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ALTERNATIVE METHODS FOR ESTIMATING SAFETY

EFFECTIVENESS ON RURAL, TWO-LANE HIGHWAYS:

CASE-CONTROL AND COHORT METHODS

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ABSTRACT

There is a need to better understand the safety implications of geometric improvements on rural, two-lane highways. Funding for transportation safety improvement projects is often limited so it is important to estimate the relative safety effectiveness of each proposed improvement and select those that are likely to produce the greatest benefit. Safety, efficiency, and economic costs are all competing factors in the cost-effectiveness of highway improvements. While engineers are able to evaluate efficiency and monetary costs quantitatively, safety is often evaluated qualitatively based on expert judgment or past experiences. Estimating the change in expected crashes due to a particular improvement (i.e. the crash modification factor or CMF) is one method for evaluating safety quantitatively. Alternatively, safety effectiveness may be estimated as the relative probability of a crash. Case-control and cohort methods are proposed and evaluated to estimate the relative probability of a crash for specific lane and shoulder widths. The estimated safety effectiveness is then compared to CMFs developed in the Highway Safety Manual to test the validity of the methods.

As highway safety has evolved, a number of different methods have been applied to estimate the safety performance of roadway segments. This research summarizes current methods in highway safety analysis and evaluates two alternative methods for estimating the safety implications of roadway features. Methods derived from epidemiological studies are proposed. Epidemiology often seeks to relate risk factors within a population to a particular outcome or disease. In the highway safety context, the "outcome" is a crash and the "risk factor" is a particular geometric feature or countermeasure within a specific population of roadway segments.

There is a direct application of epidemiological methods in highway safety. Case-control and cohort designs estimate the effect of risk factors using the odds ratio and relative risk, respectively. The odds ratio and relative risk represent the expected percent change in the probability of a crash due to a particular risk factor. In highway safety, crash modification factors represent the expected percent change in the number of crashes due to a given geometric improvement. There is a need for better methods to estimate crash modification factors or alternative measures of safety effectiveness and epidemiological designs appear well suited for this task.

This research reviews the strengths and weaknesses of the case-control and cohort approaches and evaluates their effectiveness for estimating safety effectiveness of geometric design elements. Empirical examples are provided using data from Pennsylvania and Washington. Geometric, traffic and crash data were obtained for more than 25,000 rural, two-lane highway segments in Pennsylvania for years 1997 – 2001 inclusive. Similar data were obtained for more than 55,000 rural, two-lane highway segments in Washington for years 1993 – 1996 and 2002 – 2003 inclusive. Case-control and cohort designs are applied to evaluate the incremental safety effects of lane and shoulder width from the odds ratio and relative risk, respectively. Matching is applied in the case-control design to isolate the effects of lane and shoulder width by accounting for confounding variables, such as ADT, speed limit, and segment length. Conditional logistic regression is used to account for the matching procedure and estimate the odds ratio. Confounding is addressed in the cohort study by including potential confounders as covariates in the model. Survival and count models are applied with the cohort design to estimate the relative risk for lane and shoulder width.

Base models were estimated without adjustment for confounding variables, and the estimated safety effectiveness for lane and shoulder width were inconsistent with the CMFs presented in the Highway Safety Manual. A thorough analysis of several potential confounding variables identified ADT, speed and segment length as the most critical confounders when estimating safety effectiveness for lane and shoulder width. Enhanced models were developed with adjustment for ADT, speed, and segment length; results were consistent with the Highway Safety Manual indicating a general decrease in crash risk as lane and shoulder width increase. These findings were consistent for both the case-control and cohort designs. Based on the consistency of results from this investigation, the case-control and cohort methods appear to be well suited for estimating safety effectiveness for lane and shoulder width.

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CHAPTER I INTRODUCTION

1.1 Background

The highway transportation system is very forgiving in the sense that it can handle a great deal of variability in driver performance, vehicle characteristics and environmental conditions before the breakdown of the system and occurrence of a crash. Crashes are truly rare events, not from a national perspective, but from a localized point of view. At any given location the occurrence of a crash event is relatively rare when compared to the level of traffic. However, with more than four million miles of roadway in the United States, these rare local events add-up to a real problem; more than six million crashes and over 40,000 fatalities annually (USDOT, 2005).

Although the number of fatal crashes increased slightly (0.7 percent) from 2000 to 2001, the fatality rate reached a historic low of 1.51 fatalities per 100 million vehicle miles of travel in 2001 (USDOT, 2002). Traffic-related fatality rates are showing a slow decline due to increases in vehicle-miles of travel each year, but the total number of fatalities has leveled-off around 42,000 annually. The occupant fatality rate per 100,000 persons in the population declined by 23 percent from 1975 to 1992, but decreased by only 1 percent from 1992 to 2001. Similarly, the occupant injury rate per 100,000 persons in the population declined by 14 percent during the five year period from 1988 to 1992, but decreased by only 11 percent during the ten year period from 1992 to 2001 (USDOT, 2002). In 2002, motor vehicle crashes were the number one cause of death among Americans 4 to 34 years of age and the eighth leading cause of death overall (USDOT, 2005). With such a vast network and limited budget for highway safety improvements, it is important to identify locations and improvements that will realize the greatest benefits. Therefore, it is critical to analyze these rare events, determine the factors contributing to each event, devise methods to reduce the likelihood of an event, and estimate the effectiveness of each particular improvement.

The road user, vehicle, and roadway environment are all factors that may contribute to the occurrence of a crash event and there are often multiple factors involved at once. Indiana University's tri-level study of the causes of traffic accidents reported that human error was a definite causal factor in about 65-70 percent of roadway crashes and a probable cause in over 90 percent of crashes. The roadway was reported as a definite causal factor in 15-20 percent of crashes with the vehicle reported as the definite cause in just 4 percent (Treat et al., 1977). While the human factor plays a significant role in the event of a crash, it is often the most difficult factor to control due to the large variability of user characteristics in the driving population and sensitivity to regulations. The roadway and vehicle are, however, easier to control through the design process. Vehicle designs, for example, must meet several safety standards and frequently undergo rigorous performance and safety testing in a controlled environment before and after they appear on the market. Roadway designs must also adhere to guidelines, however, the engineer may choose from a range of design values to develop several alternative designs. The question remains, which alternative will result in the best design with regard to safety, mobility, cost, and the environment?

Cost and environmental impacts are easily quantified during the preliminary design process, but the level of safety is more difficult to realize. Randomized clinical trials would be the most powerful method for evaluating the safety of alternative roadway designs. Unfortunately, road safety testing in a controlled environment is not practical or ethical. The only true measure of the safety performance for a new highway is to observe the number of crashes experienced after construction. It may be possible, however, to estimate the number of expected crashes for a particular design based on existing highways with similar characteristics. It would be even more useful to estimate the relative safety effect of each geometric element (e.g. lane width, shoulder width, degree of curvature, and length of curve), thereby allowing the engineer to evaluate each design by parts. This results in the use of observational studies to evaluate roadway safety by associating particular roadway features with crashes.

Preventing a crash event or at least reducing the likelihood of a crash occurrence should be the primary concern of highway safety professionals. Geometric and traffic control improvements may play a significant role in reducing the likelihood of a crash, thereby reducing morbidity and mortality on our nation’s highways. The effectiveness of such improvements, however, is yet to be determined in many cases. Some have even argued that geometric improvements do not have a significant impact on the safety performance of highways (Noland, 2003). While these claims seem of dubious merit, there have been relatively few well-designed studies that show the safety effects of geometric and traffic control features. It is reasonable to assume that the geometric design and traffic control of a roadway can contribute to the overall safety of the facility; but, the question remains, how much?

Safety effects of geometric designs and enhancements have not been fully explored and techniques for analyzing the effectiveness of roadway improvements have suffered from a number of limitations. Until recently, estimates of safety performance have been developed using averages from historical crash data, predictions from statistical models, results of before-after studies, and expert judgments (Harwood et al., 2000). These methods are discussed in detail in chapter two along with common limitations. Estimates from these studies have provided an idea of the relative safety effectiveness for many roadway improvements; however, due to the aforementioned limitations among others, the actual effectiveness is uncertain or unclear. For example, lane widening has been shown to produce reductions in crashes up to 40 percent (Zegeer et al., 1981). These reductions, however, may represent the effects of other unknown or unaccounted factors.

Appropriate tools and methods for analyzing the safety implications of alternative designs need to be provided for planners, designers and decision-makers to make well-informed decisions. Currently, there are still those who believe that safety is addressed through the design guides; however, many of the current design guidelines are not based on scientifically rigorous approaches with respect to safety. In addition, these guides typically allow a range of acceptable values and the resulting effects on safety are not well understood. In transportation, there is a need to move toward decisions that are based on a thorough analysis of safety implications in addition to the economic, environmental, and societal costs of improvements.

