.,* 1995). The reason for that may be that in this study there was one indicator variable for each level of education to begin with. This allowed each level to have its own coefficient. In the paper of Kanellaidis *et al.,* (1995) there was only one variable used with higher numbers signifying higher levels of education. This restriction may well have caused the difference and also the fact that in this study there were many observations from people with college degrees (see Table 10.10).

Upgrades and curves tended to generally cause lower speeds and higher standard deviations which fits with intuition. The presence of fog caused people to slow down to lower mean speeds. It was also revealed that speed and deviation are endogenous as presumed beforehand and thereby validating the use of the 3SLS regression method. Both variables were statistically significant in each others equation. The results for those variables were consistent as high speeds signified lower standard deviations and high standard deviation signified lower speeds.

The study found that the speed limits set by the IVU and VMS did have an effect on drivers. The higher the speed limit the larger the contribution to mean speed. The speed limits change depending on the scenery conditions shown in Table 9.1 and this must be taken into account when comparing the four run types shown in Table 9.2. Figure 11.1 shows the different contributions to speed depending on run type and scenery type.

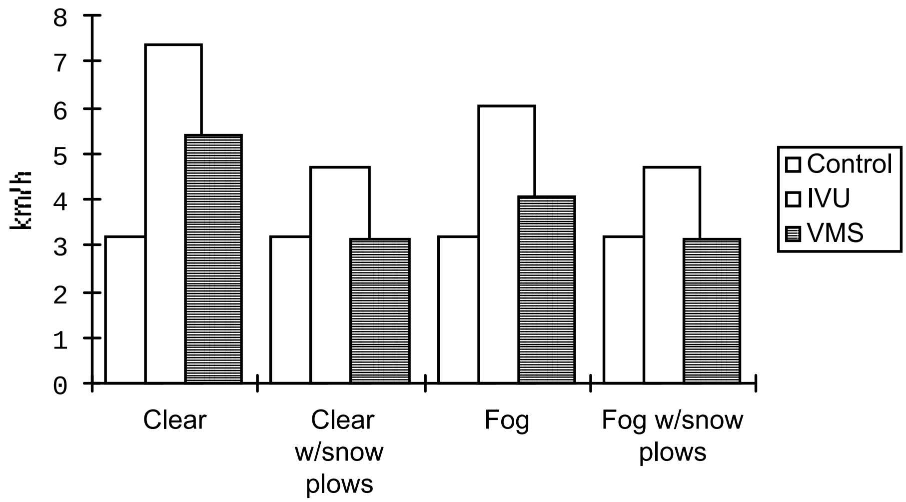

Figure 11.1: A comparison of the contributions to mean speed depending on run type and scenery condition. The contribution for IVU/VMS marks the baseline of zero km/h.

The figure shows that drivers with IVU only drive faster than others on the average. The drivers with VMS only drove faster than those using both systems or no system in the clear and fog areas but in the snow plow sections they drove at approximately the same mean speed as those with no system. Drivers with both systems drove at the lowest mean speed. The drivers that received additional help from the IVU or the VMSs do therefore seem to have put some trust in the messages to give information about upcoming dangers such as the snow plows used in this study. The IVU and VMS drivers may therefore have been given an added sense of security which shows itself in higher speeds during the areas they considered safe, i.e. the sections without snow plows. This is affected by the lack of additional traffic in the stream which would have lead to the fog section in particular to be considered more dangerous than it was when the drivers knew they were the only driver except for possible obstacles.

The reason for the lower mean speed of drivers with both IVU and VMSs may be because drivers who saw every message twice were more affected by the messages in the sense that they slowed down more than those with either IVU or VMSs. That results in lower mean speed than predicted for the IVU only and VMS only drivers. This result is supported by the standard deviation model were the drivers with IVU and VMS have the largest coefficient for the difference in speed limits. Figure 11.2 shows a scenario that helps to explain why the standard deviation is higher for the IVU, VMS and IVU/VMS runs than for the control run.

Figure 11.2 is not based on any particular subject but is a schematic representation of possible speed characteristics. The differences in speed are exaggerated. This figure shows the drivers in the IVU/VMS driving at a faster speed in the beginning but upon seeing the snow plows ahead message they slow down. They keep that speed until they see another message, which does not indicate that there are more snow plows ahead. The drivers in the control run, slow down when they first see a snow plow, pass it and speed up again. Their mean speed is higher but the deviation is higher for the IVU/VMS run.

The use of IVUs or VMSs does seem to be a two-edged sword. Drivers using IVU and/or VMS did slow down when the messages indicated danger ahead but in the IVU only case the drivers drove faster on the average than other drivers. While in the VMS only run the drivers drove faster than the drivers in the control run and IVU/VMS run during the areas without snow plows. The drivers did therefore seem to trust the messages given by the IVU or VMSs. The drivers who saw both IVU and VMS may also have driven faster than the drivers with neither system in high speed limit zones and may have driven slow for longer in the low speed limit zones as seen in Figure 11.2 and still have lower mean speed. This explains the higher standard deviation of the IVU/VMS run.

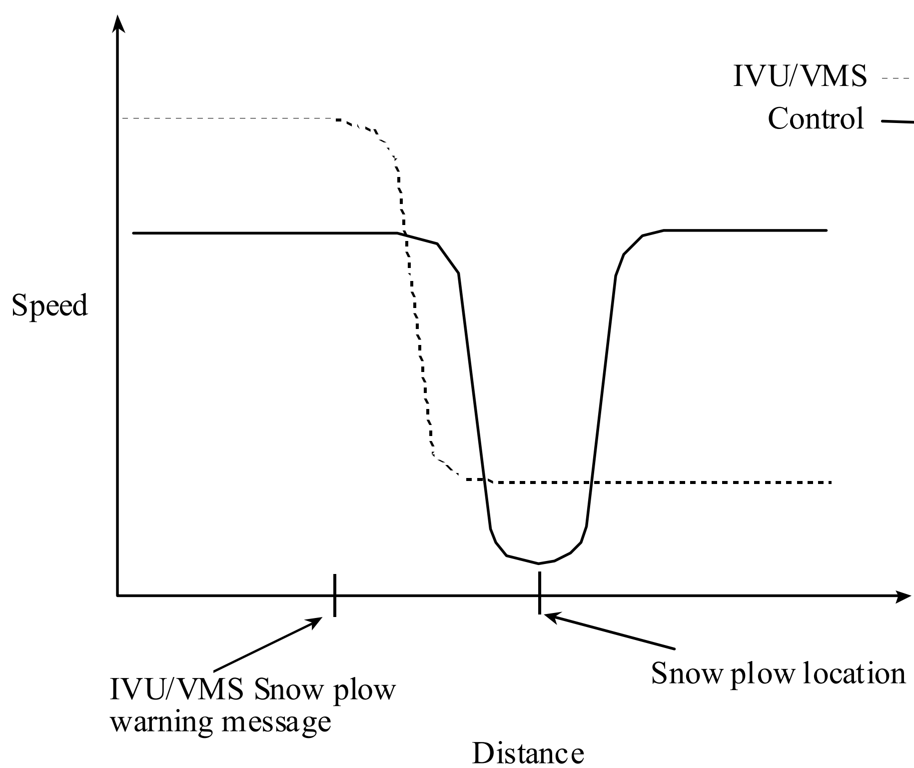

Figure 11.2: Schematic figure showing a scenario were the different speed characteristics of a IVU and/or VMS run and the control run result in lower deviation for the control run.

This has interesting implications for advanced traveler information systems. Erroneous messages can prove to be more dangerous than no message at all. Care must therefore be taken when designing such a system to ensure message correctness. To better understand the effects of VMSs and IVUs on mean speed and deviation it would be interesting to conduct a study in which the messages are not always correct but contain different levels of accuracy from low to high accuracy. This is important because message correctness would probably not be perfect in reality. It would also be interesting to study different types of adverse weather conditions such as rain, snow and ice.

This study also shows that if the traffic stream has vehicles with IVUs and others without any information system the standard deviations and the speed characteristics of the two groups would be different which increases the risk of accidents. If all vehicles have an IVU or see VMSs of some sort and this results in higher mean speeds it is not necessarily bad if the risk for accidents goes down because drivers drive faster in safe areas but slow down in unsafe areas. It would therefore be interesting to perform an analysis to better see the effect of advanced traveler information systems on accident frequency. This should be done for traffic streams with vehicles without information systems, with information systems and mixtures of vehicles with and without systems.

Chapter 12

Traffic advisory systems and driving behavior

12.1 Introduction

This Chapter is separated into five sections. The second section discusses the data analysis approach and the significant findings appear in the third section. A market analysis of the in-vehicle product is prepared for section four and potential applications for the efforts of this study are discussed in section five.

12.2 Data analysis

a) Introduction

The validity of information collected from simulators have previously been questioned due to the existence of "simulator biases" (Morikawa, 1989). To ensure that the quality of the data collected minimizes as many biases as possible, precautions/steps were taken given the list of biases associated with simulation work identified by Koutsopoulos, Polydoropoulou and Ben-Akiva (1995). For example, the technology bias (bias associated with simulator use by people who are more technically oriented) can be reduced if the subject pool is from a diverse driving population (i.e. varying age, income, education, etc.).

The data to be analyzed comes from two major sources: (1) Data collected on a log file from the Silicon Graphics Workstation, and (2) data collected from the surveys (age, gender, income, driving habits, use of Snoqualmie pass, and opinions of the in-vehicle unit).

Analysis of the data is conducted using several statistical software mediums. For the multivariate models, SST (Statistical Software Tool) will be the primary medium, and for the analysis of variance (ANOVA), SAS (Statistical Analysis Software) will be the software choice.

The simulator study provides information on the use of in-vehicle and out of vehicle systems. Thus, several predictor variables will be obtained, and the analysis of these variables will include the use of 3 stage least squares, and analysis of variance. These two analysis technique and how they will relate to the analysis of the simulator data is discussed in the following sections.

b) Three stage least squares estimation

A simultaneous model of equations predicting mean speeds, standard deviations of mean speed, and a one kilometer lag in the two previously mentioned variables was developed. The intent of this model was to observe effects due to mean speeds and the changes in speeds over a one kilometer stretch as it relates to the previous one kilometer stretch. Since these four variables are interrelated, a simultaneous set of equations was estimated using the three stage least squares (3SLS) estimation technique. An estimation of simultaneous equations occurs when endogeneous variables in one equation feed back into variables in another equation. The consequences of these estimation procedures is that the endogeneous variables and the error term are correlated. If we estimate using an ordinary least square, our parameter estimates would be biased and inconsistent.

The structural equation system for mean speeds, standard deviation of the mean speed, the lag in mean speed and the lag in standard deviations in the mean speed is written as a follows:

$$\begin{aligned} u &= \beta_{10} + \beta_{1i}X_{1i} + \beta_{1m}\sigma + \varepsilon_1 \\ \sigma &= \beta_{20} + \beta_{2i}X_{2i} + \beta_{2j}u + \varepsilon_2 \end{aligned} \qquad (12.1)$$

where u is the mean speed for each driver in a 1 kilometer stretch, v is mean speed of the kilometer prior, σ is the standard deviation of the mean speed, and τ is the standard deviation of the kilometer prior. All four variables are interrelated to each other. X_{1i} and is X_{2i} the vector of exogeneous variables (for i=1,2....k variables), β_{10}, and β_{20}, are estimable scalars and, β_{1i} and β_{2i} are estimable vectors. The error terms for each equation is defined as ε_1, and ε_2, and are assumed to be normally distributed with a mean of zero and a constant variance.

The R^2 value is then used to determine the goodness of fit of the equations. The calculations for R^2 is:

$$R^2 = \frac{\left[\sum_i (y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})\right]^2}{\left[\sum_i (y_i - \bar{y})^2\right]\left[\sum_i (\hat{y}_i - \bar{\hat{y}})^2\right]} \qquad (12.2)$$

where y_i is the actual value for the dependent variable, $\bar{y}$ is the mean of the actual values, $\hat{y}$ is the predicted values, and $\bar{\hat{y}}$ is the mean of the predicted values.

The adjusted R^2 is then calculated to compensates for the fact that R^2 will get larger with more variables. This equation is given as:

$$R^2_{adjusted} = 1 - \frac{n-1}{n-k}\left(1 - R^2\right) \tag{12.3}$$

where n is the number of observations in your sample, and k is the number of variables in your equation.

Greene (1993) provides a complete description of this procedure. For this particular analysis, the statistical software package, SST (Statistical Software Tools 2.0) was used.

c) Analysis of variance

Analysis of variance (ANOVA) models can be used for studying relationships between a response variable of a continuous nature (i.e. time, speeds and counts) and one or more independent variables for experimental and observational data. This analysis technique differs from logit estimations because ANOVA, which is based on a general linear model, allows the examination of a quantitative response variables while logit models are more suitable for qualitative responses. The use of ANOVA techniques provides a method to compare multiple means of treatment combinations whose responses are normally and independently distributed. This method has the advantage of testing whether there are any differences among groups (or treatment combinations) with a single probability associated with the test (Cody and Smith, 1994). The hypothesis tested is that all groups have the same mean.

Please note also that several assumptions must be met before conducting an ANOVA (Hicks, 1993). They are as follows:

(1) The process must be in control (i.e. it is repeatable), and there is independence among groups.

(2) The sampling distribution of the sample means must be normally distributed

(3) The variance of the errors within the levels of the treatments is homogeneous.

The basic model for a one-way ANOVA can be written as:

$$Y_{ij} = \mu + \tau_j + \varepsilon_{ij} \tag{12.4}$$

where Y_{ij} is the response or dependent variable, μ is the overall mean for the response variable over populations, τ_j represents the effects of each treatment, and ε_{ij} is the error term. For two or more way ANOVAs, this model can be expanded to represent the effects of each factor, and the existence of blocking, confounding, and repeated measures. Further reading on this subject can be found in Hicks (1993).

In this research work, ANOVAs can be conducted for the data that will be collected from the driving simulator. They include data collected every second on speed changes, lane changes, and braking. The dependent variables used to determine if there are any differences due to using variable message signs and in-vehicle displays will be, for each subject, the mean speed (and standard deviation) over each weather/vehicle stretch.

The model for the experimental design is depicted in Table 5.

Table 12.1: Setup for simulator experiment.

			EXISTENCE OF FOG			
			No Fog		Fog	
			PRESENCE OF VEHICLES			
			Snow Plows	None	Snow Plows	None
SIGNAGE TYPE	In-Vehicle Unit	Subj 1-12				
	Variable Message Signs	Subj 13-24				
	Both	Subj 25-36				
	None	Subj 37-48				

Each of the four weather/incident conditions will be observed by the driver in three mile stretches. Therefore, the participants will drive a total of 12 miles. It was decided, that due to the mechanics of a full-size simulator, participants will not be able to be immersed in the environment longer than 15 minutes before feeling “car sick”. Given that drivers will probably go an average of 50 to 60 miles per hours, a 12 miles stretch should be reasonable for the participants while enabling a feasible amount of data to be collected.

For the sign conditions where variable messages are observed, signs are placed one and a half miles apart for a total of 8 signs. There are four different order of presentations for the four weather/incident conditions (i.e., fog with snow plows, fog with no snow plows, no fog with a snow plow, and no fog with no snowplow) and they are randomly assigned to each participant.

This randomization of order and assignment reduces experimental error due to learning which may occur if the weather/incident conditions were presented in the same order for each sign condition. It also takes into account variations due to different geometric configurations along each stretch. However, a restriction on randomization is present given that data for all weather conditions must be collected for a given subject and sign type before another subject and sign type can be tested.