The proposed approach relies on the use of case-control and cohort methods to estimate safety effectiveness and approximate crash modification factors. CMFs are one tool that can be used by engineers and decision-makers to determine the relative effectiveness of geometric improvements. Safety performance functions provide an estimate of the expected number of crashes for a particular roadway segment or intersection under a set of base conditions, and crash modification factors are applied to adjust the estimate based on actual geometric conditions (Harwood et al., 2000). Currently, the development of crash modification factors has been based on a limited number of previous studies, which are discussed in chapter two.

In summary, safety has improved significantly over the last thirty years; however, there is still much room for improvement, particularly in addressing the issue at its source – the crash itself. Geometric improvements and related countermeasures are potential solutions to further enhance highway safety, but proper statistical analyses are necessary to unveil the actual effects on safety. It is critical for engineers and decision-makers to be equipped with the proper tools and analysis techniques to evaluate the safety implications of their decisions. If the actual effectiveness of roadway improvements is to be realized, then a sound methodology is required to separate the effects in question from the effects of other variables and potential confounders. The proposed methods seek to develop improved estimates of safety effectiveness, responding to limitations that exist in the current literature.

1.2 Proposed Research and Objectives

The previous discussion defines the problem and helps define two major research objectives. The first objective is to conceptualize an alternative process for developing a prototypical crash modification factor. Understanding the process for developing crash modification factors will help to identify strengths and weaknesses in current analysis techniques. In addition, this will help to layout a framework for building upon current techniques using alternative methods to develop crash modification factors. The second objective is to explore and evaluate alternative methods for developing crash modification factors. These alternative methods use the ratio of the odds and risk to directly estimate the incremental effects of roadway improvements on highway safety while controlling for other variables that affect crashes.

1.3 Outline of Thesis

The following chapter discusses traditional analysis techniques to estimate safety effectiveness of geometric elements as well as the strengths and weaknesses associated with each method. The use of case-control and cohort methods are identified in other areas of highway safety research and their application to highway safety research is discussed. The literature review also identifies studies estimating the expected safety benefits of lane and shoulder width improvements. These studies are evaluated based on the methods used and their ability to isolate the actual effects of the variable in question. Studies evaluating other geometric variables are identified to establish a basic understanding of their relationship to expected crashes, which is later used to determine potential confounding variables. Chapter three provides an overview of crash modification factors as well as a conceptual framework for the development of a prototypical crash modification factor. The proposed alternative designs are then discussed methodologically in chapter four followed by a discussion of the data used in the analyses. An empirical investigation of the methods is discussed in chapter six using data from Pennsylvania and Washington. The thesis concludes with a discussion of the major findings and opportunities for future research.

CHAPTER II PREVIOUS STUDIES FOR HIGHWAY SAFETY RESEARCH

2.1 Previous Methods to Estimate Safety Effectiveness of Highway Design Variables

A number of different methods have been applied to estimate the safety performance of roadway segments. Until recently, estimates of safety performance have been developed using averages from historical crash data, predictions from statistical models, results of before-after studies, and expert judgments. While decision-making has been based on intuition and judgment, there is a need to move toward decision-making based on scientifically rigorous procedures (Hauer, 2005b). In particular, engineers are equipped with the tools to quantify the cost and operational effects associated with alternative designs, but currently lack the necessary tools to evaluate safety quantitatively. The remainder of this section describes previous methods for quantifying safety and the associated strengths and weaknesses. The literature is a basis for this research and shows where current weaknesses may be overcome through the use of alternative methods.

2.1.1 Historical Crash Data

Historical crash data provide important information regarding the trend of crashes over time at a particular location. These data are useful to determine if crashes are generally increasing or decreasing, but have been incorrectly applied for estimating the relative safety effectiveness of a particular countermeasure or roadway improvement. The expected safety benefit has been incorrectly estimated by comparing the actual number of crashes after implementation to the number of crashes before the improvement. The weakness of this approach is that crash data are highly variable. Crashes will likely decrease at a "high-crash" location regardless of whether or not an improvement is made. This phenomenon is known as regression-to-the-mean, which makes it difficult to identify "real" problem locations and accurately estimate the expected effectiveness of improvements. A decrease in the observed number of crashes could be the result of the countermeasure, random fluctuation, or some combination of the two.

Historical data are more appropriately used to identify sites with promise (SWIP) (Hauer, 1996). Sites with promise are identified using the empirical Bayes method. The empirical Bayes method estimates the expected number of crashes for a group of similar sites and then identifies particular locations that experience a high crash frequency relative to the expected frequency. Each SWIP may then be further investigated to determine if an obvious pattern exists or whether the high crash rate is mere chance.

2.1.2 Predictions from Statistical Models

Statistical techniques are very popular and have been used for several years to develop models to estimate the expected number of crashes at a particular location. Roadway and crash data are typically obtained from state or local highway agencies, and regression models are fit to the data to predict crash rates or frequencies based on roadway and traffic characteristics. Some have argued, however, that analysts have over-simplified the procedure, which leads to misuse of the methods and misunderstanding of the results (Hauer, 2004).

Selecting an appropriate distribution and functional form for the model have been major weaknesses of many studies. Models have been developed using multiple-regression analysis; however, the normal distribution may not be appropriate for crash data. One weakness of multiple-regression is that it allows negative predicted values, which is not realistic in highway safety. In addition, crash data are usually right-skewed due to the large number of zero crash locations and multiple-regression is not well-suited to handle this distribution. Recently, count models (e.g. Poisson and negative binomial) have been applied to crash data because they are better suited to handle datasets with a large number of small values (i.e. zeros and ones).

Once a modeling technique has been selected, the question now is what functional form to use. Linear relationships are often used to describe the relationship between the independent and response variables; however, a non-linear form may better describe the data. The question regarding functional form is not easy to answer and may depend on previous knowledge of variable relationships as well as current exploration of suitable forms.

Lack of control for confounding variables and unexplored potential interactions are two other common limitations of past and current research (Hauer, 2000). A confounding variable is a variable that completely or partially accounts for the apparent association between an outcome and a risk factor. Specifically, a confounder is a variable that is a risk factor for the outcome under study, and is associated with, but not a consequence of, the risk factor in question (Collett, 2003). Average daily traffic and segment length are both significant predictors of crash frequency and may also be associated with several design characteristics. If a specific design characteristic (e.g. lane or shoulder width) is suspected to be a risk factor of crashes then the effects of ADT and segment length must be separated before the true effects of the variable of interest may be known (Persaud et al., 1999 and Hauer et al., 2004). This holds for many variables and emphasizes the importance of controlling for outside effects (i.e. effects from sources other than the variable of interest). Reasons for confounding include lack of available data and variables that are not practical to measure or cannot be measured. Interactions are related to the functional form of a model and should be fully explored.

Regression models are well suited to predict the expected number of crashes for a particular location, but may not be appropriate to estimate the effects of individual variables (Hauer, 2005a). A predictive model may be based on several parameters that are estimated during the regression procedure. The parameter coefficients represent the effect of each variable on the response, which provide reliable predictions as a whole but show counterintuitive relationships for some variables individually. Counterintuitive relationships may be due to strong correlations between variables in the model, which makes it difficult to separate their individual effects. In addition, if an included variable is strongly correlated to a significant omitted variable, the coefficient of the variable in the model may represent part of the effect of the omitted variable rather than its own effect. Therefore, traditional regression techniques are not recommended for isolating the effects of individual geometric or traffic control features.

2.1.3 Before-After Studies

Three types of before-after safety evaluation study designs are described in Harwood et al. (2002). The most basic of the three methods is the before-after yoked comparison. The yoked comparison involves a one-to-one matching between a treatment and comparison *site*. A comparison site is identified for each treatment site, adding additional support to the effectiveness of a particular countermeasure. The key assumption in the yoked comparison approach is that the change in crashes between the before and after periods at a comparison site is representative of the change in crashes that would have occurred at the treatment site had the improvement not been implemented.

The strength of the yoked comparison is its simplicity and minimal data requirements. Fewer required sites will allow investigators to ensure that the treatment and comparison sites have similar characteristics. There are, however, three major weaknesses to this approach. First, there is only one comparison site for each treated site, which limits the amount of data for estimating safety effectiveness and is likely to produce relatively wide confidence limits. Second, the yoked comparison cannot deal with regression-to-the-mean. Regression-to-the-mean can only be accounted for with knowledge of the expected value of before-period crash experience at the treated sites. Third, the yoked comparison method has difficulty dealing with crash frequencies equal to zero. In the case of zero crashes the effectiveness of the treatment is undefined. This problem may be resolved by substituting a small value (e.g. 0.01, 0.1) for zero, but nonetheless represents a weakness of the yoked comparison.