Since each subject will go through each weather/incident condition, the experimental design is often referred to as a repeated measured design, which is essentially a special case of a nested factorial experiment (Hicks, 1993). Therefore, given the stated conditions, the experiment is set up as a nested factorial whose mathematical model is:

$$\begin{aligned} Y_{ijkl} = \ & \mu + \text{Sign}_i + \text{Subj}_{(i)j} + \delta_{(ij)} \\ & + \text{Weather}_k + \text{Sign} * \text{Weather}_{ik} + \text{Subj} * \text{Weather}_{(i)jk} \\ & + \text{Vehicles}_l + \text{Sign} * \text{Vehicles}_{il} + \text{Subj} * \text{Vehicles}_{(i)jl} \\ & + \text{Weather} * \text{Vehicles}_{kl} + \text{Sign} * \text{Weather} * \text{Vehicles}_{ikl} \\ & + \text{Subj} * \text{Weather} * \text{Vehicles}_{(i)jkl} + \varepsilon_{ijklm} \end{aligned} \qquad (12.5)$$

where:

Y_{ijkl} represents the mean speed and standard deviation for the *j*th subject (where j = 1,...,12) in the *i*th sign type (i = 1,2,3,4) , kth weather condition (k = 1,2), and *l*th vehicle condition (l =1,2),

μ is the overall mean,

Sign_i represents the effects of one of four sign "treatments" that will be used (1. Variable message signs, 2. in-vehicle information, and 3. VMS and IVU information, and 4: No information),

Weather_k represents the effects of one of two fog conditions (Fog or no fog),

Vehicles_l represents the effects of the presence or absence of other vehicles (Snow Plow or no Snow Plow),

$\text{Subj}_{(i)j}$ represents the effects of each subject nested under the sign type. There will be 8 subjects for each sign type.

$\delta_{(ij)}$ represents the restriction error caused by the *j*th subject on the *i*th sign. That is, a restriction on randomization is present since data for all ocurrences of weather and vehicles must be completed for subject *j* on sign *i* before another experiment can be run.

ε represents the within error term which is normally and independently distributed $N(0, \sigma^2)$

The expected mean square calculations for this model are shown in Appendix I.

The experimental error term in this model is not retrievable since the number of observations in each cell is 1 (i.e. m=1). Thus, the random error is confounded in the Subject * Weather * Vehicle interaction, and the tests for significant effects due to Subjects, and any interactions with Subjects cannot be conducted. Likewise the restriction error is confounded with Subjects. The F tests for all other variables will be conducted as follows:

$F_{Sign} = MS_{Sign} / MS_{Subj}$

$F_{Weather} = MS_{Weather} / MS_{Subj*Weather}$

$F_{Sign*Weather} = MS_{Sign*Weather} / MS_{Subj*Weather}$

$F_{Vehicles} = MS_{Vehicles} / MS_{Subj*Vehicles}$

$F_{Sign*Vehicles} = MS_{Sign*Vehicles} / MS_{Subj*Vehicles}$

$F_{Weather*Vehicles} = MS_{Weather*Vehicles} / MS_{Subj*Weather*Vehicles}$

where MS stands for Mean Square and is calculated as Sum or Squares for the variable of interest divided by the degrees of freedom for the variables of interest.

d) Surveys

Two surveys were given to the participants. The first survey asked questions specific to the use of the in-vehicle unit used in the experiment. The development of the questionnaire was done using the Likert scales as defined by the US Army Research Institute for the Behavioral and Social Sciences (1976). This survey is shown in Appendix C. The second questionnaire asked participants to provide information on their usage of the Snoqualmie Pass (Appendix D). This later survey asked questions similar to the survey distributed by Morse (1995). From these surveys, a market analysis can be conducted on the in-vehicle unit that was used in the experiment and an assessment on participants opinions regarding the safety of using the Snoqualmie pass can be conducted.

e) Summary

In this section, a description of the analysis that will be conducted has been presented. In addition to descriptive statistics, there are two types of inferential statistical analysis that will be the primary focus of the study. Multinomial logit estimations will be used to model the discrete variables relating to system usage, and ANOVA techniques will be used to determine if there are significant differences among the sign types. Surveys with additional information on participants' opinions of using the Trafficmaster in-vehicle unit and their usage of the Snoqualmie pass was also collected. The results of the data analysis is presented in the next section.

12.3 Results

a) Introduction

This section presents the results of the analysis conducted on the data collected from the laboratory study. It is separated into two major sections plus the section summary. The first section will present the findings from the analysis of variance and the second section will describe the mathematical model estimated.

b) ANOVA results

Performance on the sign conditions was analyzed by means of a nested factorial model ANOVA. This model was described in the previous section. The four dependent variables used with this model was: average speed in each road/weather stretch consisting of three miles or 4828 m, standard deviation, minimum speed and maximum speed.

i) Mean Speeds

There were no significant differences in the average speeds driven by subjects regardless of whether they were provided additional information on an in-vehicle unit, variable message sign, both or none ($F(3,47)$[1]$=1.77$, $p>0.05$). There were, however, significant differences in the average speed when encountering fog ($F(1,47)=46.87$, $p<0.01$), snowplows ($F(1,47)=61.75$, $p<0.01$), and for the two-way interaction between fog and snowplows ($F(1,47)=7.03$, $p<0.05$). As shown in Figure 12.1, the mean speeds were higher on clear days than when fog and snowplows were present.

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[1] Results of F-tests are reported as F(*df1*, *df2*)=F value where *df1* is the degrees of freedom associated with the treatment being tested, and *df2* is the degrees of freedom for the error term used. The F Value is calculated using the standard F test calculations discussed in the previous chapter.

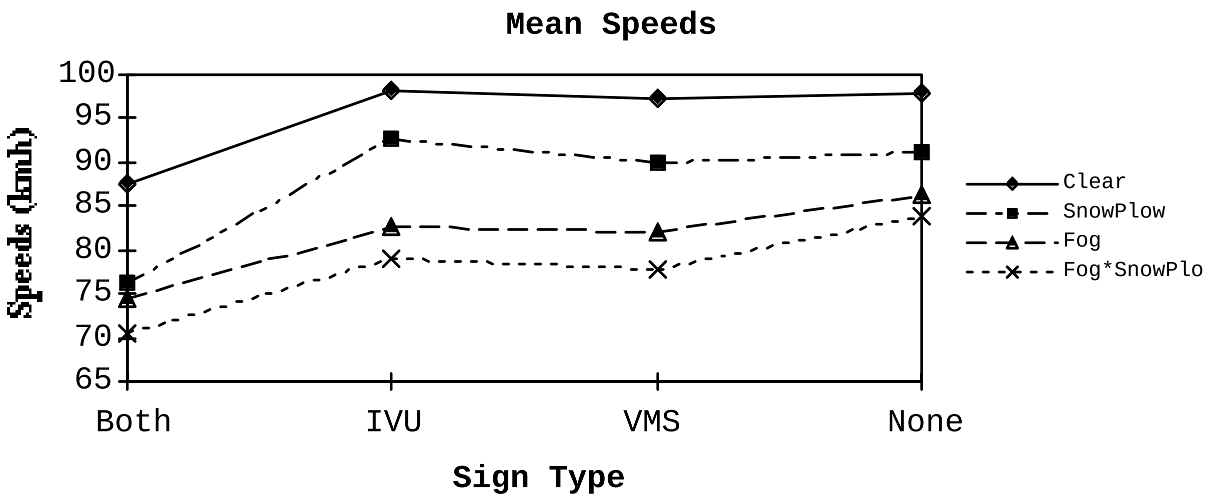

Figure 12.1: Mean speeds driven for the four different weather / road conditions.

ii) Standard deviations of Mean Speeds

In terms of the variation among speeds (standard deviation), there was also no significant differences found among the four sign conditions (F(3,47)=0.49, p>0.05). There were differences observed for snow conditions (F(1,47)=57.61, p<0.01), and the two-way interactions between snow and fog (F(1,47)=8.61, p<0.01).

iii) Minimum Speeds

For minimum speeds driven by subjects, there were also no significant differences found among the four sign conditions (F(3,47)=1.01, p>0.05). There were differences observed in minimum speeds for foggy conditions (F(1,47)=9.35, p<0.01), and given the presence of snowplows (F(1,47)=36.63, p<0.01). However, there were no significant differences in any of the two or three-way interactions.

iv) Maximum Speeds

For maximum speeds attained by drivers, there were differences found among the sign conditions (F(3,47)=2.41, p<0.10). The Duncans Multiple Range Test indicated that drivers under the "no sign" condition were more willing to go at higher speeds than drivers who viewed "both ivu and vms". There were also differences observed between the maximum speeds attained under a "fog" condition and a "no fog" condition (F(1, 47)=32.70, p<0.01).

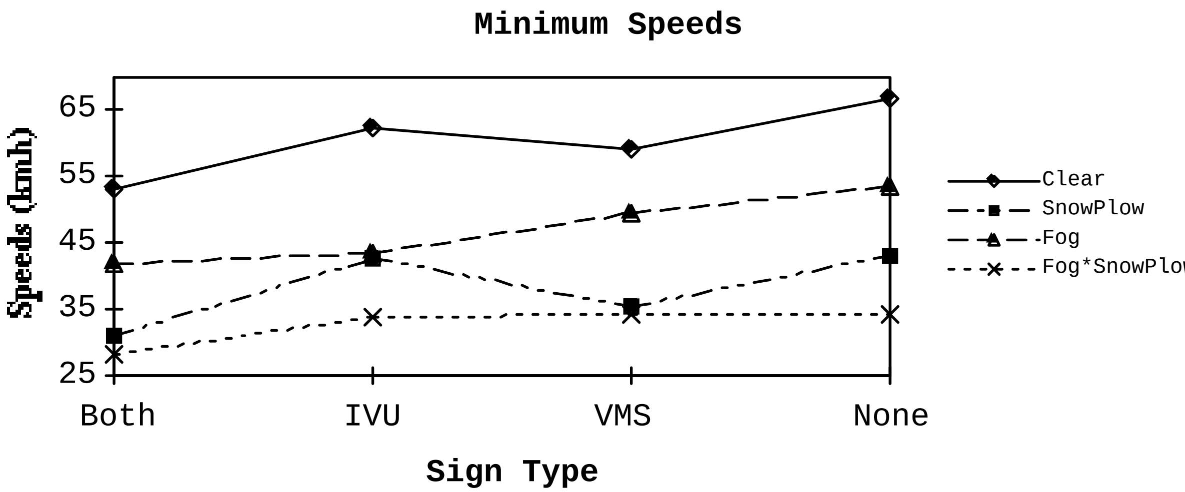

Figure 12.2: Minimum speeds driven for the four different weather / road conditions.

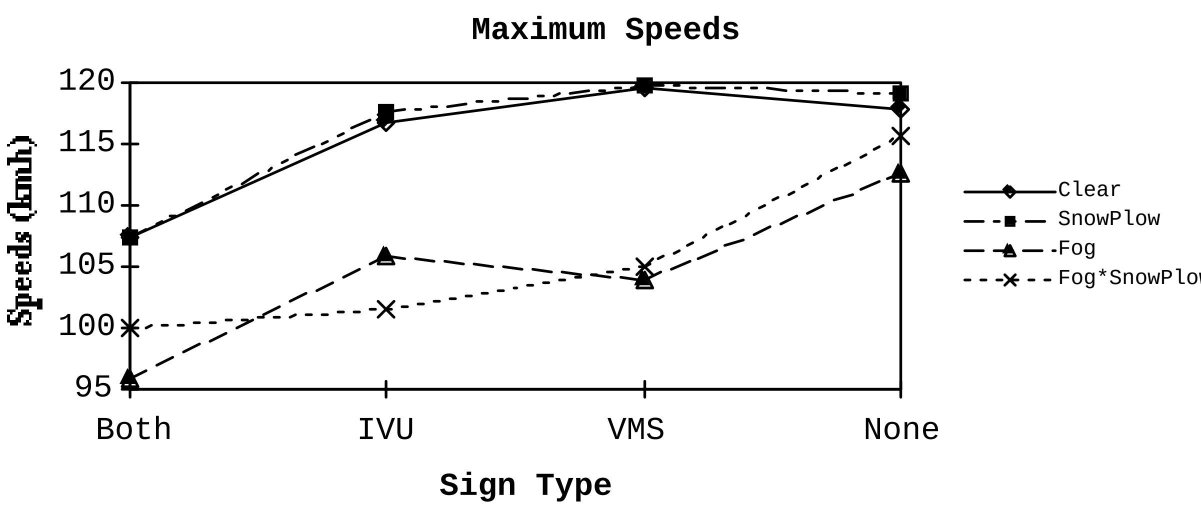

Figure 12.3: Maximum speeds driven for the four different weather / road conditions.

12.4 Market analysis

a) Introduction

A major application of this study is the marketability of the in-vehicle product being used in this study. A great deal of ITS research is currently being done in the public sector due to the cost of research and development. In order to make a smooth transition to the private sector, a business or organization needs to be assured that some profit can be generated from the sale of the product and/or service. As stated earlier, this particular product, the Trafficmaster, is currently being used in England and operated by a private firm. However, many changes had to be made to ensure a profit. The unit used in this study was one of the first designs and has several observed concerns which are discussed in this section.

b) The display

The unit operates with a liquid crystal display (LCD) that is difficult to read if the screen is not tilted toward the driver. This can create problems that will be discussed later. The system that was tested also had a hardcoded map that does not move, but a person can zoom in on a particular quadrant. It does not provide information to the driver on where he or she is at in respect to the road. There are also no color coded information for easing viewing.

c) The subjects response to system

However, many insights can be obtained from observing the drivers use of the system, their comments and their survey information. People who used the Trafficmaster during experimentation were not more inclined to want to use the system when compared to those who did not use it during experimentation (χ^2=0.41). As shown in Figure 12.4, the number of people who said "yes" they would use the IVU did not differ much between the two experimental groups (IVU versus no IVU). This indicates that the drivers preference for this system was not improved with prolonged usage. However, when participants were asked what their overall opinions of the system was, they believed it to be reasonably good (Figure 12.5). Further, they believed the screen appearance to also be reasonably good (Figure 12.6).

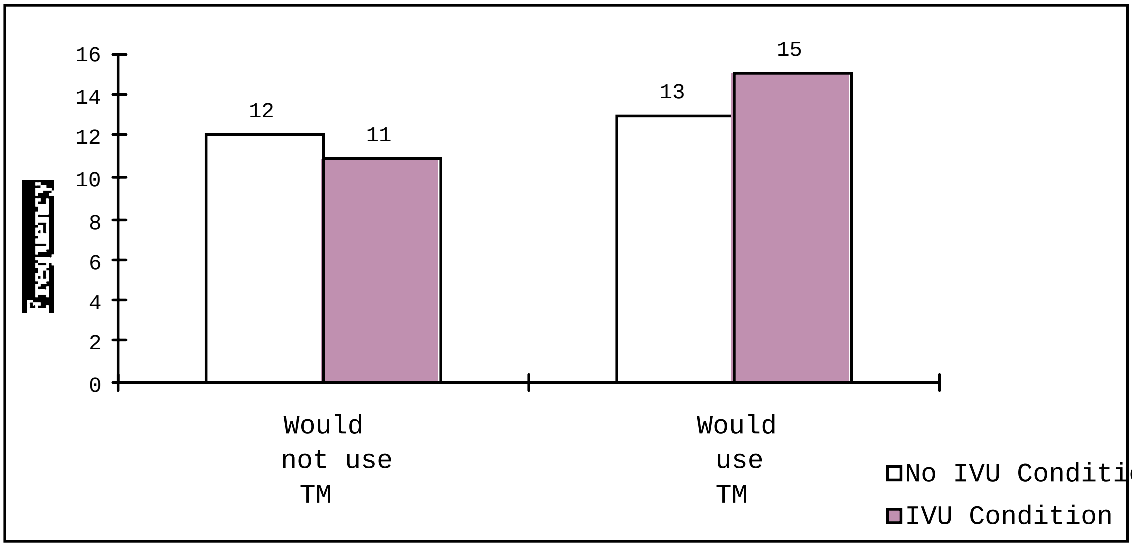

Figure 12.4: Comparison of subjects responses to preference for Trafficmaster under IVU and no IVU experimental condition.

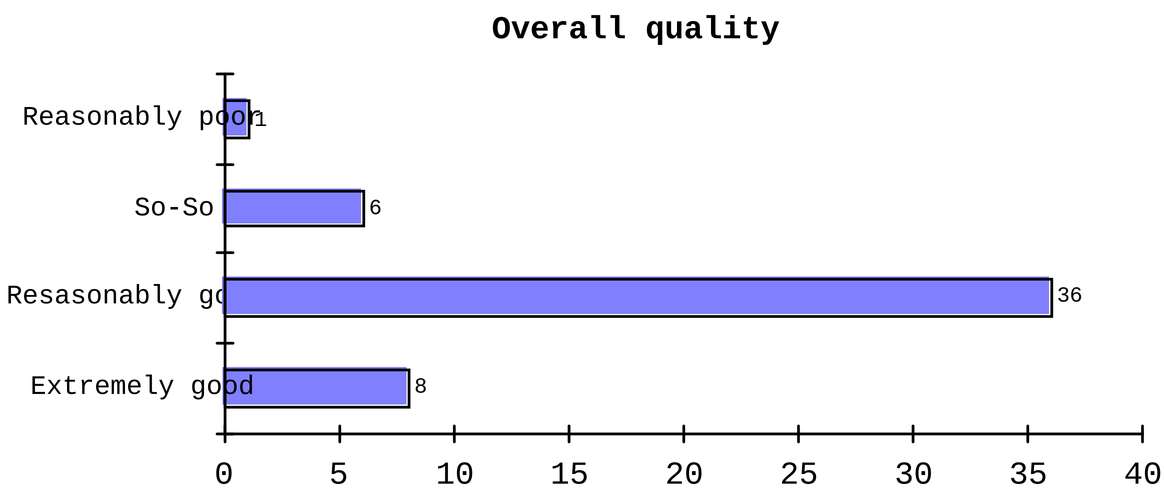

Figure 12.5: Frequency of response to overall quality of Trafficmaster.

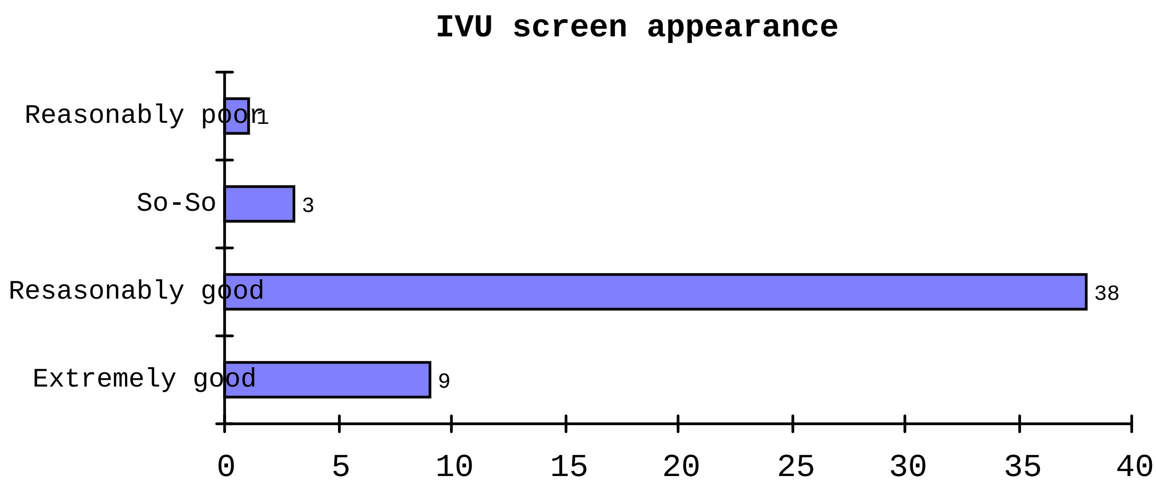

Figure 12.6: Frequency of response to Trafficmaster screen appearance.

Many participants noted that the beep was a very useful element but also commented that they found it annoying after a while. For this study, the in-vehicle unit was placed on top of the car's dashboard, toward the center of the dash. Many people felt that was too far away to view while driving.

12.5 Applications and further research

a) Introduction

This section discusses the significance of the research to be conducted and how it can be applied to other research areas. In essence, this research will provide a contribution to the ITS field by furthering the analysis on the usefulness and application of in-vehicle systems. It will provide a procedure for an alternative data collection method, using a full-scale driving simulator. In addition, this study will provide insight in how drivers will react to various road information, presented through different mediums, on a mountain pass.

DRIVE (1992) has identified three level of safety problems associated with the introductions of advanced and communication technologies in vehicles, (1) traffic safety, (2) system safety, and (3) the man-machine interface design and system usability. In this research, all three safety issues will be addressed and analyzed. These issues are very important to the design and deployment of in-vehicle systems because lack of consideration can cause less effective driving behaviors. Therefore, understanding how drivers will react to these various systems is essential for its success. If drivers do not react accordingly, the system has failed and further implementation should cease. However, since past research has shown that there is a willingness to comply with these systems (Vaughn et al., 1992; Ng et al., 1995), then further research should be conducted to ensure that we have the best system possible.

This research also relates the information from stated preference data (collected for hypothetical situations) with revealed preference data (how the driver will react in an actual situation). One may argue that information collected from a driving simulator is still considered stated preference (Koutsopoulos et al., 1995) because the drivers are still not on a real road, but hypothetical ones. However, if the simulated configurations are designed to emulate a true real-world setting, data collected can be very significant.

Overall, the potential application in regards to this data is to predict revealed preference to using in-vehicle and out of vehicle information. Stated preference information has already been collected in terms of whether or not they will use this system on Snoqualmie pass, and how willing are they to obey the information provided.

Part V

Post VMS installation research

This Part contains research that has been performed after the installation of the VMS signs on I-90 at Snoqualmie Pass. Chapter 13 contains a paper in preparation that studies the effect of variable message signs (VMS) on the relationship between hourly cross-sectional mean speeds and speed deviations on I-90 at Snoqualmie Pass, WA (Ulfarsson, Shankar and Vu, 2001).

Chapter 13

The effect of variable message signs on the relationship between mean speeds and speed deviations

13.1 Introduction

Intelligent transportation systems (ITS) use technology to affect or control the transportation network. Variable message signs (VMS) use dynamic information to improve transportation network efficiency and safety. Typically VMSs are used to give information about the road ahead, e.g. road condition, congestion, incidents, weather etc.

Various studies have been made to analyze different aspects of VMS usage and effectiveness. Drivers have been found to reduce speeds when VMSs have warned about slippery road conditions ahead and drivers increased their headways upon seeing VMSs with minimum headway warnings (Raemae and Kulmala 2000). The effect on speed in their study was small and had decreased one year later. Luoma et al. (2000) surveyed drivers who had viewed the signs in Raemae and Kulmala's (2000) study, and found that the drivers reported refocusing attention on the road and reported testing the road for slipperiness. Drivers also stated they used more caution during passing maneuvers (Luoma et al. 2000).

Driver's stated response to VMSs has been used to incorporate simulated driver response into a traffic assignment model to aid the forecasting of the effect of VMSs on transportation networks (Hounsell et al. 1998; Chatterjee and Hounsell 1999). Stated responses have also been used to assess the effect of VMSs on route choice, suggesting route choice can be strongly influenced (Wardman et al. 1997).

VMSs have been used to affect driver route choice, as a part of efforts to increase transportation network efficiency and reduce congestion. The VMSs use information from various sources such as traffic sensors and incident response teams to display appropriate messages. The impact on driver route choice behavior has been studied and shows that good driver compliance cannot necessarily be assumed (Emmerink 1996; Bonsall and Palmer 1999). VMSs have been found to decrease total congestion and increase travel time reliability by reducing the variance of travel times and congestion by significantly affecting route choice (Kraan et al. 1999). The greater the congestion the more likely drivers are to follow VMS directions to alternative routes (Yim and Ygnace 1994). Female drivers and commuters have been found to be less likely to change to alternative routes because of VMSs, and males are most willing to pay for in-vehicle traffic information (Emmerink et al. 1996).

VMSs that receive information from loop detectors that calculate vehicle speed and length have been used to improve safety at an accident-prone location (McManus 1997). VMSs have been found to be able to reduce the number of injury accidents at an interchange between two freeways (Swann et al. 1995).

This research analyses the relationship between cross-sectional mean speed and speed deviation in a rural area where VMSs have been installed by using a simultaneous equations approach. The relationships are examined both at a VMS site and at a site close by but outside the influence of the VMSs for comparison.

13.2 Empirical setting

Variable message signs (VMS) have been installed on Interstate 90 (I-90) in the Snoqualmie Pass through the Cascade mountain range, some 50 km east of Seattle. This is a rural location, with high elevations (roughly 1 km about sea level), and significant precipitation (averaging 216 cm of rainfall and 1140 cm of snowfall annually). is on a 1.5% upgrade, while the westbound alignment is on a 2.5% downgrade. I-90 is a three-lane divided freeway in both directions at this location. The eastbound alignment This section of I-90 has high lane-speed deviations affected by roadway geometrics, seasonal changes in weather, and the percentage of trucks in the flow. The frequency and severity of accidents on this section of I-90 are significantly affected by the speed deviations, as examined by Shankar, Mannering and Barfield (1995, 1996). Lane-mean speeds and lane speed deviations on this section, before the installation of the VMSs, were analyzed by Shankar and Mannering (1998). This section of I-90, going eastbound, has been modeled in a driving simulator. The responses of drivers to VMSs and information from in-vehicle units in the driving simulator were studied by Ulfarsson (1997), Boyle (1998), Ng and Mannering (2001). The drivers did slow down upon seeing VMSs that posted reduced speed but they drove faster than drivers with no information upon seeing VMSs that posted the normal speed limit with a positive message about the road conditions (Ulfarsson, 1997). The messages that have been implemented at Snoqualmie Pass on I-90 are used to report reduced speed conditions under adverse conditions.

Dual magnetic loop detectors were used to collect data from late August 1997 until April 1998. Speed data were aggregated over one hour (time mean speed) and grouped into bins of 10 mph. The relationship between mean speed and speed deviation is not likely to be different if the speed data were aggregated over shorter time periods. The observed vehicles were classified into four classes based on wheelbase lengths, up to 25 ft, 26 to 39 ft, 40 to 64 ft, and 65 to 114 ft. We group the upper two categories together and refer to it as heavy trucks. The data, speed and vehicle counts by class are cross-sectional in each direction, i.e. information is summed for the three eastbound lanes and separately for the three westbound lanes. The date and time of each observation was also recorded.

Data was collected from two different locations on I-90. The main location is within the influence of the VMSs (VMS site, around milepost 53), and the secondary location is further west (non-VMS site, around milepost 47), downhill towards Seattle and is outside the area covered by the VMSs. The VMSs are not always in use at the VMS site so their status, on/off, was collected for the duration of the data collection. The data from the VMS site will be compared with the results from the non-VMS site. Vehicles traveling westbound will first reach the VMS site and if the VMSs are in use the speeds and deviations will be under their influence, while the non-VMS site is more than 3 km west of the last VMS. This gives the opportunity to test whether the effect of the VMSs lasts outside the immediate area where they are located.

Table 1 shows the aggregate results for the duration of the study period for mean speed and speed deviation, grouped by VMS on/off status, at the VMS site and the non-VMS site.

13.3 Modeling approach

This research analyzes the effect of variable message signs (VMSs) on cross-sectional mean speeds and speed deviations, measured over one hour. The overall flow of the modeling and estimation is shown in Fig. 1.

Lane mean speeds and speed deviations at this location, before the installation of the VMSs, were modeled by Shankar and Mannering (1997). They had data for each of the three lanes of the freeway while we have lane totals, i.e. information for total volume in all three lanes of the roadway. Shankar and Mannering (1997) showed that mean speed in a lane is dependent on the mean speed in adjacent lanes, and similarly that deviation in a lane was dependent on the deviation in adjacent lanes. These effects are unobserved in this research since we do not have lane dependent information. Shankar and Mannering (1997) also show that the mean speed and deviation are inter-linked as well, speed deviations depend on mean speed. The mean speeds and deviations, both eastbound and westbound, are also contemporaneously correlated because they share unobservable effects.

To account for the endogeneity of cross-sectional mean speeds and speed deviations in each other equations, and for the contemporaneous correlation across equations, the equations are modeled simultaneously as a system. The appropriate method is the three stage least squares (3SLS) method, described by Greene (2000). It uses information from the whole equation system to achieve asymptotically more efficient estimates than limited information approaches, such as equation-by-equation two stage least squares. Equation by equation ordinary least squares (OLS) estimation will be biased due to the simultaneous equations bias (Greene 2000).

We estimate cross-sectional mean speed and deviation eastbound, and westbound in one equation system. The mean speed and deviation eastbound are endogenously dependent on each other, similar for westbound; while eastbound mean speed and deviation are contemporaneously correlated with westbound values. The equation system (structural) describing the mean speed and deviation becomes,

$$\begin{aligned}
s_e &= \alpha_{se} + \beta_{se}X_{se} + \gamma_{se}d_e + \lambda_{se}Z_{se} + \varepsilon_{se},\\
d_e &= \alpha_{de} + \beta_{de}X_{de} + \gamma_{de}s_e + \lambda_{de}Z_{de} + \varepsilon_{de},\\
s_w &= \alpha_{sw} + \beta_{sw}X_{sw} + \gamma_{sw}d_w + \lambda_{sw}Z_{sw} + \varepsilon_{sw},\\
d_w &= \alpha_{dw} + \beta_{dw}X_{dw} + \gamma_{dw}s_w + \lambda_{dw}Z_{dw} + \varepsilon_{dw},
\end{aligned} \tag{13.1}$$

where s and d are the cross-sectional mean speed and deviation respectively, the subscripts e and w stand for eastbound and westbound; X are vectors of exogenous explanatory variables, Z are vectors of endogenous explanatory variables; $\alpha, \beta, \gamma, \lambda,$ are estimable structural coefficients; and ε are disturbance terms. Each term is indexed by direction and dependent variable.

The exogenous variables are, seasonal indicators, day of week indicators, and time of day indicators. The endogenous variables are traffic flow variables, such as high/low flow indicators and percentage of heavy trucks (trucks with wheelbase 40 ft and longer) in the traffic flow. These are endogenous because traffic flow is likely to depend on the mean speed and/or speed deviation. To handle this endogeneity, these variables are instrumented separately by regressing them on the exogenous variables with OLS. The predicted value from those regressions where then used as instrumental variables in the 3SLS regression. The VMS on/off indicator variable is endogenous to mean speed and speed deviation because the VMSs are turned on during adverse conditions but not during normal flow. This means the VMSs are more likely to be active when road conditions have lead to slower speeds. To account for this we use a logit model to estimate the probability of the VMSs being on as a function of the exogenous variables. We use the predicted probability as an instrument to replace the actual VMS on/off indicator.

When applying a simultaneous equation model to predict results, e.g. in a simulation, we need to break the simultaneity so that we may calculate a predicted mean speed and speed deviation, as the calculation of one needs the prediction of the other. This can be resolved easily by inserting the equation for speed deviation into the speed deviation variable in the mean speed equation and vice versa to arrive at the reduced form model. It has the two equations independent of each other and is of the form:

$$\begin{aligned} s &= \pi_{\alpha s} + \pi_{\beta s} X_s + \pi_{\lambda s} Z_s + \eta_s, \\ d &= \pi_{\alpha d} + \pi_{\beta d} X_d + \pi_{\lambda d} Z_d + \eta_d, \end{aligned} \tag{13.2}$$

where s and d are the cross-sectional mean speed and speed deviation respectively; the subscripted s and d refer to the mean speed and speed deviation equations; X are vectors of the exogenous variables in (13.1), Z are vectors of the endogenous variables in (13.1) that are instrumented before being included in either (13.1) or (13.2); π are the reduced form coefficients; and η are disturbance terms. The reduced form model is of the same form for eastbound and westbound but the coefficient values will be different. The reduced form coefficients are related to the structural coefficients through the equations shown here for the eastbound direction:

$$\begin{aligned} \pi_{\alpha se} &= \frac{\alpha_{se} + \gamma_{se}\alpha_{de}}{1 - \gamma_{se}\gamma_{de}}, & \pi_{\beta se} &= \frac{\beta_{se} + \gamma_{se}\beta_{de}}{1 - \gamma_{se}\gamma_{de}}, \\ \eta_{se} &= \frac{\varepsilon_{se} + \gamma_{se}\varepsilon_{de}}{1 - \gamma_{se}\gamma_{de}}, & \pi_{\lambda se} &= \frac{\lambda_{se} + \gamma_{se}\lambda_{de}}{1 - \gamma_{se}\gamma_{de}}, \end{aligned} \tag{13.3}$$

and we have a similar set of relationships for the westbound direction. The reduced form coefficients can be estimated directly from (13.2) via OLS but that does not give efficient estimates, so we prefer to calculate the reduced form coefficients using (13.3). It is important to consider the reduced form coefficients along with the structural coefficients from the 3SLS estimation of (13.1). If we examine the structural estimation only it is hard to see the full effect of a variable because it enters both directly and through the simultaneously determined endogenous variable, as can be seen in the formulas for the reduced form coefficients (13.3). The sign on a reduced form coefficient can even be of the opposite sign. This ‘multiplier’ effect is easily overlooked in (13.1).