Another approach is the before-after study with a comparison *group*. This approach is similar to the yoked comparison, but a group of comparison sites is used in place of the single comparison site. The comparison group is superior to the yoked comparison in that it relies on a group of similar sites, rather than a single site, to determine estimates of safety effectiveness. Thus, the increased size of the crash sample in the comparison group should decrease the variance of the estimate and width of the confidence limits. The obvious weakness is the additional data requirement. The amount of data required for analysis is greater than the yoked comparison and it may not be possible to find an entire group of sites with similar characteristics to the treatment site. Similar to the yoked comparison, the comparison group approach cannot determine the treatment effectiveness when the crash rate is zero, and it cannot address the bias created by regression-to-the-mean.

The third before-after evaluation method is the before-after approach with empirical Bayes, which is the only one of the three methods that can account for regression-to-the-mean bias. The empirical Bayes procedure compares the safety effect of a treatment with the expected safety had the treatment not been implemented. The estimate of the expected safety for a particular site is calculated using data from the particular site as well as data from other sites with similar characteristics. Reference groups needed for the empirical Bayes approach are likely to be smaller than those in the comparison group approach because regression modeling makes efficient use of the data. The treatment effectiveness may also be assessed within the desired precision level where this was not possible with the comparison group approach. Finally, the empirical Bayes approach eliminates the difficulty with zero crashes that appeared as weaknesses in the other two approaches. The literature supports the use of empirical Bayes for safety evaluation when the above mentioned problems (e.g. regression-to-the-mean, zero crashes, etc.) are a concern (Harwood et al., 2000; Hauer et al., 2002).

2.1.4 Expert Judgments

Expert judgments are useful for making qualitative, rather than quantitative, statements. The term "expert" implies that the decisions are based on years of experience in the highway safety field and the term "judgment" implies that the estimate is an opinion. Although these judgments may be inexact, they can have an important role in making reliable safety estimates. Using past experiences as a point of reference, experts may be able to make comparative judgments (e.g. alternative A is more effective than alternative B for a specific location). Thus, an expert's judgment is only as good as his/her past experience and frame of reference, which may be based on historical accident data, statistical models, or before-and-after study results.

2.2 Current Methods for Estimating Safety Effectiveness

2.2.1 Interactive Highway Safety Design Model

Harwood et al., (2000) developed a crash prediction algorithm that incorporates elements of historical crash data, statistical models, before-after methods, and expert judgments. The crash prediction algorithm includes a calibration procedure, an empirical Bayes procedure, and crash modification factors (CMFs) to adjust the base models and more accurately reflect conditions at a specific location. This research is currently recognized as the best available method for evaluating safety, and a software program has been developed to incorporate the methods applied in this research. The Interactive Highway Safety Design Model (IHSDM) is currently available to evaluate roadway segments and intersections on two-lane, rural facilities (IHSDM, 2005).

2.2.2 Highway Safety Manual

The Highway Safety Manual (HSM) is another tool, currently under development, to help engineers quantify the expected safety performance of a particular roadway (Harwood et al., 2000). The Highway Safety Manual includes a crash prediction algorithm and crash modification factors for two-lane, rural roads and intersections. The crash prediction algorithm is used to estimate the expected number of crashes for base conditions, and the crash modification factors are applied to adjust the estimates based on the actual geometry at a particular location.

CMFs based on past research studies and expert judgment have been developed for a number of geometric design elements and included as part of the Highway Safety Manual. For some geometric elements, one particular study was selected to serve as the basis for the CMF. In other cases, results of two or more studies were combined to develop the CMFs. In rare cases, the panel exercised its collective judgment to estimate values for an appropriate CMF when no literature was available. The development of CMFs was based on a variety of sources including before-after evaluations, parameter values from regression models, and expert judgment. The panel reviewed results from three studies to develop CMFs for lane width (Griffin and Mak, 1987; Zegeer et al., 1981; Zegeer et al., 1988) and two of these studies were further evaluated to develop CMFs for shoulder width (Zegeer et al., 1981 and 1988). These studies are further discussed in Section 2.3 along with other research focusing on the effects of lane width, shoulder width, and related geometric variables.

The CMFs from the Highway Safety Manual are used as a comparison to determine if the results obtained from this research are reasonable. CMFs represent the expected number of crashes for a given value of a geometric element compared to the baseline for that element. In general, crashes are expected to decrease as lane and shoulder width increase and effects are greater for higher volume roadways (Figures 1 and 2). The CMFs do not show a change in effect for volumes below 400 vehicles per day or greater than 2,000 vehicles per day because previous research did not allow interpolation beyond these points. The appropriate crash modification factor is obtained by first identifying the existing or projected ADT on the roadway and then identifying the desired lane or shoulder width. For example, the CMF is 1.05 for a roadway with 2,000 vehicles per day and 11 foot lanes. If the ADT on the same road is expected to decrease to 1,000 vehicles per day then the CMF would be reduced to approximately 1.02. The CMFs for lane and shoulder width are based on specific crash types that are most likely related to cross-sectional features (i.e. head-on, run-off-the-road, and sideswipes in either direction). These crash modification factors must be adjusted when compared to models of total crashes as discussed in the analysis and results section.

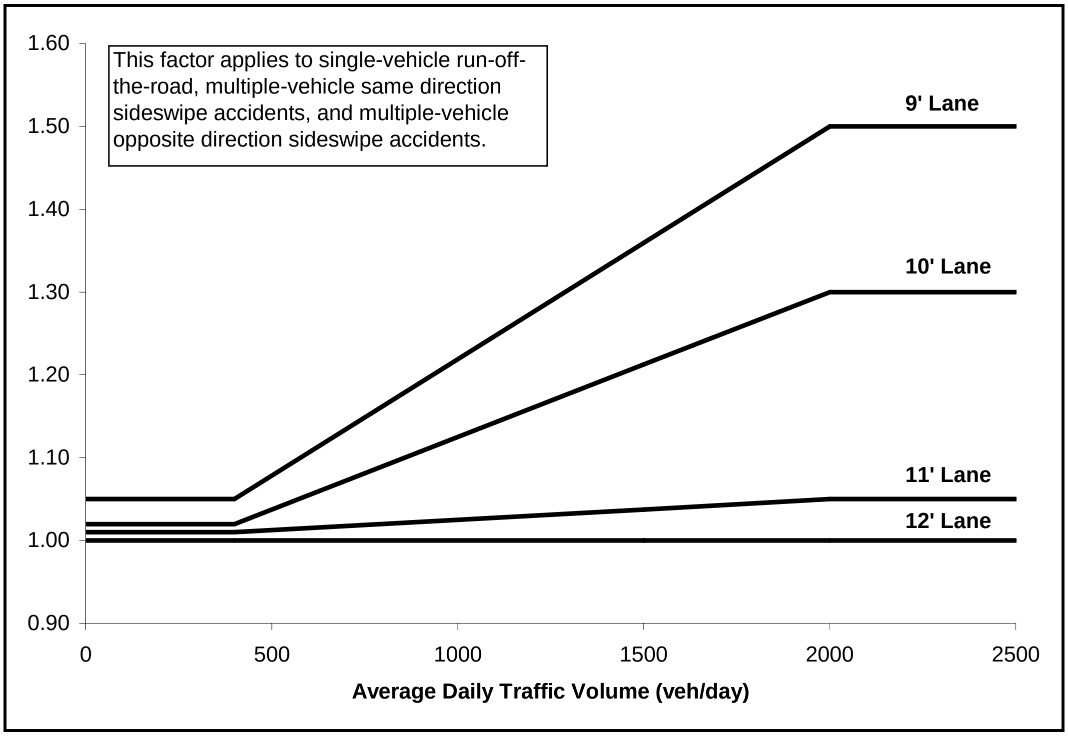

FIGURE 1 Recommended CMF for Lane Width (Harwood et al., 2000)