To examine the effect of the VMSs outside of the VMS influence zone, we consider a non-VMS site west of the VMS site. The non-VMS site is about 10 km west of the VMS site, downhill towards Seattle. We seek to compare the estimated equations for the westbound direction at the VMS site to estimated westbound equations at the non-VMS site. To perform such a comparison, the westbound equations at both sides must be of the same form. We use the instrumented VMS on/off probability from the VMS site in the equations for the non-VMS site to see if it is has a significant effect on the mean speed and speed deviation at the non-VMS site. For the purpose of this comparison we use only time periods from which we have observations at both sites. This reduces the number of available observations slightly.

We perform two tests across sites. We first test for transferability of the 3SLS estimated coefficients for the westbound direction at the VMS site to the non-VMS site. We first estimate an unrestricted model of the westbound mean speed and speed deviation at the non-VMS site using 3SLS and calculate the unrestricted (U) total sum of squared residuals (TSSR) for the system. We then restrict the westbound coefficients at the non-VMS site to the corresponding VMS values and calculate the restricted (R) TSSR. We then compare the unrestricted and restricted TSSRs by using the F-test:

$$F_{\text{calc}}(J, N-K) = \frac{(TSSR_R - TSSR_U)/J}{TSSR_U/(N-K)}, \qquad (13.4)$$

where J is the number of restrictions, N is the number of observations, K is the number of parameters in the unrestricted model. Here $J = K$ because we restrict all coefficients in the restricted model to the VMS values. For a description of the F-test see for example Greene (2000).

The second test we perform is the transferability of the reduced form coefficients that are calculated from the 3SLS estimates with (13.3). We calculate the unrestricted sum of squared residuals (SSR) by applying the computed reduced form for the non-VMS site to the non-VMS site data. Then we calculate the restricted SSR by applying the computed reduced form for the VMS site to the non-VMS site data. We do this separately for the mean speed and speed deviation equations. We use (13.4) to calculate the F-statistic, but replace the TSSR with the equation specific SSR.

13.4 Results

The observed data was categorized by VMS on/off status, east/west direction, and site. The average and standard deviation of observed hourly mean speeds and speed deviations are shown in Table 1. Table 1 also includes a t-statistic for the test of significant differences between the averages for VMS on and VMS off. All the t-statistics significantly reject the hypothesis of no difference. The significant difference between the averages for the eastbound direction at the non-VMS site cannot be attributed to the use of the VMS. Recall that the non-VMS site is west of the VMS site so any difference between VMS on/off values for the eastbound direction at the non-VMS site is caused by other factors than the VMSs since drivers haven't even seen the first VMS yet. This difference can be explained because the VMS are only activated when conditions warrant, i.e. are in some sense adverse. We therefore expect mean speeds to be lower and speed deviations to be higher when the VMSs are on because of the conditions. For the VMS site and the non-VMS site westbound direction, the total reduction in mean speed and increase in speed deviation cannot therefore be fully attributed to the VMSs. This is exactly the endogeneity between VMS usage and flow that we dealt with by instrumenting the VMS indicator variable by replacing it in the models with the logit model predicted probability of the VMSs being on.

Table 13.1 shows that the reduction in mean speed and increase in speed deviation is significantly greater at the VMS site, and than the non-VMS site indicating that the effect of the VMSs is to reduce mean speed and increase speed deviation, but the effect is localized around the area of the VMS site, as the difference at the non-VMS site westbound is not nearly as significant. The aggregate results shown in Table 13.1 suggest that we should expect a negative sign on the VMS instrument in the mean speed equation, and a positive sign in the speed deviation equation, and that the VMS instrument be significant at the VMS site but possibly insignificant at the non-VMS site.

Table 13.1: Average mean speeds and speed deviations in km/h during the study period at the VMS and non-VMS sites in both directions. Standard deviation of the sample is in parentheses. The t-statistic is for the hypothesis of equal averages between the VMS on and off conditions.

	VMS Site			Non-VMS Site		
Eastbound						
	Number of observ.	Average (St. dev.)	t statistic	Number of observ.	Average (St. dev.)	t statistic
Mean speed						
VMS on	2,681	100.388 (15.014)	-46.688	2,464	119.578 (9.712)	-10.785
VMS off	2,196	118.516 (12.100)		904	122.376 (5.123)	
Speed deviation						
VMS on	2,681	16.727 (4.596)	36.432	2,459	11.254 (2.054)	4.431
VMS off	2,196	11.765 (4.840)		904	10.972 (1.457)	
Westbound						
	Number of observ.	Average (St. dev.)	t statistic	Number of observ.	Average (St. dev.)	t statistic
Mean speed						
VMS on	3,215	117.245 (11.070)	-12.732	2,346	121.398 (9.030)	-6.992
VMS off	1,744	120.925 (8.901)		1,023	123.442 (7.202)	
Speed deviation						
VMS on	3,215	12.684 (3.243)	8.297	2,345	10.860 (1.769)	3.410
VMS off	1,744	11.907 (3.096)		1,023	10.666 (1.387)	

The four-equation system in (13.1) is estimated with 3SLS for the VMS site and the results for each equation in turn are presented in Tables 13.2–5, with the corresponding reduced form coefficients calculated from (13.3). The estimated equation system in Tables 13.2–5 has a system R^2 = 0.76335. The two westbound equations in (13.1) are estimated with 3SLS for the non-VMS site to study the effect and significance of the VMSs outside the immediate VMS site. The estimation results along with calculated reduced form coefficients are presented in Tables 13.6–7; this system has a system R^2 = 0.65172.

Table 13.2: Cross-sectional eastbound mean speed equation at the VMS site, 3SLS estimates and computed reduced form coefficients.

Variable	3SLS estimated coefficient	Standard error	t - statistic	Reduced form coefficient
Constant	168.640	2.852	59.136	116.938
Speed deviation	-2.982	0.148	-20.096	
Variable message sign	-20.990	0.877	-23.922	-18.022
[*Percentage of heavy trucks*]				-18.192
Flow more than 400 vph indicator	-3.245	0.490	-6.617	1.106
Weekend indicator	-0.654	0.284	-2.307	0.379
Autumn indicator (Sept., Oct., Nov.)	-8.345	1.166	-7.160	12.319
Spring indicator (March, April, May)	9.763	0.425	22.974	6.050
PM peak indicator (4:01 – 6:59 PM)	4.926	0.615	8.014	-0.205
Evening/night indicator (7:01 PM – 5:59 AM)	-1.977	0.250	-7.916	-4.861

R^2	0.779
Corr. R^2	0.779
Sum of squared residuals	273,062
Std. error of the regression	7.621
Mean of dependent variable	109.056
Number of observations	4,711

Indicator variables are 1 if the condition given by their name holds, 0 otherwise.
Variables in *italics* are instrumented because of possible endogeneity.
Variables in **bold** are dependent variables in another equation in the system.
Variables in [brackets] enter the equation in the reduced form only.

Table 13.3: Cross-sectional eastbound speed deviation equation at the VMS site, 3SLS estimates and computed reduced form coefficients

Variable	3SLS estimated coefficient	Standard error	t - statistic	Reduced form coefficient
Constant	40.606	2.385	17.027	17.337
Mean speed	-0.199	0.020	-10.074	
Variable message sign	-4.581	0.466	-9.831	-0.995
Percentage of heavy trucks	2.481	0.985	2.518	6.100
Flow more than 400 vph indicator	-1.239	0.159	-7.791	-1.459
Weekend indicator	-0.271	0.133	-2.041	-0.347
Autumn indicator (Sept., Oct., Nov.)	-4.478	0.328	-13.652	-6.930
Spring indicator (March, April, May)	2.449	0.187	13.076	1.245
PM peak indicator (4:01 – 6:59 PM)	1.680	0.207	8.128	1.721
[Evening/night indicator (7:01 PM – 5:59 AM)]				0.967

R^2	0.752
Corr. R^2	0.752
Sum of squared residuals	32,889
Std. error of the regression	2.645
Mean of dependent variable	14.396
Number of observations	4,711

Indicator variables are 1 if the condition given by their name holds, 0 otherwise.
Variables in *italics* are instrumented because of possible endogeneity.
Variables in **bold** are dependent variables in another equation in the system.
Variables in [brackets] enter the equation in the reduced form only.

Table 13.4: Cross-sectional westbound mean speed equation at the VMS site, 3SLS estimates and computed reduced form coefficients

Variable	3SLS estimated coefficient	Standard error	t - statistic	Reduced form coefficient
Constant	170.329	1.626	104.786	142.013
Speed deviation	-2.529	0.112	-22.646	
Variable message sign	-26.339	1.707	-15.430	-32.370
[*Percentage of heavy trucks*]				-13.761
[*Flow* less than 100 vph indicator]				1.006
Autumn indicator (Sept., Oct., Nov.)	-4.380	0.509	-8.609	4.305
Spring indicator (March, April, May)	3.446	0.253	13.595	3.974
[AM peak indicator (6:01 – 9:59 AM)]				-0.955
Evening/night indicator (7:01 PM – 5:59 AM)	-2.166	0.186	-11.625	-4.296

R^2	0.724
Corr. R^2	0.724
Sum of squared residuals	121,739
Std. error of the regression	5.087
Mean of dependent variable	119.231
Number of observations	4,711

Indicator variables are 1 if the condition given by their name holds, 0 otherwise.
Variables in *italics* are instrumented because of possible endogeneity.
Variables in **bold** are dependent variables in another equation in the system.
Variables in [brackets] enter the equation in the reduced form only.

Table 13.5: Cross-sectional westbound speed deviation equation at the VMS site, 3SLS estimates and computed reduced form coefficients

Variable	3SLS estimated coefficient	Standard error	t - statistic	Reduced form coefficient
Constant	39.039	1.667	23.413	11.197
Mean speed	-0.196	0.012	-16.815	
Variable message sign	-3.961	0.608	-6.520	2.385
Percentage of heavy trucks	2.744	0.353	7.780	5.442
Flow less than 100 vph indicator	-0.201	0.077	-2.607	-0.398
Autumn indicator (Sept., Oct., Nov.)	-2.590	0.133	-19.483	-3.434
Spring indicator (March, April, May)	0.570	0.090	6.303	-0.209
AM peak indicator (6:01 – 9:59 AM)	0.190	0.058	3.299	0.378
[Evening/night indicator (7:01 PM – 5:59 AM)]				0.842

R^2	0.751
Corr. R^2	0.751
Sum of squared residuals	11,712.7
Std. error of the regression	1.578
Mean of dependent variable	12.260
Number of observations	4,711

Indicator variables are 1 if the condition given by their name holds, 0 otherwise.
Variables in *italics* are instrumented because of possible endogeneity.
Variables in **bold** are dependent variables in another equation in the system.
Variables in [brackets] enter the equation in the reduced form only.

Table 13.6: Cross-sectional westbound mean speed equation at the non-VMS site, 3SLS estimates and computed reduced form coefficients

Variable	3SLS estimated coefficient	Standard error	t - statistic	Reduced form coefficient
Constant	171.650	5.951	28.843	112.258
Speed deviation	-3.753	0.172	-21.801	
Variable message sign	-11.496	8.464	-1.358	17.650
[*Percentage of heavy trucks*]				-14.143
[*Flow* less than 100 vph indicator]				1.130
Autumn indicator (Sept., Oct., Nov.)	-0.731	2.181	-0.335	7.255
Spring indicator (March, April, May)	0.629	0.301	2.093	2.856
[AM peak indicator (6:01 – 9:59 AM)]				-0.356
Evening/night indicator (7:01 PM – 5:59 AM)	-0.970	0.206	-4.712	-3.361

R^2	0.652
Corr. R^2	0.651
Sum of squared residuals	29,597.3
Std. error of the regression	3.067
Mean of dependent variable	123.366
Number of observations	3,152

Indicator variables are 1 if the condition given by their name holds, 0 otherwise.
Variables in *italics* are instrumented because of possible endogeneity.
Variables in **bold** are dependent variables in another equation in the system.
Variables in [brackets] enter the equation in the reduced form only.

Table 13.7: Cross-sectional westbound speed deviation equation at the non-VMS site, 3SLS estimates and computed reduced form coefficients

Variable	3SLS estimated coefficient	Standard error	t - statistic	Reduced form coefficient
Constant	37.107	1.903	19.504	15.827
Mean speed	-0.190	0.009	-21.120	
Variable message sign	-4.421	2.620	-1.688	-7.767
Percentage of heavy trucks	1.088	0.257	4.229	3.769
Flow less than 100 vph indicator	-0.087	0.044	-1.964	-0.301
Autumn indicator (Sept., Oct., Nov.)	-0.753	0.690	-1.092	-2.128
Spring indicator (March, April, May)	-0.052	0.108	-0.480	-0.593
AM peak indicator (6:01 – 9:59 AM)	0.027	0.038	0.729	0.095
[Evening/night indicator (7:01 PM – 5:59 AM)]				0.637
R^2	0.649			
Corr. R^2	0.648			
Sum of squared residuals	1,712.53			
Std. error of the regression	0.738			
Mean of dependent variable	10.563			
Number of observations	3,152			

Indicator variables are 1 if the condition given by their name holds, 0 otherwise.
Variables in *italics* are instrumented because of possible endogeneity.
Variables in **bold** are dependent variables in another equation in the system.
Variables in [brackets] enter the equation in the reduced form only.

Tables 13.2–5 show that mean speed and speed deviation are significant in each other equations, with higher mean speed reducing speed deviation, and higher speed deviation reducing mean speed. This relationship between mean speed and speed deviation has, for example, been observed in a driving simulator study by Ulfarsson (1997). The instrumented

VMS variable is significant in all four equations, but with a negative sign in all of them. Contradicting the aggregate results in Table 13.1, which show that speed deviation is higher when VMSs are on. The computed reduced form coefficients show that when the effect of the mean speed equation is accounted for the VMSs have a slightly negative effect in the eastbound equation and a positive effect in the westbound equation. The VMSs therefore appear to significantly reduce mean speed at the VMS site, but they can increase speed deviations slightly. This is not surprising since drivers can be expected to follow VMS directions to different degrees and thereby increase speed deviation. The reduced form coefficients on the season indicators (autumn and spring) show higher mean speeds during those times relative to winter. This captures the effect of more adverse winter weather, such as snow, ice, and rain. The speed deviations are lower in autumn than during winter and spring, which also fits the expected effect of weather during those times. The reduced form coefficients for the eastbound PM peak and the westbound AM peak show lower mean speeds and higher speed deviations during those times. The nighttime mean speed is also lower and nighttime speed deviation is higher. The higher the percentage of heavy trucks (wheelbases 40 ft or longer) reduces the mean speed and increases the speed deviation as can be logically expected. The effect is greater eastbound, which is uphill, than in the downhill westbound direction, in fact the percentage of heavy trucks remained insignificant in the 3SLS westbound mean speed equation. The reduced form for high flow eastbound is associated with higher mean speed and reduced speed deviation, and low flow westbound is similarly associated with higher mean speed and reduced speed deviation.

When comparing the results at the VMS site with the results for the non-VMS site (recall it is about 10 km west of the VMS site downhill towards Seattle) in Tables 13.6–7 we see first that the effect of the instrumented VMS variable is of low significance at the non-VMS site in both the mean speed and speed deviation equations. This lack of significance in the 3SLS results suggests the VMS variable doesn't belong in the model at the non-VMS site. Other notable difference is the lack of strong significance of the seasonal indicators for autumn and spring. This is explainable because the effect of adverse winter weather is considered to be the main cause behind lower winter speeds and higher winter speed deviation, and the non-VMS site being 10 km west of the VMS site is further down the mountain and therefore doesn't have nearly the same amount of snowfall than the VMS site up in the Snoqualmie Pass.

The lack of significance of the VMS variable at the non-VMS site in the westbound direction suggests the effect of the VMSs do not last long after drivers see the last sign. This is supported by the aggregate results in Table 13.1 that show average mean speed at the non-VMS site when VMSs are on to be closely similar to the average mean speed when the signs are off. The small difference in average mean speeds, although significant, cannot, according to Tables 13.6–7, be attributed to the effect of the VMSs. An important result from this is that drivers drive at significantly lower mean speeds at the VMS site when the VMSs are on then when they are off, but their speeds at the non-VMS site are similar in both cases. It suggests compensatory driver behavior; drivers accelerate faster between the VMS site and the non-VMS site when VMSs are on than when they are off. Greater acceleration between these sites could possibly increase accident frequency in that area and this aspect warrants a separate study.

The results of the tests of transferability of westbound 3SLS coefficients estimated at the VMS site to the non-VMS site, and of the westbound reduced form coefficients at the VMS site to the non-VMS site for separately for the mean speed and speed deviation equations are shown in Table 13.8. It shows that for all cases there is evidence to reject the hypothesis of transferability of coefficients, as the p-values are all virtually zero.

Table 13.8: Results for tests of transferability of westbound VMS site coefficients to the non-VMS site data.

Transferability of:	Unrestricted SSR	Restricted SSR	Number of restrictions	Degrees of freedom	F statistic	p value
3SLS estimated coefficients	31,310	42,560	14	3138	80.536	0
Mean speed computed reduced form coefficients	53,511	263,515	8	3144	1,542	0
Speed deviation computed reduced form coefficients	3,456	36,822	8	3144	3,793	0

Conclusions and recommendations

The results show that the endogenous relationship between mean speed and speed deviation was significant and valid. The variable message signs (VMS) were shown to significantly reduce mean speed but they also significantly increased speed deviation. The increase in speed deviation can possibly work towards increasing accident frequencies at the VMS site and thereby tempering the effect of the lower mean speeds, which work to reduce accident severities and frequencies. The effect of the VMSs is not found to be significant at a site 10 km west of the VMS site. This, along with the simple aggregate results for average mean speeds and average speed deviation, suggests that drivers show compensatory behavior. The difference in average mean speed at the non-VMS site is small between the times when VMSs are on and off at the VMS site, and the lack of significance of the VMSs in the models at the non-VMS site support that. To achieve this, drivers must accelerate more quickly between the VMS site and the non-

VMS site when the VMSs are on to compensate for their lower mean speed, as compared to when the VMSs are off.

Compensatory behavior like this could increase accident frequencies in the area between the sites and reduce or negate the safety benefits of lower mean speeds when the VMSs are on. A separate study to examine this effect is necessary to fully understand the safety effects of the VMSs on I-90 at Snoqualmie Pass, Washington.

Part VI

Conclusions

In this final Part a summary of the preceding information will be given. First, there is a short summary of the evaluation approach followed by a summary of the results and implications of the research described in this report.

Chapter 14

Summary of evaluation approach

As the preceding discussion indicates, data has been collected from a number of sources. Also, there is some redundancy built into the data collection effort (e.g., between in-field and laboratory simulations) that allows us to statistically establish the validity of our evaluations. That is, it will determine the extent of the transferability of our laboratory simulation results to the field and the validity of our using post-crossing diaries for IVU users instead of detailed speed and/or point speed data. A summary of all proposed and actual data sources, collection dates, and evaluation uses is presented in Table 14.1. We feel the current data collection effort has been more than adequate to arrive at statistically defensible results.

Table 14.1: Summary of data sources and use

Source	Dates Collected	Use
Accident records	1987-on	_ Evaluation of before and after VMS and VSL impacts
Speed data from magnetic loops and sign radars	Fall 1994-on	_ Evaluation of before and after VMS and VSL impacts
In-depth accident analysis	Fall 1995-on	_ Determine cause of accident for IVU equipped vehicles
System component reliability records	Fall 1997-on	_ Evaluate the reliability records of system components (i.e. IVUs, VMSs, VSLs, weather stations, etc.)
Laboratory simulations	Summer 1997-on	_ Evaluation of IVUs alone _ Evaluation of VMSs and VSLs alone _ Evaluation of IVUs, VMSs and VSLs in combination
Post-crossing survey of non-IVU users	Spring 1998-on	_ Evaluation of VMSs and VSLs
GPS-equipped vehicles	Undecided	_ Evaluation of IVU use and VMSs and VSLs impact on speeds _ Evaluation of the effects of IVUs, VMSs and VSLs in Winter 1995-96
Post-crossing diary for IVU users	Undecided	_ Evaluation of IVU use alone and impact on speeds (possible 30-day period) _ Evaluation of the combined effects of IVUs, VMSs and VSLs
In-service assessment of VMS at Snoqualmie Pass	1997 to 1999	-- Evaluation of VMS on relationships between mean time-mean speeds and mean time-mean speed deviations -- Evaluation of spatial transferability of speed-speed deviation relationships under VMS. That is, is there is a shift between VMS and non-VMS zones?

Chapter 15

Summary of results and implications

The analysis of the historical accident data lead to a general model that can be used to examine accident frequency as a function of geometric and weather-related variables. This model can be used to examine the effect of VMSs and IVUs on accident frequency by collecting accident data after these systems have been introduced and then estimating a model similar to the ones done in this research. The coefficients, or factors, in the model can then be compared to examine the effect of the VMSs and IVUs. If accident frequencies have changed, this method will also show why by showing which coefficients have been significantly changed. This is important to ensure accuracy of the comparison of before and after data. It is also possible to perform an analysis of coefficient elasticities. The elasticity of a coefficient, tells by how many percent the outcome changes when the input is changed by 1%. This gives more information about the actual size of the effect of the VMSs and IVUs.

Some of the general results of this research were that sections with grade exceeding 2% have a significantly higher number of accidents than flatter sections. Maximum rainfall and the number of rainy days significantly increase accident frequency.

The historical accident data was also used in a model that analyses accident severity as a function of various geometric, weather and human factors. The model can be used to examine if the VMSs lead to a significant shift towards less severe accidents when it is compared with a comparable model using data collected after the installation of VMSs. This can provide basis for research into changes of accident cost, which can lead to information regarding accident cost savings with the use of the VMSs.

Speed data was collected at a single site and used to examine lane mean speeds and speed deviations from the mean before the introduction of VMSs and IVUs. Relationships between lane speeds and speed deviations were found and they were statistically valid. Lane speed is affected by adjacent lane speed and the lane speed deviations are affected by adjacent lane speed deviations, the speed in the lane and the speeds in adjacent lanes. This research shows that this method of modeling mean speeds is promising. Future research should explore variations in the geometric, seasonal, and weather variables that may vary between different sites. Also, more microscopic data could be used to try to uncover dynamic effects in the traffic flow. The study performed here offers generic information and it would be beneficial for planning purposes with the added understanding of cause-effect relationship between lane mean speed and lane speed deviations.

Among the studies performed on the data from the simulation experiment was the modeling of mean speed and deviation by estimating an endogenous system of equations. That study focused on the effect of geometric and socioeconomic variables on mean speed and deviation along a 12 mile stretch of a computer simulated version of I-90 at Snoqualmie Pass. The effects of VMSs and IVUs were also tested. The effect is seen through the variable speed limit set by the messages on the VMSs and IVUs. The drivers with IVU only were found to have higher mean speeds than the other drivers. They do change their speed when the IVU message informs of an upcoming snowplow but, still, have a higher mean speed than those without a system. The drivers with VMSs only have higher mean speeds than those with neither system in the areas without snowplows but their mean speed is similar in the snowplow regions. Drivers with both IVU and VMSs drive slower than the other drivers. Their speed deviations where higher than for drivers with IVU only, VMS only, or drivers without a system. This indicates that drivers put some trust in the system and drive faster when the system does not indicate danger than do drivers without a system, which must be on the lookout themselves. It is interesting that the mean speed was lower for those with both IVU and VMSs and the deviation was highest for this group. These results must be taken with a grain of salt, because they stem from a simulator study and the drivers know they will not be injured or harmed by reckless driving. They also know there are no other vehicles on the road except for snowplows. These results indicate that erroneous messages may prove to be more dangerous than no messages. Further research into the effect of inaccurate messages on drivers is therefore needed. These results also show that the VMSs and IVUs may increase speed deviation. This can lead to safety concerns, especially if the traffic stream is mixed, that is, made up of drivers without information systems and drivers with systems, because these two groups are likely to have different speed profiles and this may incrase accident risk. Further research into the effect of IVUs in a mixed traffic stream is therefore necessary.

To further analyze the accident frequency and severity a model of reported speed reduction under adverse weather conditions was estimated by using survey data. This study found that drivers reported driving at very diverse speeds under adverse conditions such as on wet or icy road. It is hoped that the installation of VMSs and/or IVUs that set variable speed limits would limit this diversity and therefore increase safety.

However, as was found by the previously mentioned simulation study the speed deviation of drivers using VMSs and/or IVUs was larger than for those without such a system. There are two comments on this. First, it is not the difference between drivers with IVUs and those without IVUs that is expected to be reduced, but rather, the speed deviation within the whole group of drivers using the system. To find this a much larger sample of subjects must be used for it to be statistically valid to compare them to each other. Another angle that might be taken to analyze this further would be to examine the mean speed and speed deviation on a smaller scale to isolate the speed between messages from the message areas. Such research might answer the hypothesis that drivers with VMSs and/or IVUs drive with less speed deviation as a group on the sections between messages, but if there is a message giving a different speed limit in a section the speed deviation is increased for that section.

The survey study found many relationships between the socioeconomic factors and the reported speed reductions. One general conclusion was that drivers generally drive as fast as the law allows and give little consideration to road conditions. The variable speed limits set by the VMSs and IVUs should therefore increase safety by setting the limits according to the current conditions. This will, however, not work if drivers get the feeling that the VSLs are merely suggestions but not a legal limit that is enforced. Enforcement is therefore likely to play a big part of the success of VSLs.

The survey was also used to analyze whether drivers would use an IVU and what socioeconomic factors contribute to that decision. It was found that perception of conditions played a big role. Drivers indicated that they would generally only obey if they conditions warranted, especially for the command to put on chains. Putting on chains is so onerous that drivers need more than an IVU telling them to put them on if they do not perceive their need. These results can then be compared with the results from a similar survey collected from the participants in the simulator study.

In-service evaluation of variable message signs on mean speeds and speed deviations showed that the endogenous relationship between mean speed and speed deviation was significant and valid under ITS. The variable message signs (VMS) were shown to significantly reduce mean speed but they also significantly increased speed deviation. The increase in speed deviation can possibly work towards increasing accident frequencies at the VMS site and thereby tempering the effect of the lower mean speeds, which work to reduce accident severities and frequencies. The effect of the VMSs is not found to be significant at a site 10 km west of the VMS site. This, along with the simple aggregate results for average mean speeds and average speed deviation, suggests that drivers show compensatory behavior. The difference in average mean speed at the non-VMS site is small between the times when VMSs are on and off at the VMS site, and the lack of significance of the VMSs in the models at the non-VMS site support that. To achieve this, drivers must accelerate more quickly between the VMS site and the non-VMS site when the VMSs are on to compensate for their lower mean speed, as compared to when the VMSs are off.

Compensatory behavior like this could increase accident frequencies in the area between the sites and reduce or negate the safety benefits of lower mean speeds when the VMSs are on. A separate study to examine this effect is necessary to fully understand the safety effects of the VMSs on I-90 at Snoqualmie Pass, Washington.

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Appendix A

Snoqualmie Pass survey response summary

The number of responses and statistics are in **bold** type.

Washington State Department of Transportation

University of Washington

Washington State Transportatio n Center

Snoqualmie Pass Traveler Information Project Survey

The Washington State Department of Transportation and the Washington State Transportation Center at the University of Washington are working together to study travel behavior and traveler information needs on Interstate 90 near Snoqualmie Pass. We would like to understand your travel preferences and your perception of traveler information and its effectiveness.

Please give this survey to the person in your household who most often drives on Interstate 90 between North Bend and Cle Elum. In this survey, I-90 between North Bend and Cle Elum is considered as Snoqualmie Pass. Ask him or her to fill out the survey and return it by mail by June 15, 1995. No postage is necessary. We appreciate your response. This survey is anonymous and your answers will not be associated with your name.

Your Trip

1. How many people (including yourself) are usually in the vehicle when you drive on Snoqualmie Pass?

   (Check only one)

   100 √1 **209** √2 **55** √3 **43** √4 **15** √5 or more

2. Approximately how many times each season do you drive on Snoqualmie Pass?

   During the **winter** (Dec. - Feb.) _____ times

   During the **summer** (Jun. - Aug.) _____ times

During the **spring** (Mar - May) _____ times

During the **autumn** (Sep. - Nov.) _____ times

Variable	Mean	Median	Std. Dev.
Winter	**11.1**	**2**	**19.8**
Spring	**8.7**	**2**	**17.5**
Summer	**8.5**	**2**	**17.5**
Fall	**8.0**	**2**	**17.5**

3. Estimate your average speed for Snoqualmie Pass trips when road is: (Check only one per line)

dry:	√less than 35	√35-44	√45-54	√55-64	√65-74	√75 mph or more
wet:	√less than 35	√35-44	√45-54	√55-64	√65-74	√75 mph or more
icy:	√less than 35	√35-44	√45-54	√55-64	√65-74	√75 mph or more
Average	**29.5**	**39.5**	**49.5**	**59.5**	**69.5**	**79.5**

Variable	Mean	Median	Std. Dev.
Dryspd	**63.3**	**69.5**	**10.6**
Wetspd	**55.9**	**59.5**	**13.2**
Icespd	**40.3**	**39.5**	**13.2**

4. What is your primary purpose for driving on Snoqualmie Pass? (Check only one)

158 √Recreation **84** √Business **115** √Visit family

14 √Errands **38** √Other

5. Have you ever had an accident on I-90 on Snoqualmie Pass?

410 √No - skip to the next section. **21** √Yes => how many? ____(**1**)____

6. During your Snoqualmie Pass trip, how important is . . .

(Check one box in each row)

	Very Important √1	√2	Moderate Importance √3	√4	Not Important √5
Saving trip time?	**121**	**78**	**164**	**39**	**23**
Increasing trip safety?	**275**	**88**	**45**	**10**	**8**

7. How often do you wear seatbelts while driving? (Check only one)

395 √all the time **26** √most of the time

4 √some of the time **5** √rarely

3 √never

8. How important is the following **weather** information for helping you plan your Snoqualmie Pass trip?

(Check one box in each row)

	Very Important √1	√2	Moderate Importance √3	√4	Not Important √5
Current weather conditions? (snow, rain, etc.)	**284**	**73**	**50**	**11**	**14**
Snow/ice accumulations on road?	**318**	**47**	**35**	**11**	**16**
Weather forecast?	**189**	**88**	**90**	**34**	**27**

9. How important is the following **roadway** information for helping you plan your Snoqualmie Pass trip?

(Check one box in each row)

	Very Important		Moderate Importance		Not Important
	√1	√2	√3	√4	√5
Presence of hazard/accident	**243**	**84**	**75**	**16**	**10**
Number of lanes closed/blocked	**212**	**110**	**81**	**15**	**8**
Type of accident / hazard	**151**	**102**	**120**	**35**	**16**
Level of congestion	**153**	**136**	**105**	**22**	**12**

10. From which one of the following sources do you **most** prefer to obtain road and weather information?

(Check only one)

7 √CB radio

29 √Commercial TV station

5 √Cellular phone

25 √Electronic message signs on freeway

86 √Commercial radio station

11 √Observation of traffic conditions

162 √Advisory radio indicated by flashing lights on highway signs

2 √Talking to other drivers

43 √Other ___________________

Your Opinions

11. Please indicate the extent to which you agree or disagree with the following statements.

	Strongly Disagree	Disagree	Neutral	Strongly Agree	Agree
In good weather conditions, Snoqualmie Pass is more dangerous than other sections of I-90.	**100**	**196**	**68**	**51**	**14**
Trucks present a higher danger on Snoqualmie Pass than other sections of I-90.	**37**	**123**	**76**	**142**	**53**
In snow or rain, Snoqualmie Pass is more dangerous than other sections of I-90.	**18**	**64**	**59**	**210**	**80**
On snow or ice, four-wheel-drive vehicles can safely be driven faster than two-wheel-drive vehicles.	**154**	**134**	**61**	**67**	**17**
Under dry road conditions a 65 mph speed limit on Snoqualmie Pass is safe.	**9**	**27**	**26**	**238**	**131**
In rainy road conditions a 65 mph speed limit on Snoqualmie Pass is safe.	**30**	**155**	**91**	**126**	**28**
Under most wintry road conditions a 65 mph speed limit on Snoqualmie Pass is safe.	**139**	**193**	**44**	**48**	**8**

Let's say you were given an in-vehicle traffic information system (e.g., a small computer screen in your vehicle), that had the capability to show you current traffic conditions and up-coming road conditions.