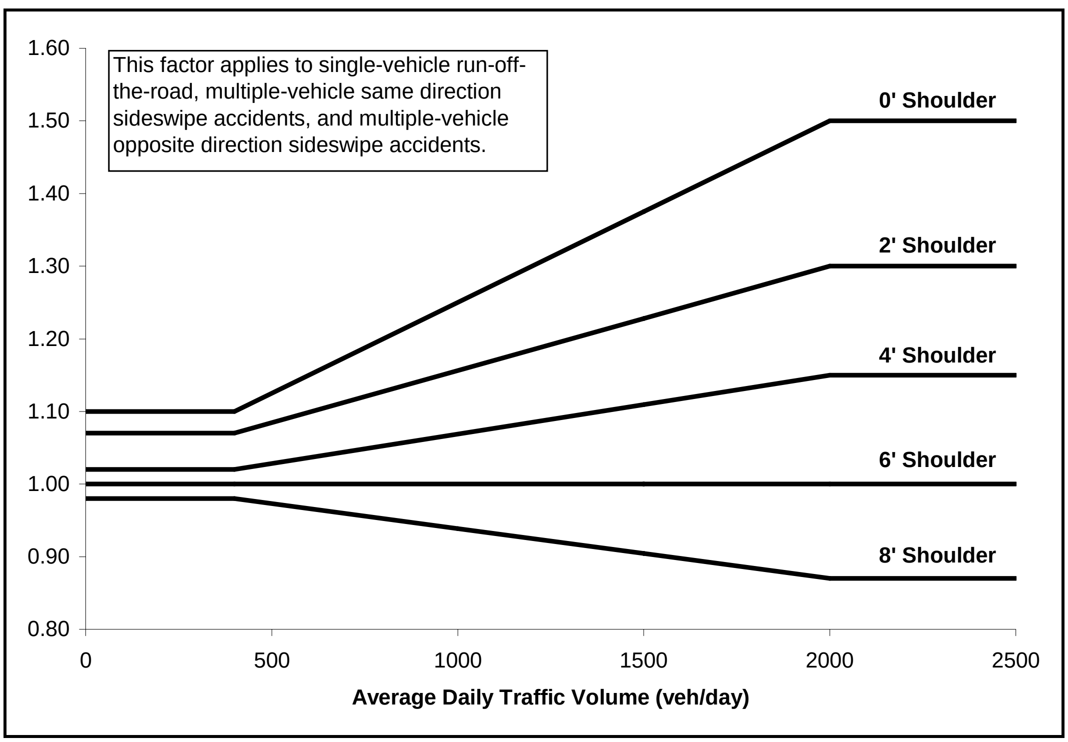

FIGURE 2 Recommended CMF for Shoulder Width (Harwood et al., 2000)

2.3 Relationship between Roadway Geometry and Expected Crashes

Research studies to date are approximations, at best, of geometric relationships to safety. The understanding of these relationships is not, however, adequate to predict the response in crash rate due to changes in individual geometric design elements. The modeling of relationships between crashes and roadway geometry dates back to at least the 1950s when Raff (1953) investigated the effects of horizontal and vertical alignments on highway safety. Since then, there have been a number of studies utilizing different methods to quantify the safety effects of roadway improvements. The following literature review is a summary highlighting key research and issues related to the safety effects of lane width, shoulder width, and other related geometric elements.

Vogt and Bared (1998) conducted a thorough literature review of the relationships between crashes, roadway geometry, and traffic conditions. The review summarized the results from several studies and indicated possible relationships between crashes and individual geometric and traffic variables, but noted that results were not consistent across studies. General relationships between crash expectancy, roadway geometry, and traffic characteristics are described below.

The expected number of crashes increases as average daily traffic (ADT) increases. ADT is one of the most significant predictors of crash frequency on a particular roadway segment or intersection and has been shown to increase the log-likelihood eight times more than the next most important variables including commercial driveway density, posted speed, and segment length (Hauer et al., 2004). Hauer (1994) also recommends using ADT rather than vehicle-miles (i.e. ADT * segment length) as the measure of traffic exposure because ADT may interact with other controllable variables when modeled as an independent variable. Many studies have modeled crash frequency as a linear function of ADT; however, the relationship between crashes and traffic flow has been shown to follow a nonlinear pattern. Hauer et al. (1987) show that crashes increase at a decreasing rate as traffic flow increases, which affects the functional form of the model.

Several studies have been conducted in an attempt to quantify the effects of lane and shoulder width. In general, crashes are expected to decrease as lane and shoulder width increase, but results have been inconsistent across studies. Some earlier studies indicated that increased lane widths (Head, 1960) and shoulder widths (Belmont, 1954; Blensly and Head, 1960) were associated with higher crash frequencies; however, there was little control for confounders and results may reflect the effects of other variables. Perkins (1957) concluded that lane and shoulder width have no effect on the expected crash frequency on rural, two-lane roads, but did not exclude intersection crashes from the analysis.

Other early studies produced more intuitive results and suggested that crashes decrease with increasing lane and shoulder width. Cope (1955) analyzed data from pavement widening projects and reported crash reductions up to 47 percent when widening cross sections from 18 to 22 feet. Stohner (1956) evaluated 8,700 miles of two-lane, rural highways in New York. Results from one year of crash data suggested that property damage only (PDO) crashes continue to decrease as shoulder width increases, but injury crashes decrease only up to shoulder widths of eight feet and then increase for greater widths. Billion and Stohner (1957) analyzed a similar dataset from New York but included four years of crash data. Results indicated that medium shoulder widths (5 – 7 feet) are optimal on level tangent sections, but "wider" shoulders produce the greatest safety benefits on "poor" alignments (i.e. roadways with relatively sharp curves and steep grades).

The effects of lane width on crash frequency have not always been shown to be strictly positive or negative. Several studies have shown safety benefits from lane widening up to a certain point, after which the safety benefits are lost. This trend was shown as early as the 1950s, where Belmont (1954) reports a decrease in crash risk up to lanes of 11 feet, after which crash risk increases. Dart and Mann (1970) showed a similar result with an optimal lane width of 11 feet although results are questionable due to the lack of control for confounding variables. Roy Jorgensen Associates (1978) estimated CMFs for lane width using a multiplicative model and controlling for shoulder width, ADT, horizontal curvature, and shoulder type. Again, the optimal lane width in regards to safety was shown to be between 21 and 22 feet. Zegeer et al. (1981) generated summary tables by grouping segments based upon facility type, AADT, access points, lane width and shoulder width; results showed a "U-shaped" for lane width where crash risk was higher for lanes less than and greater than 11 feet.

While the effects of shoulder widening vary between studies, the effects of the presence of a shoulder have been more consistent indicating improved safety with shoulders. Heimbach (1974) compared crash frequencies between highways with similar characteristics except for the presence of shoulders. The study included four years of crash data for rural highways in North

Carolina and segments were matched by ADT, access control, posted speed, number of lanes, and lane width. Limited data prevented the analysis of several combinations of shoulder width and type; therefore, paved shoulders were compared to no paved shoulder. The study concluded that paved shoulders were associated with a lower crash frequency and severity than similar unpaved shoulders. Turner et al. (1981) similarly compared paved versus unpaved shoulders and reported that paving reduces crashes for two-lane, rural highways.

Later studies applied before-after techniques (Rogness et al., 1982; Ogden, 1997) and statistical models (Hadi et al., 1995; Vogt and Bared, 1998; Strathman et al., 2001) to relate crash frequency with lane and shoulder width. Ogden (1997) used a before-after with comparison site approach and reported that shoulder width improvements of two to three feet may reduce fatal and injury crashes up to 41 percent on rural highways. Hadi et al. (1995) developed several negative binomial regression models to estimate the effects of cross-sectional design elements on total, fatality, and injury crash rates for various types of rural and urban highways. The study concluded that lane and shoulder width were negatively associated with crash rates, but results varied based on facility type. Vogt and Bared (1998) developed crash prediction models for two-lane, rural highways using data from Washington and Minnesota. Several variables were included in the model, and results indicated that lane and shoulder width have a significant effect on safety; each additional foot of lane and shoulder width is expected to reduce crashes by about 8.5 percent and 6 percent, respectively. Strathman et al. (2001) also developed a crash prediction model for several different facility types. The non-freeway model indicated that crashes are expected to decrease as lane and shoulder width increase on rural facilities, but results for lane width were opposite for urban segments.

The effect of lane and shoulder width on *specific* crash types has been studied to a lesser extent. Studies have shown that cross-sectional elements such as lane and shoulder width are most associated with specific crash types including head-on, run-off-the-road, and sideswipes in either direction (Zegeer et al., 1981; Zegeer et al., 1988). Pant et al. (2003) later investigated the effects of several variables, including lane and shoulder width, on several crash types and severities. For most crash types, crash rates were shown to decrease as lane and shoulder width increased; however, rear-end crashes were shown to increase under certain circumstances. Lane and shoulder width were also shown to have differential effects on crash severity.