12. Would you use it? **394** √ Yes **37** √ No

13. Would you obey the system if it told you to:

(Check only one per line)

Slow down	**243**	Yes, immediately	**179**	Only if conditions warrant	**5**	No
Put on chains	**158**	Yes, immediately	**248**	Only if conditions warrant	**13**	No

Yourself

14. Are you? (Check one box)

271 √Male **155** √Female

15. Are you? (Check one box)

263 √Married **96** √Single

16. What is your age?

9	√Under 21	**19**	√22-25	**24**	√26-30	**22**	√31-34	**58**	√35-40	**57**	√41-45
60	√46-50	**56**	√51-55	**35**	√56-60	**28**	√61-65	**30**	√66-70	**33**	√Over 70

17. What is your approximate annual household income?

3	no income	**13**	√under $10,000	**22**	√$10,000-19,999
36	√$20,000-29,999	**65**	√$30,000-39,999	**67**	√$40,000-49,999
102	√$50,000-74,999	**54**	√$75,000-100,000	**33**	√over $100,000

18. What is your highest level of education?

10	√some high school	**67**	√technical college degree (A.A.)
113	√high school diploma	**140**	√college degree
95	√post graduate degree		

	Mean	Median	Std. Dev.
19. Including yourself, how many people live in your household?	**2.8**	**2**	**1.4**
20. How many children living in your household are under age 6?	**0.2**	**0**	**0.5**
21. How many children living in your household are aged 6 to 16?	**0.5**	**0**	**0.9**
22. How many people living in your household work outside the home?	**1.4**	**2**	**1.0**
23. How many licensed and operable motor vehicles do you have?	**2.5**	**2**	**1.3**

24. What is the zip code of your work place? ________ your home? ________

25. Are you willing to participate in further research activities, such as an interview or perhaps a simulation experiment? **260** √Yes **165** √No

26. Are you willing to use an in-vehicle traffic information unit that will provide weather and traffic information to you while crossing Snoqualmie Pass? **311** √Yes **113** √No

If you answered "Yes" to either of the two preceding questions, please include your name and address below so that we may contact you for further information and assistance.

Please use this space for any comments:

No Comment	**128**
Negative comment	**9**
Neutral Comment	**32**
Positive Comment	**5**
Name & Address	**259**

Thank you for taking the time to complete this survey. When you are finished, please fold the survey form so that the "University of Washington" address is displayed, tape the survey form closed, and drop it in a mailbox before June 15, 1995. Remember, no postage is necessary.

Appendix B

Instructions for participants

If there was No Variable Message on the road and the participant DID NOT view an In-vehicle unit while driving, the instructions were as follows:

(Paragraph 1) Thank you for participating in this experiment. Your input will provide valuable insight into the needs of drivers as they travel over different road conditions.

(Paragraph 2) Today, you will be driving through a graphical representation of a 3 lane mountainous road that is similar to the Snoqualmie Pass on Interstate-90.

About the car simulator:

(Paragraph 3) You need to turn on the lights to get the simulator ready. The simulator will start as soon as you turn on the ignition. As in a regular car, you use the brake pedal to slow down, the gas pedal to speed up, and the steering wheel to maneuver between lanes.

(Paragraph 4) You will be given a 5 minute practice session to familiarize yourself with how the simulator works and to see what the scenes look like. As you drive through this road, you may observe different fog conditions, and encounter snow plows at varying points. Your task is to drive through the road scenes safely and as you typically would in normal driving conditions.

(Paragraph 5) If you feel comfortable with using the simulator after the practice session, we will start the actual experiment. If not, we can continue the practice session for another 5 mile loop.

(Paragraph 6) If there are any question at this time, please let me know.

If the participants viewed variable message signs while driving, then Paragraph 5 changed to:

(Paragraph 5) You will be given a 5 minute practice session to familiarize yourself with how the simulator works and to see what the scenes look like. As you drive through this road, you will observe different fog conditions, and encounter snow plows at varying points. In addition, you will see variable message signs that will alert you of anything that you., as a driver, may need to know about. Your task is to drive through the road scenes safely and as you typically would in normal driving conditions.

If they viewed messages on an In-vehicle unit while driving through the simulator, the following instructions were added after Paragraph 3

About the in-vehicle unit

This first scene is a map of where you are going (eastbound on I-90). You will be driving through the first quadrant only (milepost 35 to 47), so if you want to zoom in on that quadrant, press 1.

Messages will appear in the lower right side of the screen. Whenever a new message is sent, you will hear a beep. The recommended speed limit appears on the lower left side of the screen.

Appendix C

Survey on the Trafficmaster in-vehicle unit

Survey on TrafficMaster In-vehicle Unit

Please rate the usefulness of the following items on the in-vehicle unit:

	Extremely useful	Of considerable use	Of use	Not very useful	Of no use	Didn't notice it
1. The beep	___	___	___	___	___	___
2. The on-road traffic messages	___	___	___	___	___	___
3. The map display	___	___	___	___	___	___
4. The pre-trip information (e.g, weather, incident info)	___	___	___	___	___	___
5. The speed limit information	___	___	___	___	___	___

6. The screen appearance was

___ Extremely good

___ Reasonably good

___ So-So

___ Reasonably poor

___ Extremely poor

7. Compared to variable message signs on the road, this system was

___ Much better

___ Slightly better

___ Same

___ Slightly worse

___ Much worse

8. Operating this in-vehicle system was:

    ___ Very easy

    ___ Easy

    ___ Borderline

    ___ Difficult

    ___ Very difficult

9. Overall, I think this system was:

    ___ Extremely good

    ___ Reasonably good

    ___ So-So

    ___ Reasonably poor

    ___ Extremely poor

10. If this in-vehicle unit was on the market today, and available for your primary route, would you buy it? (Check only one)

    ___ Yes __ No

    If yes, how much would you pay for this unit (total)? $ ______

11. If the services provided to the unit (i.e. mapping, weather, traffic information) were available as a pay per month service (like a cellular phone), would you pay for it? (Check only one)

    ___ Yes __ No

    If yes, how much much would you pay for the services (per month)? $______ per month

Appendix D

Snoqualmie Pass traveler information project survey

Snoqualmie Pass Traveler Information Project Survey

Your Trip

1. How many people (including yourself) are usually in the vehicle when you drive on Snoqualmie Pass?

   (Check only one)

   □ 1 □2 □3 □4 □5 or more

2. Approximately how many times each season do you drive on Snoqualmie Pass?

   During the **winter** (Dec. - Feb.) _____ times

   During the **summer** (Jun. - Aug.) _____ times

   During the **spring** (Mar - May) _____ times

   During the **autumn** (Sep. - Nov.) _____ times

3. Estimate your average speed for Snoqualmie Pass trips when road is: (Check only one per line)

   dry: □less than 35 □35-44 □45-54 □55-64 □65-74 □75 mph or more

   wet: □less than 35 □35-44 □45-54 □55-64 □65-74 □75 mph or more

   icy: □less than 35 □35-44 □45-54 □55-64 □65-74 □75 mph or more

4. What is your primary purpose for driving on Snoqualmie Pass? (Check only one)

   Recreation Business □Visit family

   Errands Other

5. Have you ever had an accident on I-90 on Snoqualmie Pass?

No Yes => how many? ________

6. During your Snoqualmie Pass trip, how important is . . .

(Check one box in each row)

	Very Important		Moderate Importance		Not Important
Saving trip time?	1	□2	□3	□4	□5
Increasing trip safety?	1	□2	□3	□4	□5

7. How often do you wear seatbelts while driving?
(Check only one)

all the time most of the time

some of the time rarely

never

8. How important is the following **weather** information for helping you plan your Snoqualmie Pass trip?

(Check one box in each row)

	Very Important		Moderate Importance		Not Important
Current weather conditions? (snow, rain, etc.)	1	□2	□3	□4	□5
Snow/ice accumulations on road?	1	□2	□3	□4	□5
Weather forecast?	1	□2	□3	□4	□5

9. How important is the following **roadway** information for helping you plan your Snoqualmie Pass trip?

(Check one box in each row)

	Very Important		Moderate Importance		Not Important
Presence of hazard/accident	1	□2	□3	□4	□5
Number of lanes closed/blocked	1	□2	□3	□4	□5
Type of accident / hazard	1	□2	□3	□4	□5
Level of congestion	1	□2	□3	□4	□5

10. From which one of the following sources do you **most** prefer to obtain road and weather information?

(Check only one)

CB radio

Commercial TV station

Cellular phone

Electronic message signs on freeway

Commercial radio station

Observation of traffic conditions

Advisory radio indicated by flashing lights on highway signs

Talking to other drivers

Other ____________________

Your Opinions

11. Please indicate the extent to which you agree or disagree with the following statements.

	Strongly Disagree	Disagree	Neutral	Strongly Agree	Agree
In good weather conditions, Snoqualmie Pass is more dangerous than other sections of I-90.	___	___	___	___	___
Trucks present a higher danger on Snoqualmie Pass than other sections of I-90.	___	___	___	___	___
In severe weather conditions (e.g., snow, or heavy rain), Snoqualmie Pass is more dangerous than other sections of I-90	___	___	___	___	___
On snow or ice, four-wheel-drive vehicles can safely be driven faster than two-wheel-drive vehicles.	___	___	___	___	___
Under dry road conditions a 65 mph speed limit on Snoqualmie Pass is safe.	___	___	___	___	___
In rainy road conditions a 65 mph speed limit on Snoqualmie Pass is safe.	___	___	___	___	___
In foggy road conditions a 65 mph speed limit on Snoqualmie Pass is safe.	___	___	___	___	___
Under most wintry road conditions a 65 mph speed limit on Snoqualmie Pass is safe.	___	___	___	___	___

Let's say you were given an in-vehicle traffic information system (e.g., a small computer screen in your vehicle), that had the capability to show you current traffic conditions and up-coming road conditions.

12. Would you use it? Yes ☐No

13. Would you obey the system if it told you to:

(Check only one per line)

Slow down

__ Yes, immediately __ Only if conditions warrant __ No

Put on chains

__ Yes, immediately __ Only if conditions warrant __ No

Yourself

14. Are you? (Check one)

Male Female

15. Are you? (Check one)

Married Single Divorced Separated Other

16. What is your age? _______

17. What is your approximate annual household income?

no income	under $10,000	$10,000-19,999
$20,000-29,999	$30,000-39,999	$40,000-49,999
$50,000-74,999	$75,000-100,000	over $100,000

18. What is your highest level of education?

some high school	technical college degree (A.A.)
high school diploma	college degree
post graduate degree	

19. Including yourself, how many people live in your household? _____

20. How many children living in your household are under age 6? _____

21. How many children living in your household are aged 6 to 16? _____

22. How many people living in your household work outside the home? _____

23. How many licensed and operable motor vehicles do you have? _____

24. What is the zip code of your work place? ________ your home? ________

THANK YOU FOR YOUR TIME!

Appendix E

Variable messages used

Table E.1 contains the four different message series used. Each run that uses VMSs contains eight signs. Since the runs differ in the placement of fog and snow plows there is need for different series of VMSs. These messages are also sent to the simulator's in-vehicle unit when it is in use with one difference, the "Curvy Road - Drive Slowly" message was accompanied by a speed limit of 88.5 km/h (55 mph) in the IVU.

The participants in the study receive the messages in three different ways or to at all as directed by the four different types of runs (see Table 9.2).

Table E.1: The four different series (a – d) of variable messages used.

Sign #	Message a	Sign #	Message b
1	FOG AHEAD SLOW DOWN 45 MPH	1	CURVY ROAD DRIVE SLOWLY
2	FOG AHEAD SLOW DOWN 45 MPH	2	CURVY ROAD DRIVE SLOWLY
3	FOG AHEAD SLOW DOWN 45 MPH	3	CURVY ROAD DRIVE SLOWLY
4	SNOW PLOWS AHEAD SLOW DOWN 35 MPH	4	SNOW PLOWS AHEAD SLOW DOWN 35 MPH
5	CURVY ROAD DRIVE SLOWLY	5	FOG AHEAD SLOW DOWN 45 MPH
6	SNOW PLOWS AHEAD SLOW DOWN 35 MPH	6	FOG AHEAD SLOW DOWN 45 MPH
7	CURVY ROAD DRIVE SLOWLY	7	FOG AHEAD SLOW DOWN 45 MPH
8	CURVY ROAD DRIVE SLOWLY	8	SNOW PLOWS AHEAD SLOW DOWN 35 MPH

(Continued)

Table E.1: The four different series (a – d) of variable messages used. (Continued).

Sign #	Message c	Sign #	Message d
1	FOG AHEAD	1	CURVY ROAD
	SLOW DOWN 45 MPH		DRIVE SLOWLY
2	SNOW PLOWS AHEAD	2	SNOW PLOWS AHEAD
	SLOW DOWN 35 MPH		SLOW DOWN 35 MPH
3	FOG AHEAD	3	CURVY ROAD
	SLOW DOWN 45 MPH		DRIVE SLOWLY
4	FOG AHEAD	4	CURVY ROAD
	SLOW DOWN 45 MPH		DRIVE SLOWLY
5	CURVY ROAD	5	FOG AHEAD
	DRIVE SLOWLY		SLOW DOWN 45 MPH
6	CURVY ROAD	6	SNOW PLOWS AHEAD
	DRIVE SLOWLY		SLOW DOWN 35 MPH
7	CURVY ROAD	7	FOG AHEAD
	DRIVE SLOWLY		SLOW DOWN 45 MPH
8	SNOW PLOWS AHEAD	8	FOG AHEAD
	SLOW DOWN 35 MPH		SLOW DOWN 45 MPH

Appendix F

Geometric Configuration of the Simulation Highway

Table F.1: Geometric configuration of the simulation highway.