Miaou et al. (1993) also investigated the effects of lane and shoulder width; however, the primary objective of the study was to test the applicability of several model forms. Linear regression and Poisson models were developed to estimate the expected number of truck crashes based on roadway geometry. Linear regression models were deemed to be inadequate for crash prediction. Poisson models were shown to posses more desirable qualities for crash prediction although limitations still exist. Results indicated that truck crash rates were expected to increase as lane width deviates from a typical 12 foot lane.

Three studies were selected as the basis for lane width CMFs in the Highway Safety Manual, and two were further explored to develop CMFs for shoulder width. These studies are discussed in further detail due to there relevance to this research. Griffin and Mak (1987) investigated the safety effects of lane widening on two-lane, rural roads in Texas. Weighted least squares procedures were used to estimate single vehicle and multi-vehicle crashes on roadway widths of 18 to 28 feet. Segments were sub-divided by four categories of ADT, and a separate model was developed for each level. No relationship was found between multi-vehicle crashes and roadway width at any level of ADT, but single vehicle crashes were shown to decrease as lane width increased in the three highest ADT categories. Reductions were reported on the order of 5 to 50 percent; however, these reductions may reflect the effects of other variables because the models did not account for other potential confounders (e.g. speed and curvature).

Zegeer et al. (1981 and 1988) estimated the safety effects of lane and shoulder width on rural, two-lane roads. Both studies found that run-off-road, head-on, and sideswipe crashes (same direction and opposite direction) were most associated with cross-sectional features. The earlier study (Zegeer et al., 1981) used a comparative method to determine safety effects; similar segments were grouped based upon facility type, AADT, access points, lane width and shoulder width and summary tables were generated. Crash reductions were reported ranging from 10 to 39 percent for wider lanes and reductions ranging from 6 to 21 percent for shoulder widening. In the later study, Zegeer et al. (1988) developed a multiplicative crash prediction model to determine the potential safety benefits of lane and shoulder widening. The model was used to predict the total number of run-off-road, head-on, and sideswipe (same direction and opposite direction) crashes. Predictors included ADT, lane width, paved and unpaved shoulder width, roadside hazard rating, and terrain. Results for lane width were consistent with earlier findings showing crash reductions ranging from 12 to 40 percent; however, the effects of shoulder widening were much greater than before with reductions ranging from 16 to 49 percent for paved shoulder widening, and 13 to 43 percent for unpaved shoulder widening. The fact that results are so different for shoulder width between the two studies raises some concern. This may indicate that some of the effect on expected crashes may be due to confounders.

Horizontal and vertical alignments produce similar negative effects; sharper and longer curves are expected to result in a greater number of crashes. Several studies have shown similar results for the relationship between crashes and horizontal curves. The expected number of crashes has been shown to increase linearly with increasing degree of curve (Raff, 1953; Leisch & Associates, 1971; Matthews and Barnes, 1982), but a non-linear trend has been shown when crash frequency is plotted against the radius of curve (Leisch & Associates, 1971; Matthews and Barnes, 1982). Crashes are expected to decrease rapidly as curve radius increases for relatively small radii with a less rapid decrease for increases in larger radii. There is some evidence that degree of curve may be correlated with other significant variables such as ADT, lane width, and shoulder width. Curves with smaller radii tend to be associated with a lower ADT, narrow lanes and narrow shoulders (Deacon, 1986); therefore, the expected increase in crashes for sharper curves may be influenced by other covariates. Curve length has also been shown to significantly affect the expected number of crashes, but results are not consistent. Glennon et al. (1985) show that length of curve is negatively correlated with crash frequency while others have determined that crashes are expected to increase with increasing length of curve (Zegeer et al., 1991 and 1992).

The above referenced studies are only a summary of previous findings regarding the effects of geometric and traffic elements on crashes. Results are not consistent across all studies with some results contradicting others. Those results that are consistent, in terms of the direction of effect, are not always similar in magnitude. There is still much work to be done in this area to validate past studies and investigate the effects of those countermeasures and geometric elements that are not well understood.

2.4 Alternative Methods for Estimating Safety Effectiveness

Alternative methods for analyzing safety include the estimation of risk, relative risk, odds, and odds ratios rather than the expected number of crashes. The risk and odds are the chance of an event occurring given a certain set of attributes. Risk is estimated as the number of events for a particular group of subjects divided by the total number of subjects at risk for that particular group (i.e. cases plus non-cases). Relative risk may then be determined for any particular group compared to a baseline group by dividing the two risks; the risk for the baseline group is used as the denominator. Odds and odds ratios are estimated similar to the risk and relative risk; however, the odds are calculated as the number of events divided by the number of non-events. The odds ratio is calculated as the ratio of two odds, using the baseline group as the denominator.

Cohort and case-control studies apply relative risk and odds ratios to estimate the chance of an outcome. Calculation of the risk or odds depends upon the study design, which will be discussed in later chapters. The remainder of this section discusses the limited use of case-control and cohort applications in highway safety.

2.4.1 Case-Control Applications

Case-control methods have been used in certain areas of highway safety, but few if any have focused on the effects of geometric design elements. A review of the literature identified case-control studies ranging from the effectiveness of motorcycle-helmet use to the crash risk of truck drivers. Each identified study is briefly discussed including a description of the sampling method and relevance to the investigation of geometric design elements.

Tsai et al., (1995) investigated the effectiveness of helmet use and type for the prevention of head injuries among motorcycle riders in Taipei, Taiwan. A case-control method was used to investigate crash-involved motorcycle riders comparing those with head injuries (cases) to those not suffering head injuries (controls). The case-control method was used to control for confounding variables such as age, gender, and helmet type that may influence the risk of head injury. Cases and controls were selected from a group of 1351 victims of motorcycle accidents located in one of 15 hospitals in Taipei, Taiwan. This study is unique because a second group of "on-street" controls was also selected. For every daytime (8am-6pm) motorcycle injury, pictures of four motorcycles were taken at the same time of day at the same location. Multiple logistic regression was used to estimate the relative risk of head injury associated with the use of different types of helmets as well as other predictors. This study illustrates the application of multiple logistic regression to estimate relative risk and the use of covariates to make adjustments for confounders.

Stevenson et al., (1995) identified factors which contribute to the risk of childhood pedestrian injuries and describe their role in injury causation. A *matched* case-control study was implemented in the metropolitan area of Perth, Australia, to determine the human, vehicle and environmental factors that contribute to childhood pedestrian injuries. Cases were defined as children aged 1 to 14 years who had sustained an injury in a collision with a motor vehicle while walking, running, or crawling on a roadway, road verge or footpath. Two control subjects were individually *matched* with each case based on age and gender. Controls were selected from a random sample of schools in Perth for children 6 years and older and through the Midwives Notification System for younger children. Matching ensures that adjustment is possible for the matching variables and helps to control for other variables that may be difficult to measure. For example, risk-taking behavior is difficult to measure individually, but may be associated with age and gender. By matching on age and gender, the estimated risk may also be adjusted for the effects of risk-taking behavior. Matching by county or district may be a useful method to account for the effects of driver populations and local weather conditions when estimating the safety performance of roadway segments.

A population-based case-control study was conducted in the suburbs of Melbourne, Australia, to assess socio-demographic factors and measures of exposure as risks of injury (requiring hospital attendance) in children riding bicycles (Carlin et al., 1995). Cases were defined as all children, ages 5-14, involved in a bicycle-related injury occurring in a defined region of Melbourne, Australia, and presenting to one of two medical hospitals. Controls were recruited from the same population using a sample of randomly selected telephone numbers. Exposure to risk was defined in two ways, distance and time. Exposures were generally broken into categories representing approximate groups, in order to avoid assuming a log-linear relationship between risk and exposure. Logistic regression was used to determine odds ratios and 95 percent confidence intervals. An alternative analysis was also performed using conditional logistic regression, pairing each case with a control interviewed during the same week, to test for confounding of seasonal factors. Examining subcategories of distance, the analysis suggests a weak association of distance traveled on busy streets, no association with travel on local streets, and strong association with distance traveled on sidewalks. There was also a significant risk to children that spend any amount of time riding for play. This study identifies two issues; exposure and conditional analysis. Expected crash frequency is related to ADT and segment length, which are measures of exposure for highway segments. These variables should, however, be included as categorical variables to determine if the effects are significant for all levels of ADT and segment length. A conditional analysis is important for matched studies because estimates of the relative risk or odds ratio should be conditional on the matching scheme. This issue is further discussed in Section 4.4.

Jovanis et al., (2005) investigate hours of service as a risk factor for large truck crashes. Cases were selected from a population of truck drivers experiencing a crash and controls were randomly selected from the same population of drivers, but were defined as those not experiencing a crash. Two controls were matched to each case by month of crash and terminal of operation to account for seasonal effects and regional differences between terminals. The matching allows for control of seasonal and regional differences when assessing the effects of hours of service on crash risk. Other variables considered in the analysis included driving pattern over a seven day period and type of operation (i.e. sleeper or non-sleeper unit). This study also illustrates the use of matching to make adjustments for variables that are difficult to measure.