Type	Length m	Radius of horizontal curve m	Angle of horizontal curve °	Radius of vertical curve m	Angle of vertical curve °	Final grade °
straight	144.78				0	0
straight	123.44				0	0
straight	126.49				0	0
horizontal	191.51	609.6	-18		0	0
straight	289.56				0	0
vertical	386.18			22126.58	1	1
horizontal	138.31	609.6	13		0	1
straight	193.24				0	1
horizontal	63.84	609.6	6		0	1
horizontal	614.43	502.92	-70		0	1
vertical	209.09			3993.38	3	4
horizontal	52.13	597.41	5		0	4
horizontal	52.13	597.41	5		0	4
vertical	321.87			-4610.43	-4	0
horizontal	184.33	502.92	21		0	0
straight	321.87				0	0
horizontal	223.43	609.6	21		0	0
horizontal	180.87	609.6	17		0	0
vertical	160.93			9220.86	1	1

(Continued)

Table F.1: Geometric configuration of the simulation highway. (Continued).

Type	Length m	Radius of horizontal curve m	Angle of horizontal curve °	Radius of vertical curve m	Angle of vertical curve °	Final grade °
vertical	128.63			-7369.7	-1	0
horizontal	139.64	381	-21		0	0
straight	335.58				0	0
horizontal	127.67	609.6	12		0	0
horizontal	53.2	609.6	5		0	0
vertical	273.71			7841.23	2	2
horizontal	212.79	304.8	-40		0	2
vertical	611.43			-11677.43	-3	-1
straight	482.8				0	-1
horizontal	74.48	609.6	-7		0	-1
vertical	256.64			7352.24	2	1
horizontal	53.2	609.6	5		0	1
horizontal	95.76	609.6	9		0	1
horizontal	42.56	609.6	4		0	1
straight	434.64				0	1
vertical	160.93			4610.43	2	3
horizontal	108.31	620.57	10		0	3
vertical	209.09			11980.14	1	4
horizontal	386.58	598.63	-37		0	4
vertical	80.47			-1152.61	-4	0
straight	579.42				0	0
horizontal	113.04	381	17		0	0
vertical	160.93			9220.86	1	1
horizontal	457.5	609.6	-43		0	1
straight	257.56				0	1

(Continued)

Table F.1: Geometric configuration of the simulation highway. (Continued).

Type	Length m	Radius of horizontal curve m	Angle of horizontal curve °	Radius of vertical curve m	Angle of vertical curve °	Final grade °
horizontal	99.03	436.47	13		0	1
straight	241.4				0	1
horizontal	297.91	609.6	-28		0	1
vertical	241.4			13831.29	1	2
horizontal	182.57	316.99	33		0	2
straight	402.34				0	2
straight	112.78				0	2
horizontal	191.51	609.6	-18		0	2
straight	193.24				0	2
horizontal	201.56	312.12	37		0	2
vertical	418.49			23977.73	1	3
vertical	128.63			-7369.7	-1	2
horizontal	191.51	457.2	-24		0	2
vertical	96.62			-5536.01	-1	1
straight	310.9				0	1
vertical	139.6			3999.2	2	3
horizontal	340.46	609.6	32		0	3
horizontal	21.28	609.6	2		0	3
vertical	193.24			-5536.01	-2	1
horizontal	63.84	609.6	-6		0	1
vertical	402.34			7684.05	3	4
vertical	386.18			-22126.58	-1	3
vertical	321.87			-18441.72	-1	2
horizontal	134.51	592.84	13		0	2
straight	314.25				0	2

(Continued)

Table F.1: Geometric configuration of the simulation highway. (Continued).

Type	Length m	Radius of horizontal curve m	Angle of horizontal curve °	Radius of vertical curve m	Angle of vertical curve °	Final grade °
horizontal	127.67	609.6	12		0	2
vertical	193.24			5536.01	2	4
horizontal	191.51	609.6	18		0	4
straight	294.74				0	4
horizontal	95.76	609.6	-9		0	4
vertical	231.04			-6618.76	-2	2
straight	396.54				0	2
straight	321.87				0	2
horizontal	148.95	609.6	-14		0	2
horizontal	106.4	609.6	-10		0	2
vertical	154.23				1	3
horizontal	106.4	609.6	-10		0	3
vertical	186.23			-5335.18	-2	1
straight	177.09				0	1
horizontal	563.89	609.6	53		0	1
straight	203.3				0	1
vertical	180.44			3446.18	3	4
horizontal	90.12	469.39	-11		0	4
vertical	498.96			9529.39	-3	1
Total	19710.87					

Appendix G

Sample data

A sample of the data written from the driving simulator showing the change from fog to no fog. The level of fog increases gradually to 0.007 which stands for 800 meters of visibility.

Table G.1: Sample data from the driving simulator.

Time	Position		Speed	Lane	Gas	Gear	Brake	Fog
	Stretch #	decimal	mph					
6:39	44	0.4	69.59	2	31	4	0	0
6:40	44	0.6	68.87	2	27	4	0	0
6:41	44	0.7	66.73	2	0	4	0	0
6:42	44	0.8	63.46	2	0	4	0	0
6:43	44	0.9	60.56	2	0	4	0	0
6:44	45	0.1	57.12	2	0	4	0	0.001
6:45	45	0.4	54.55	2	4	3	0	0.001
6:46	45	0.5	52.18	2	0	3	0	0.001
6:47	45	0.7	50.03	2	11	3	0	0.001
6:48	46	0.0	49.33	2	11	3	0	0.002
6:49	46	0.1	50.33	2	26	3	0	0.002
6:50	46	0.2	52.32	2	24	3	0	0.002

Appendix H

Scenes from the simulator

This Appendix contains a number of scenes from the simulator showing examples of the good weather conditions (see Figure H.1), road signs (see Figure H.2, H.3, and H.4), the variable message signs (see Figures H.5, H.6 and H.8), the snow plows (see Figures H.7, H.6, and H.10) and the fog conditions (see Figure H.9). The scenes are taken from one of the runs used and are shown in the order seen while driving that particular run. The other runs contained the same scenes but in a different order as shown by the four series of VMS and IVU messages in Appendix E.

The 0 that can be seen, below and to the left of the middle of the figures, represents the number zero and it is the current speed in mph as seen by the driver. To accurately take pictures of these scenes the vehicle had to stop and therefore no speed in the figures.

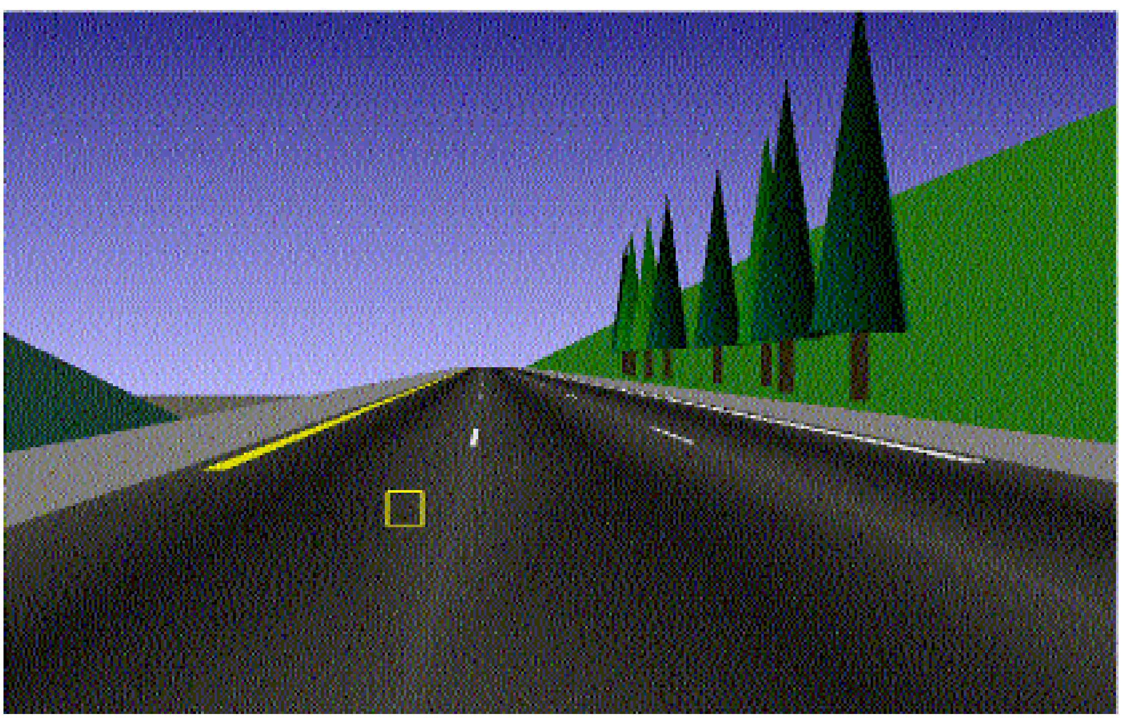

Figure H.1: A typical section of road during good weather conditions.

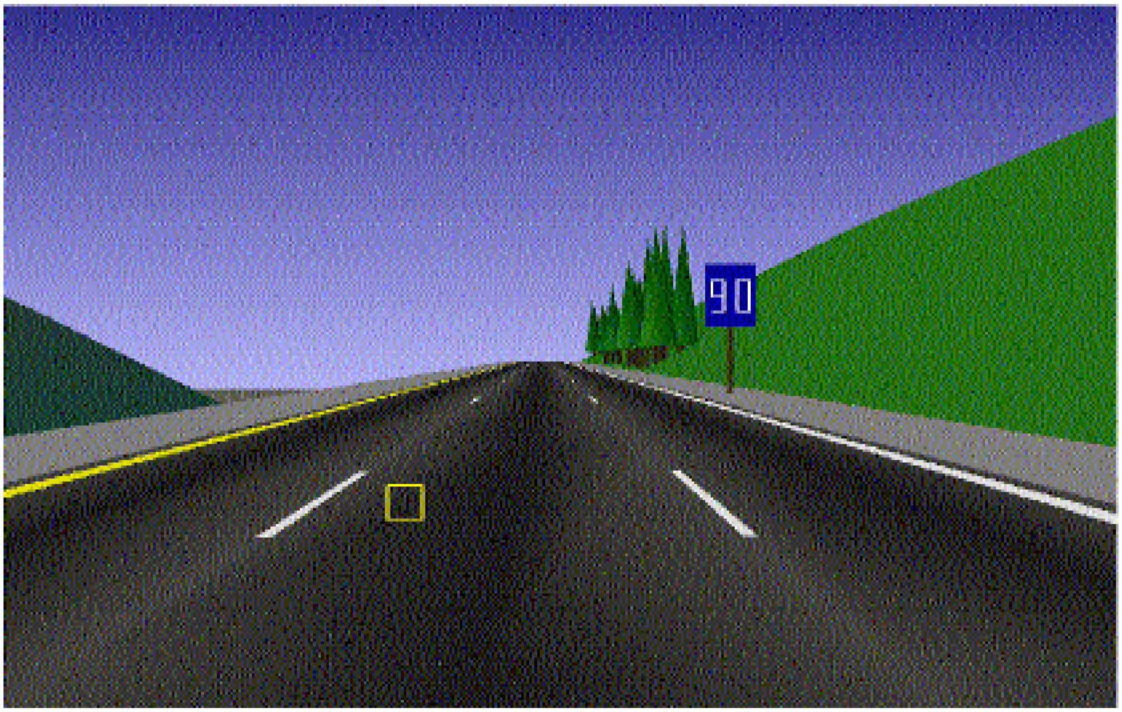

Figure H.2: An example of the I-90 sign.

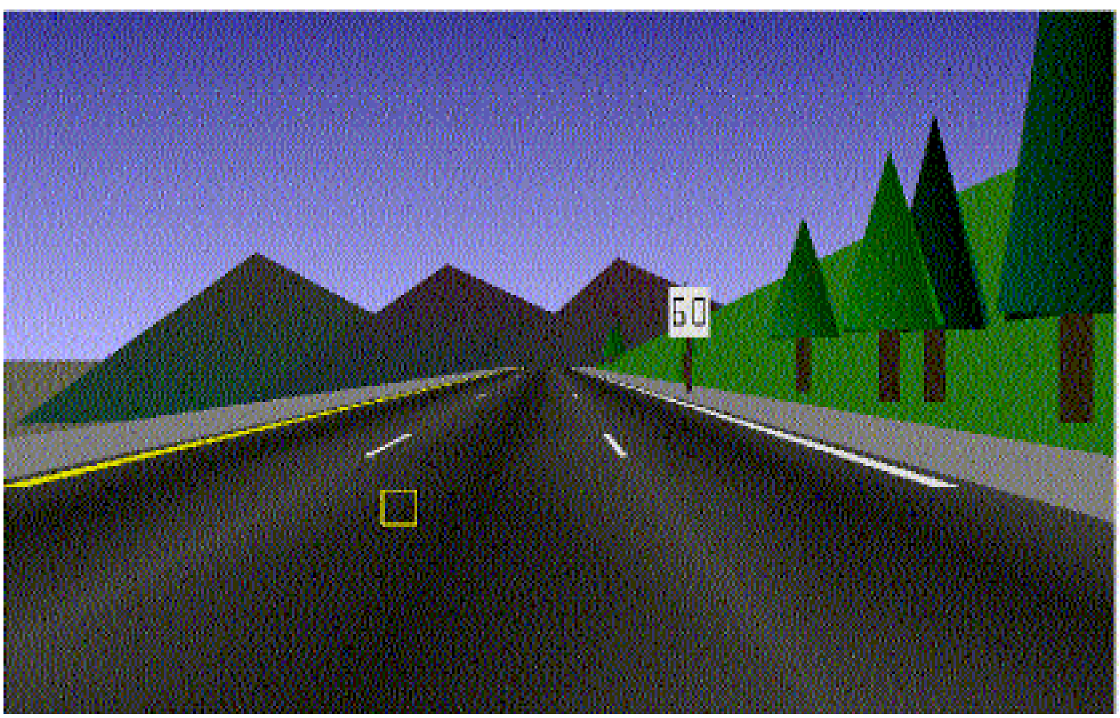

Figure H.3: An example of the speed limit sign.

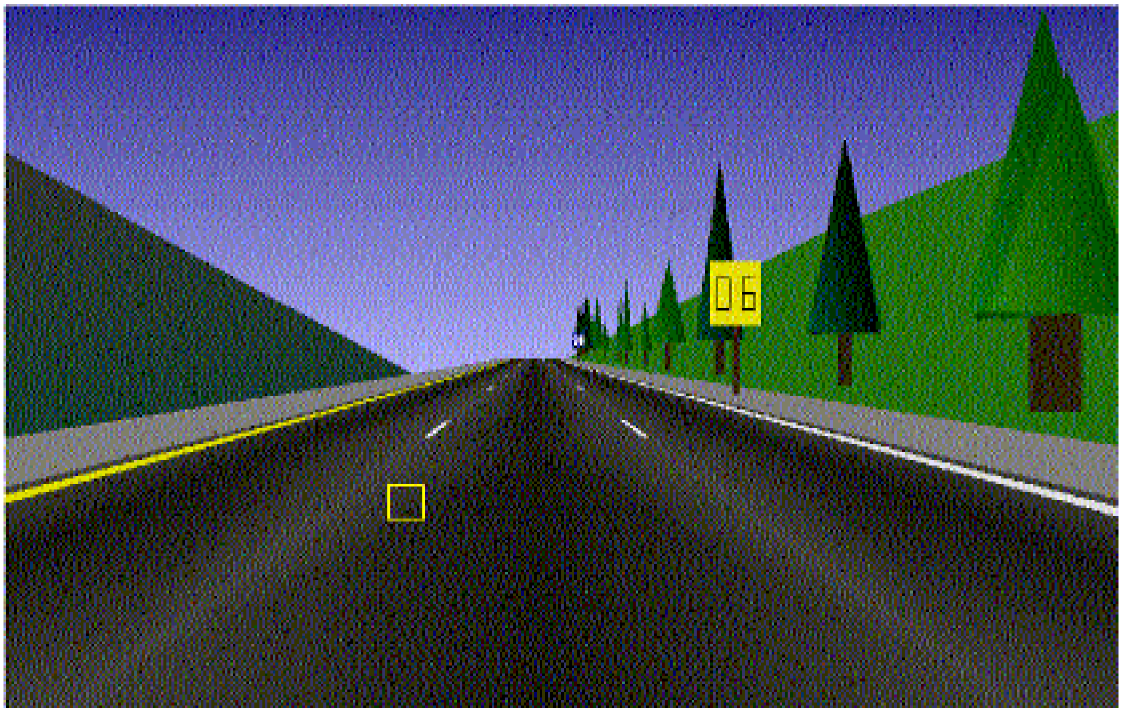

Figure H.4: An example of the IVU indicator sign.