Híjar et al., (2000) applied a case-control design to identify risk factors related to the driver, vehicle, and environment that are associated with motor vehicle crashes on highways. Cases and controls were selected from the same study population; all drivers of motor vehicles on the Mexico-Cuernavaca highway. Cases were defined as drivers of a motor vehicle who were involved in a crash and controls defined as those drivers who completed a trip without being involved in a crash along this particular highway. Variables were collected on the driver, vehicle, and environment including: age, gender, experience, duration of trip, restraint use, alcohol consumption, model, year, vehicle size, time of day, day of week, month, distance/direction, and climatic conditions. After adjustment through multiple logistic regression, the following variables were determined to significantly elevate the risk of a crash: drivers age 25 or younger, drivers age 45 or older, traveling to work, alcohol consumption within 6 hours of the trip, travel in the Mexico-Cuernavaca direction, traveling during daylight conditions, weekday travel, and travel in adverse weather conditions. This study investigated the effects of the driver, vehicle, and environment, but did not specifically examine the geometric features associated with this highway section. The results of this study, however, indicate the importance of driver population, trip purpose, and environmental condition when estimating crashes on roadway segments.

Zhang et al., (2005) apply a risk ratio to study the effects of adverse weather and congestion on motor vehicle crashes. This study is not classified as a case-control design, but deserves discussion because of the unique measure of effectiveness. The risk of a crash was calculated for several combinations of hourly traffic volume (v) and weather (w) conditions; however, the denominator represented the number of crashes occurring for a specific weather condition (w) summed over all levels of hourly traffic volume. The risk ratio was calculated for each specific weather condition by comparing the hours with crashes to the total hours during the study period as shown in Equation (1).

$$\text{Relative Risk Ratio} = RRR_{w,v}(s) = \frac{H_{v,w}^{A} / \sum_{v} H_{v,w}^{A}}{H_{v,w}^{T} / \sum_{v} H_{v,w}^{T}} \quad \dots (1)$$

Where:

s = station ID,

w = weather category, summarized as non-precipitation, rain, and snow,

v = flow rate category,

$H_{v,w}^{A}$ = number of hours with crashes occurring during the study period when the hourly flow rate was v and the weather condition was w,

$\sum_{v} H_{v,w}^{A}$ = total number of hours with accidents occurring during the study period when the weather condition was w, summed over all levels of hourly flow rate,

$H_{v,w}^{T}$ = exposure, the number of hours during study period when hourly flow rate was v and weather condition was w,

$\sum_{v} H_{v,w}^{T}$ = total number of hours during the study period when the weather condition was w, summed over all levels of hourly flow rate.

Case-control studies are used to develop an estimate of the odds ratio, but cannot estimate risk because the number of cases and controls is pre-specified. The odds ratio, however, may be a good approximation of the relative risk under certain conditions. When the number of cases is relatively small compared to the total number at risk, then the number of non-cases is an approximation of the total number at risk. If, however, the number of cases is relatively large, then the odds ratio is not a good approximation of the relative risk. In the study by Zhang et al., (2005), the odds ratio is likely a good approximation of relative risk because the number of hours with crashes would be relatively small compared to the total number of hours without crashes. Crashes are relatively rare for any particular segment; however, crashes may not rare events when considering a sample of roadway segments. The assumption of rarity is certainly a function of highway classification and may be valid for rural segments where the average number of crashes is much lower than on urban segments. This issue is explored in Section 6.5 by comparing the odds ratio and relative risk from similar case-control and cohort designs.

Case-control designs are well suited to investigate the effects of specific risk factors while controlling for other variables that may influence the outcome in question. The literature provides examples of the application of case-control designs in highway safety; relating driver, pedestrian, and environmental factors to the risk of a particular outcome. Several methods were also identified in the literature for dealing with confounding variables and analyzing case-control data.

2.4.2 Cohort Applications

Cohort designs have been used less frequently to evaluate risk factors in highway crashes. Lin et al., (2003) investigated risk factors contributing to motorcycle crashes in rural and urban areas of Taiwan. The study focused on junior college students due to the high number of crashes experienced by this age group. A representative sample of crashes was obtained and a generalized Cox Proportional Hazard model was developed to relate potential risk factors to time at risk. Covariates included riding exposure and past crash history as well as human, vehicle and environmental factors. Additional confounding and unreported incidents were reported as potential limitations of the study.

Cummings et al., (2003) investigated the effectiveness of seatbelts in reducing fatal crash involvement. Fatal-crash data were obtained from the Fatality Analysis Reporting System (FARS) for 1975 to 1998. Only those crashes that resulted in the death of the driver, right front passenger, or both were examined. Potential confounding variables included age, gender and seat position, which were estimated as covariates in the model. Matching was used to adjust for the confounding effects of vehicle type and crash characteristics by comparing crash severity for occupants within the same vehicle. A conditional Poisson regression model was developed to estimate the relative risk of death for seatbelt use and the additional covariates. Results were consistent with previous findings and indicated a lower risk of death for belted compared to unbelted occupants.

The cohort method has not been used extensively in highway safety analyses; however, the literature provided two examples of successful applications. The referenced studies illustrate methods to adjust for confounding variables and estimate relative risk. While matching is possible within the cohort design, it is not practical for investigation of lane and shoulder width because each variable consists of the multiple categories. The Cox Proportional Hazard model and Poisson regression were identified as appropriate modeling techniques, which are evaluated in Section 6.5.

2.5 Relationship of Case-Control and Cohort Designs to Previous Methodologies

The crash modification factor (CMF) is defined as the expected number of crashes with a countermeasure divided by the number expected without the countermeasure. This research evaluates the use of case-control and cohort designs as alternative methods to estimate the safety effectiveness of lane and shoulder width using the odds ratio and relative risk, respectively. The odds ratio and relative risk are formally defined in Section 4.2, but represent the probability of a crash with the countermeasure divided by the probability of a crash without the countermeasure. Note the similarity in definition between the CMF and the odds ratio or relative risk. The CMF reflects the ratio in the expected number of crashes while the odds ratio and relative risk reflect the ratio of the probability of a crash. These measures differ by some quantification of exposure to risk, which typically reflects the amount of travel on the roadway (ADT). The development of a “prototypical” CMF is discussed in the following chapter and the same ideology is then applied using case-control and cohort methods.

CHAPTER III CONCEPTUAL FRAMEWORK FOR CMF DEVELOPMENT

3.1 Overview of Crash Modification Factors

Crash modification factors (CMFs) represent the incremental safety effects due to incremental changes in roadway geometry or traffic control features. Planners and designers may apply CMFs during their decision-making process to determine the relative safety of alternative designs. For a more precise evaluation, a crash prediction model may be used to estimate the expected number of crashes at a particular location under base or nominal conditions. CMFs are directly applied to the base crash prediction model to reflect site-specific characteristics. CMFs are multiplicative factors with the nominal or base condition set equal to one. A CMF greater than one is associated with a higher expected crash experience than the base condition, and a CMF less than one is associated with a lower expected crash experience.

Well designed before-after studies are the preferred method for developing crash modification factors (Harwood et al., 2000). In the before-after analysis, a treatment is implemented and the expected crash frequency is estimated and compared for the “with” and “without” treatment periods. The effectiveness of the treatment or CMF is estimated by the change in expected crash frequency. From a practical standpoint, the CMF is difficult to estimate. Several safety improvements may be implemented simultaneously at a location, so it can be difficult to isolate the effect of a single countermeasure from the before-after study. Changes in traffic level, driver population, vehicle mix and other factors may also occur over the “with-without” time period, potentially confounding the measurements. Finally, waiting several years for sufficient ‘with” data is a practical concern.

3.2 The Prototype Crash Modification Factor

The development of a “prototypical” crash modification factor is explored to set the foundation for developing estimates of safety effectiveness using case-control and cohort designs. The “prototype” CMF is determined through a series of before-after studies in which one, and only one, improvement is made to a particular location. Each study in the series would involve a large sample of identical sites where the same improvement is made to each site and a large crash history is available with and without the improvement. Although crashes are random in nature and highly variable from year to year, a large sample with many years of data will behave with a certain underlying probability distribution from which the expected value may be calculated.