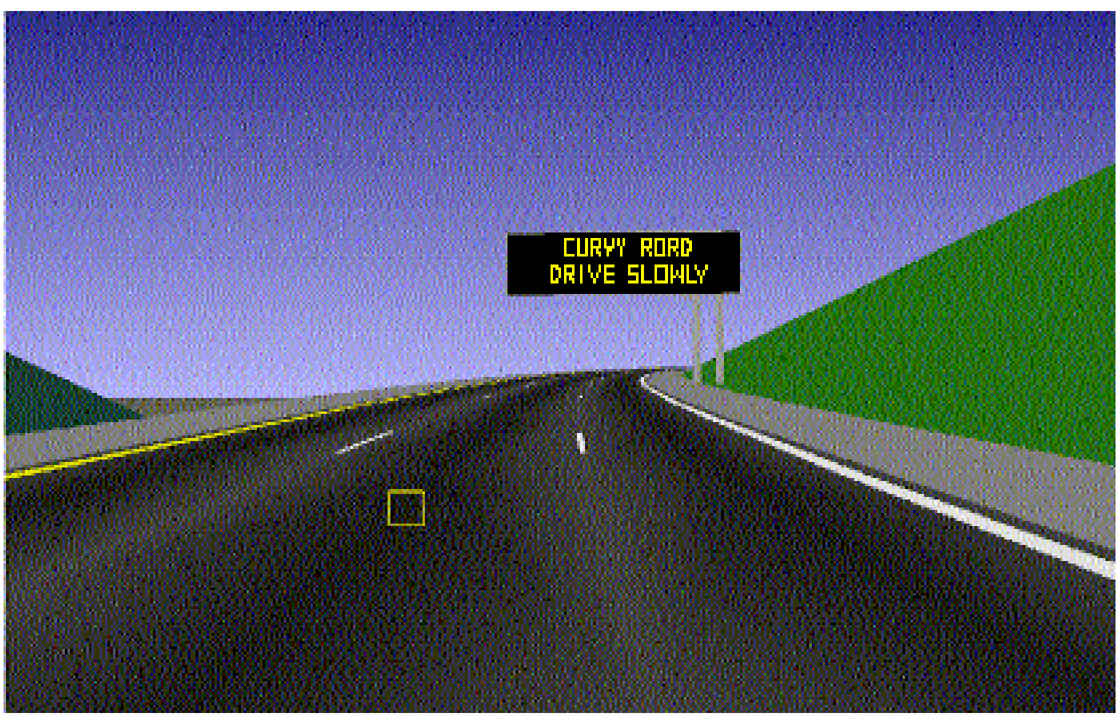

Figure H.5: The curvy road VMS.

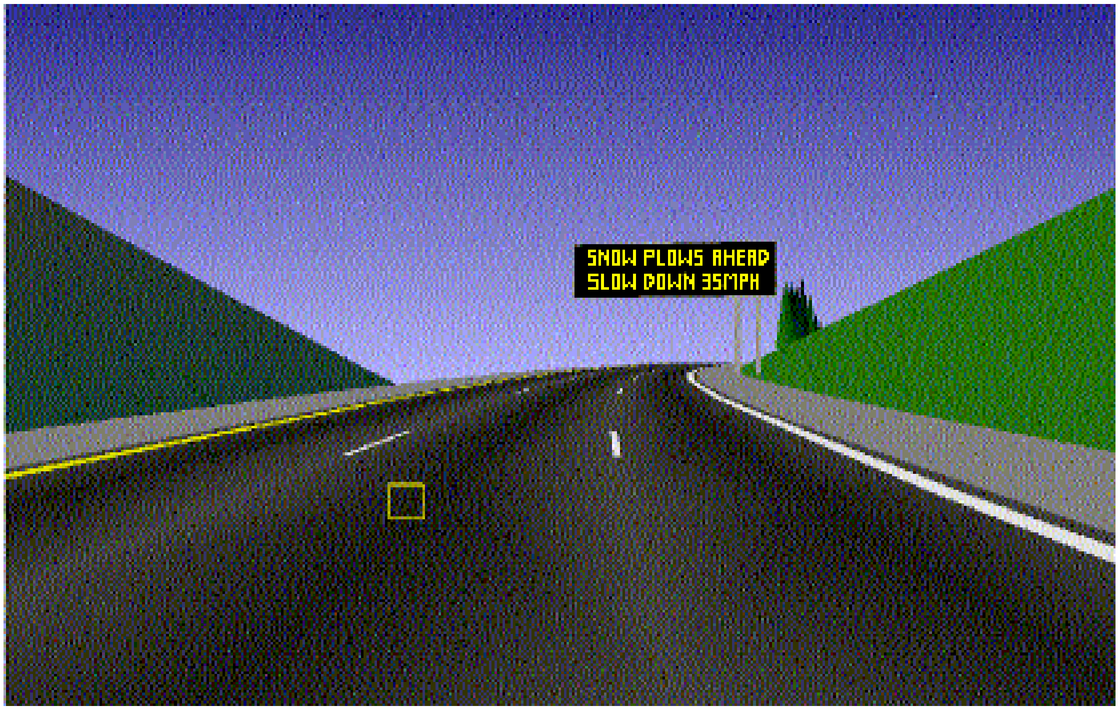

Figure H.6: The snow plow ahead VMS.

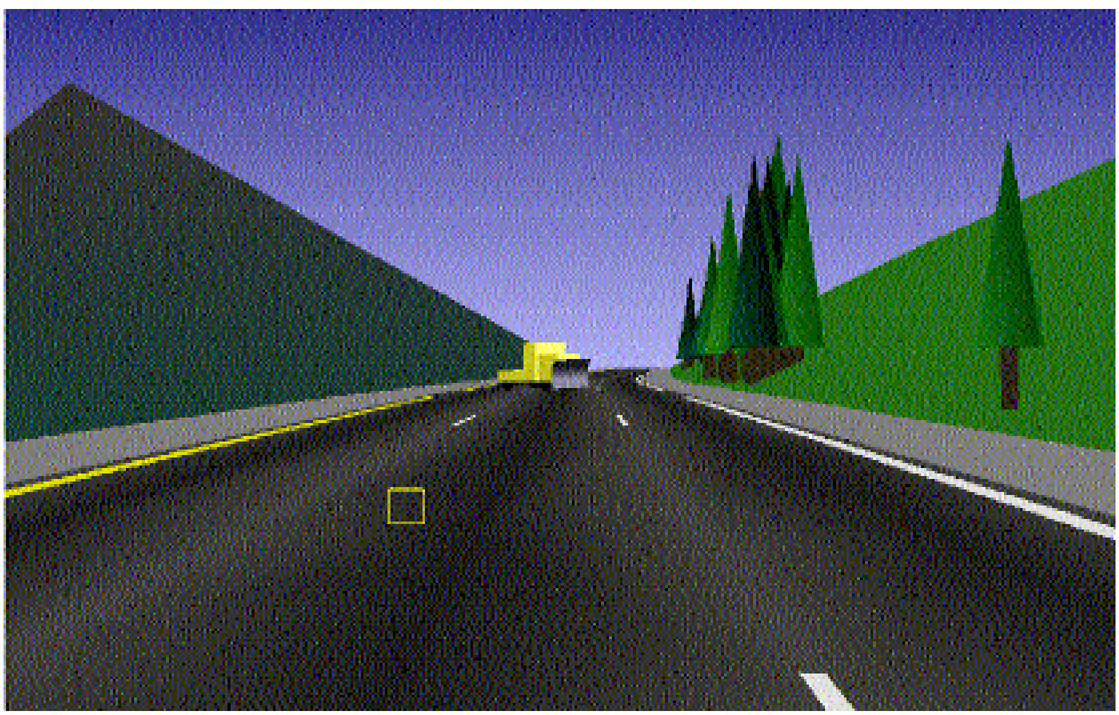

Figure H.7: A yellow snow plow blocking the two left most lanes.

Figure H.8: The fog ahead VMS.

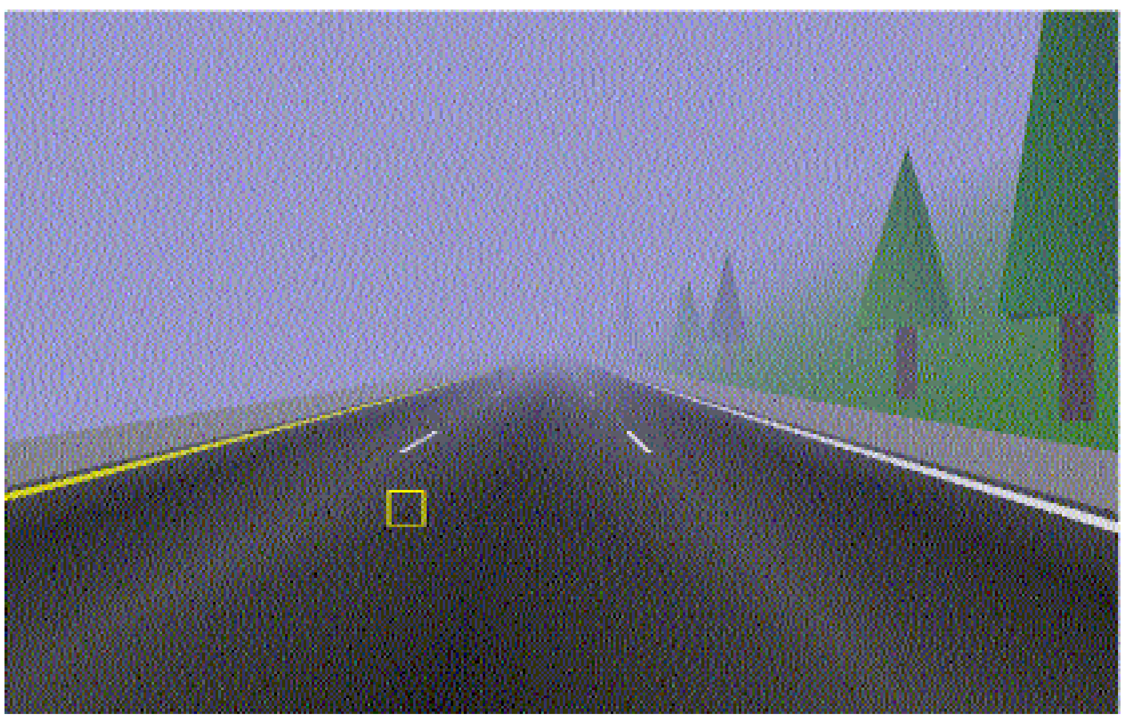

Figure H.9: A typical section of road during fog conditions.

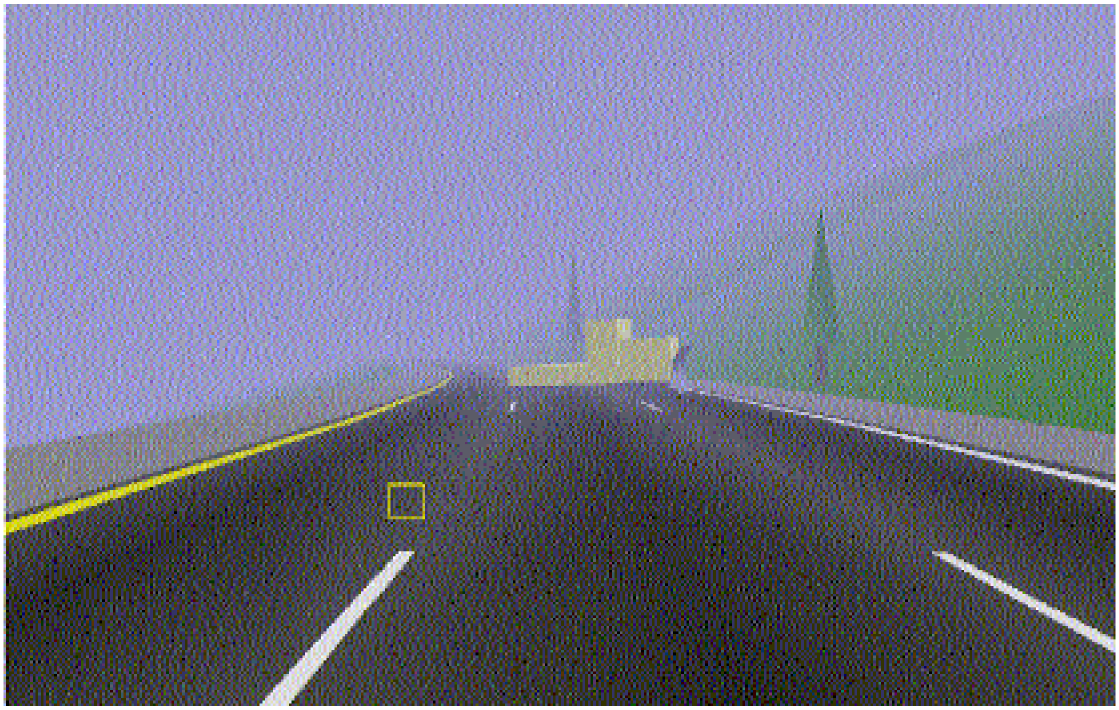

Figure H.10: A yellow snow plow blocking the two right most lanes during the fog condition.

Appendix I

ANOVA calculations

Table I.1: ANOVA, expected mean square calculations.

	df	F=0 i=4	R=1 j=12	F=0 k=2	F=0 l=2	R=1 m=1	EMS
$Sign_i$	3	0	12	2	2	1	$\sigma^2_\varepsilon + 4\sigma^2_\delta + 4\sigma^2_{Subj} + 48\phi_{Sign}$
$Subj_{(i)j}$	44	1	1	2	2	1	$\sigma^2_\varepsilon + 4\sigma^2_\delta + 4\sigma^2_{Subj}$
$\delta_{(ij)}$	0	1	1	2	2	1	$\sigma^2_\varepsilon + 4\sigma^2_\delta$ (not retrievable)
$Weather_k$ (W_k)	1	4	12	0	2	1	$\sigma^2_\varepsilon + 2\sigma^2_{Subj*W} + 96\phi_W$
$Sign*W_{ik}$	3	0	12	0	2	1	$\sigma^2_\varepsilon + 2\sigma^2_{Subj*W} + 24\phi_{Sign*W}$
$Subj*W_{(i)jk}$	44	1	1	0	2	1	$\sigma^2_\varepsilon + 2\sigma^2_{Subj*W}$
$Vehicles_l$ (V_l)	1	4	12	2	0	1	$\sigma^2_\varepsilon + 2\sigma^2_{Subj*V} + 96\phi_V$
$Sign*V_{il}$	3	0	12	2	0	1	$\sigma^2_\varepsilon + 2\sigma^2_{Subj*V} + 24\phi_{Sign*V}$
$Subj*V_{(i)jl}$	44	1	1	2	0	1	$\sigma^2_\varepsilon + 2\sigma^2_{Subj*V}$
$W*V_{kl}$	1	4	12	0	0	1	$\sigma^2_\varepsilon + \sigma^2_{Subj*W*V} + 48\phi_{W*V}$
$Sign*W*V_{ikl}$	3	0	12	0	0	1	$\sigma^2_\varepsilon + \sigma^2_{Subj*W*V} + 12\phi_{Sign*W*V}$
$Subj*W*V_{(i)jkl}$	44	1	1	0	0	1	$\sigma^2_\varepsilon + \sigma^2_{Subj*W*V}$
$\varepsilon_{(ijklm)}$	0	1	1	1	1	1	σ^2_ε (not retrievable)

Appendix J

Sample of actual WSDOT configurations of Snoqualmie Pass