The expected value calculated from the before period will be denoted $E_{WO}(x)$, which represents the number of crashes that would be expected had the improvement not been made. After the improvement is made, the expected number of crashes is determined for the time period with the improvement, say $E_W(x)$. It is important that only one improvement is made and that it is identical for each site. It is also critical that all other conditions and variables affecting crashes remain the same in the periods with and without the improvement. This will allow a direct comparison of the expected number of crashes in the before and after periods, which will be indicative of the actual safety effects for the particular improvement without confounding from other sources. The resulting crash modification factor may be calculated from Equation (2).

$$CMF_p = \frac{E_W(x)}{E_{WO}(x)} \quad \ldots (2)$$

Where,

CMF_P = prototype crash modification factor,

$E_W(x)$ = expected number of crashes with the improvement, and

$E_{WO}(x)$ = expected number of crashes without the improvement.

If a particular site improvement has a potential range of values, then the above described study would be repeated for each possible incremental change to determine the associated change in expected crashes. For example, lane widths may range from seven feet to fourteen feet or greater with typical values in the range of nine feet to thirteen feet. The development of "prototype" CMFs for lane width would include a series of studies that evaluated the expected change in crashes for each possible change in lane width. For example, the study may begin with the investigation of lane widths equal to nine feet that are improved to a lane width of 10 feet. The sample of roadway segments would have identical before and after characteristics (e.g. facility type, geometric characteristics, traffic characteristics, driver population, environmental conditions, etc.) aside from the change in lane width. This would be repeated for lane width improvements from nine to eleven feet, nine to twelve feet, and so on for each possible lane improvement under each possible combination of before conditions.

The derivation of a CMF using this "prototype" procedure is impractical for a number of reasons. Consider first the improvements made to the roadway. It is rarely the case that a single improvement is made to a particular location without changing any of the other characteristics. For example, a lane improvement may also involve shoulder improvements such as widening or stabilizing. As long as the maintenance crew is already mobilized and the lane is temporarily closed, it is more cost effective to improve several characteristics at once rather than one characteristic at several different times. Secondly, a large sample of identical sites is often difficult, if not impossible, to obtain. Due to the number of possible geometric, traffic and environmental conditions that may exist at a particular location, it is difficult to find other locations that exactly match the existing conditions not to mention identical sites that have had identical improvements. Changes in traffic level, driver population, vehicle mix, and other factors may also occur over the “with-without” time period, potentially confounding the measurements. Finally, waiting several years for sufficient “with” data is a practical concern. Considering these limitations together, it is easy to understand why the development of a “prototype” CMF is impractical.

3.3 Development of CMF Using Cross-Sectional Data

The objective of this study is to test and evaluate alternative methods for estimating measures of safety effectiveness that emulate the prototypical CMF while addressing the limitations discussed in the previous section. Case-control and cohort designs are used to relate risk factors within a study population to a particular outcome or disease. In this highway safety context, the “outcome” is defined as a crash, the “risk factor” is a particular geometric feature or countermeasure and the “subjects” are roadway segments during a specific time period. An experiment is developed in which commonly available crash, roadway, and traffic data are used to estimate the odds ratio and relative risk for lane and shoulder width which are compared to crash modification factors from the literature. The comparison of these slightly different effectiveness measures is intended as a test of the efficacy of the case- control and cohort methods.

The proposed methods utilize a large sample of cross-sectional data rather than a limited sample from sites with and without a particular improvement. Therefore, the need to identify sites with similar improvements is eliminated. This allows for a much larger sample of segments for analysis and obviates the need to wait for several years in the “with” period to accumulate sufficient crash information.

Confounding remains an issue to be addressed in the case-control and cohort methods. One option is to match sites based on identical existing conditions; however, there is now a much larger population of segments from which to select a sample. Sites may be matched exactly for discrete variables (e.g. number of lanes, lane width, shoulder width) and approximately for continuous variables (e.g. segment length and AADT) by allowing a narrow range of values. Yet other variables are matched based on the presence or absence of a specific characteristic (e.g. facility type, median type, horizontal/vertical curvature). The sites may be matched on all but one variable. The remaining variable is the variable of interest, and the relative effect of this variable may be determined. Of course, matching on multiple variables may lead to a sparse data problem within the strata, but statewide data are used to address this issue. An alternative to matching is adjustment through covariates in the model. Case-control and cohort designs applied to estimating safety effectiveness are discussed in the following section.

CHAPTER IV METHODOLOGY AND APPROACH

4.1 Overview

Epidemiological methods are applied to existing crash data to assess their potential for estimating safety effectiveness. An attractive feature of these methods is their ability to isolate the effects of a particular risk factor by controlling for other "response-related" attributes. For example, the safety effects of ADT, speed, segment length, etc. may be accounted for through matching, and the remaining effect on crashes may be attributed to the risk factor in question. The epidemiologic approach appears well suited for application in transportation safety to relate the effects of countermeasures and geometric characteristics to roadway crashes.

Two distinct methods are investigated; the *case-control* and *cohort* design. Each design is unique in regards to selecting the sample and quantifying the relationship between risk factor and outcome. In a case-control design, subjects are enrolled based upon their current outcome status (i.e. crash or no crash); prior risk factor status within each outcome group is then determined. A cohort study enrolls subjects into a particular cohort (study group) based upon their current risk factor status and the prior outcome status is then tabulated for each individual cohort. One objective of this research is to compare these methods in terms of relative strengths and weaknesses and show how they may be applied to highway safety analysis.

4.2 Case-Control Design

The purpose of a case-control study is to derive the odds ratio, which is an estimate of the relative risk. Subjects are enrolled based upon their current outcome status (i.e. cases and controls) and the prior risk factor status within each outcome group is then determined. Case-control studies assess whether exposure to a potential risk factor is disproportionately distributed between the cases and controls, thereby indicating the likelihood of an actual risk factor. Case-control studies cannot be used to measure the probability of an event (disease, crash, etc.) in terms of incidence or prevalence because case-control studies pre-specify the number of cases and controls. They are more often used to show the relative effects of risk factors or for pragmatic purposes because the time and cost are relatively low compared to the more powerful cohort design.

The most important step in a case-control study is defining the cases and controls. Ambiguous or broad definitions for cases and controls may lead to misclassification of subjects and will likely produce unclear results. As an example of a case definition, cases may be defined as roadway segments that experience at least one crash during the study period. The corresponding controls are defined as those segments that do not experience a crash during the specified study period. These definitions are fairly general and may be more specific to include only rural roadway segments or segments with specific geometric characteristics. A more specific case definition helps to isolate the effect of the risk factor in question; however, the effect of variables in the case definition cannot be estimated. The case-control design is not limited to roadway segments. In other areas of highway safety, cases may be defined as specific vehicle types or road users experiencing a specific outcome (crash or crash type) as described in Section 2.4.1. The cases are then compared to their respective controls to determine the effect of the risk factor in question.

Once the case definition has been determined, a sample is selected from the defined population based upon outcome status (i.e. whether the subject is a case or a control). It is important to select a sample based only upon outcome status. Additional criteria are applied when a matching scheme is used, but these are discussed in Section 4.3. The ratio of controls to cases may vary and often depends on the availability of time, budget, and potential subjects. The ratio of controls to cases is usually one to one; however, increasing the number of controls will increase the power of the study especially when there are relatively few cases. As the ratio of controls to cases increases, the power of the design increases but at a decreasing rate. There is often little additional power gained at ratios greater than four controls per case as shown in Figure 3 (Woodward, 2005).

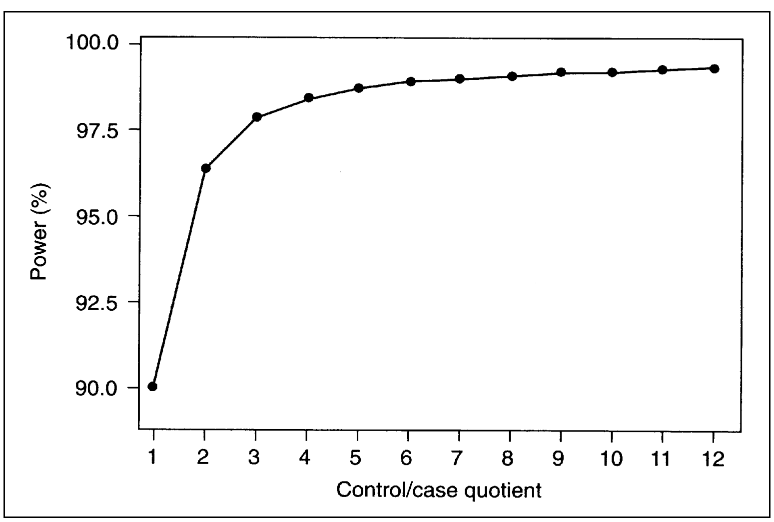

FIGURE 3 Power vs. Control/Case Quotient

Presence of a risk factor may be determined only after the sample has been obtained. Risk factors may take the form of binary variables (e.g. median barrier, roadway lighting, guide rail, etc.) or multi-level variables such as lane width (e.g. 9, 10, 11 and 12 foot lanes). Table 1 illustrates how case-control data are tabulated for a binary risk factor. In the multi-level variable case, Table 1 is expanded so the number of rows equals the number of levels of the variable. From the lane width example above, Table 1 would be expanded to four rows to include lane widths of 9, 10, 11 and 12 feet. An advantage of the case-control design is that multiple risk factors may be investigated in relation to a single outcome using the same sample. A single sample may be used to investigate any variables that are not included in the selection criteria for cases and controls. This is particularly important in highway safety as a number of variables are likely affecting the expected number of crashes on a particular segment. The ability to investigate multiple variables from the same sample is appealing due to time and money savings. Examples of different risk factors that may be explored include:

1. ADT
2. Lane Width
3. Shoulder Width and Type
4. Median Type
5. Roadway Lighting
6. Time of Day
7. *Horizontal Curvature
8. *Vertical Curvature

*Note: Horizontal and vertical curve data are not available for the State of Pennsylvania

TABLE 1 Case-Control Set-up

Risk Factor	# of Cases	# of Controls
Present	A	B
Absent	C	D

Measures of safety include the risk and odds of a crash as defined in Equations (3) and (4). The difference between the risk and odds is the denominator; the odds include only the number of cases without the risk factor while risk includes the total number with the risk factor (cases and controls).

$$Odds(risk\ factor\ present) = \frac{A}{C} \quad \ldots (3)$$

$$Risk(risk\ factor\ present) = \frac{A}{A+B} \quad \ldots (4)$$

Where,

A = number of cases with risk factor present

B = number of controls with risk factor present

Although risk and odds are a useful summary of the relationship between a risk factor and outcome, they are not sufficient to quantify the effect of the risk factor on the outcome. Therefore, the risk and odds are often reported as ratios comparing two groups or populations. The effect of the risk factor is expressed as the expected percent increase or decrease in the outcome in question due to the presence of the risk factor. The odds ratio is defined in Equation (5), which is computed as the odds of an outcome with the risk factor present divided by the odds of an outcome with the risk factor absent. This is equivalent to a simple cross-multiplication of the cells in Table 1. A ratio greater than 1.0 suggests that the presence of the risk factor increases risk, while a value less than 1.0 would suggest a decrease in risk.

$$OddsRatio(OR) = \frac{A/C}{B/D} = \frac{A*D}{B*C} \ldots (5)$$

Relative risk is computed similar to the odds ratio, but replacing the odds with the corresponding risk. A sample calculation of relative risk is provided in Section 4.5. Relative risk and odds ratios may be computed from either case-control or cohort studies; however, the appropriate measure depends upon the study design. Risk is often the preferred measure of effectiveness because it is a probability and probabilities are well understood. Risk and relative risk, however, should not be calculated from case-control studies when the sample values are not appropriate estimates of the population equivalents (Woodward, 2005). Relative risk is readily computed from cohort studies or when the proportions of cases and controls in the sample are representative of the population. Case-control studies effectively fix the number of controls based on the number of cases, which may or may not represent the appropriate proportions in the population. Therefore, the odds ratio is the appropriate measure for the chance of an outcome. The odds ratio may be a good approximation of the relative risk on the condition that the outcome is relatively rare. In the case that the outcome is rare, the number at risk may be approximated by the number of controls.

Advantages

Case-control studies are quick, relatively cheap, and well suited for studying rare events. In a retrospective case-control study, outcome status is determined at the onset of the investigation so there is no waiting time involved (i.e. time for outcome to occur), which reduces the cost. The case-control design is ideal for studying rare events because the sample may be selected so that a pre-specified number of cases are enrolled in the study, ensuring an adequate sample for analysis.

Several risk factors may be assessed from a single sample. The sample for a case-control study is selected based on outcome status and investigated to determine potential risk factors. Any variables not included in the case definition or matched may be assessed as individual risk factors because sample selection is not dependent on risk factor status. This is a particular advantage when the investigator may be interested in exploring the effects of several variables on a specific outcome. In the highway safety setting, the effects of lane width, shoulder width, shoulder type, and other geometric variables may be investigated in relation to crash frequency without drawing multiple samples. Therefore, the case-control study has economic advantages over the cohort design when the objective is to investigate multiple risk factors in relation to a single outcome.

Case-control studies are well suited to control or adjust for confounding variables and evaluate interaction. In a matched design, controls are sampled randomly and matched to each case based on similar values of the potential confounding variable. Matching provides a balanced design and automatically adjusts the estimates by canceling the effects of variables included in the matching scheme. Confounding will be further discussed in Section 4.3, which includes a discussion of matching to adjust for the masking effects of response-related variables. Transient risk factors (i.e. short-lived events) are handled more appropriately through case-control studies because cases and controls may be isolated to a particular event, such as contaminated food or an industrial accident.

Disadvantages

Case-control studies often rely on collecting past data for risk factors and outcome status, hence they are classified as a retrospective study. Retrospective studies rely on a subject's recall of past experiences or on the availability of documentation to provide information regarding risk factors and outcomes. The availability of accurate documentation is often a weakness in highway safety studies and carries over to case-control designs applied to highway safety research. At the present, roadway and crash data are available through state departments of transportation and vary in the amount and detail of available information. This type of data is not subject to recall bias because the records are documented. The quality of data, however, depends on the accuracy, consistency, and completeness of field measurement. If the roadway environment has changed since the time of data collection, it is impossible to verify whether the data are accurate. A change in the roadway environment also prevents the collection of data that are currently incomplete. Consistency becomes an issue when dealing with data that have been collected from different states or by multiple agencies within a state. This problem arises in any study design where more than one person is responsible for collecting data and applies to all highway safety studies. As data collection techniques and database management evolve, accuracy and consistency will become less of an issue when analyzing roadway data. Unfortunately, there is little that can be done to improve the accuracy, consistency and completeness of data obtained for this study. Resolution of this issue is critical to future research and is left to be addressed at a higher level within the transportation engineering profession.

Another disadvantage of case-control studies is the inability to demonstrate causality. Case-control studies are based on cross-sectional data; however, they should not be confused with cross-sectional studies in general. Case-control studies select subjects based on outcome status where general cross-sectional studies often sample based on risk factor status. Whether used for a case-control design or cross-sectional design, cross-sectional data do not involve a time sequence of data collection. In some instances, the question may be asked whether or not the risk factor preceded the event of interest. Often, this is not an issue for highway crashes because the roadway and current geometric conditions must be present before a crash may occur under the given conditions. In certain cases, it may be possible that a location experiencing an unusually high number of crashes is selected for treatment. In this case, the crashes were the cause of the treatment and care must be taken in the analysis of the effect of the treatment. Before-after studies are a popular method for estimating the treatment effect in the case where a treatment is implemented based on prior crash experience.

Although case-control studies may be used to explore multiple risk factors, they can only investigate one outcome per sample. The sampling is conducted separately within the case and control populations based on outcome status and different outcomes will produce different samples. This is not a major limitation to the case-control design, but requires additional time for sampling and data analysis.

Finally, care must be taken to ensure that cases and controls are representative of the underlying populations of the entities of interest. In other words, the chance of being included in the study must not be associated with the risk factor(s) of interest. In the medical field, cases may be of greater interest than controls and investigators may be tempted to follow-up with cases more thoroughly than controls. This is a source of bias known as differential quality of information. It is unlikely that highway safety studies will suffer from differential quality of information because data are obtained from historical records. This, of course, assumes the data are collected and coded consistently within and between jurisdictions. The issue of consistency was discussed previously.

Case-control studies are ranked just below cohort studies in terms of strength and validity when the purpose is to investigate cause and effect. Where possible, checks for bias should be carried out and it is helpful to report steps taken to avoid or minimize potential bias. To maintain validity, case-control studies must be carefully conducted by selecting cases and controls with full regard to possible sources of bias.

4.3 Matched Case-Control Design

The primary reason for a matched design is to control for confounding variables. Confounding variables include those variables that completely or partially account for the apparent association between an outcome and risk factor. Specifically, a confounder is a variable that is a risk factor for the outcome under study, and is associated with, but not a consequence of, the risk factor in question (Collett, 2003). Figure 4 illustrates relationships that classify C as a confounder of the effects of risk factor A on outcome B. Confounding variables may be accounted for during the analysis stage through adjustment with covariates or during the design stage by matching. Ignoring true confounding variables during the analysis and design stages may lead to incorrect estimates of the relative risk.

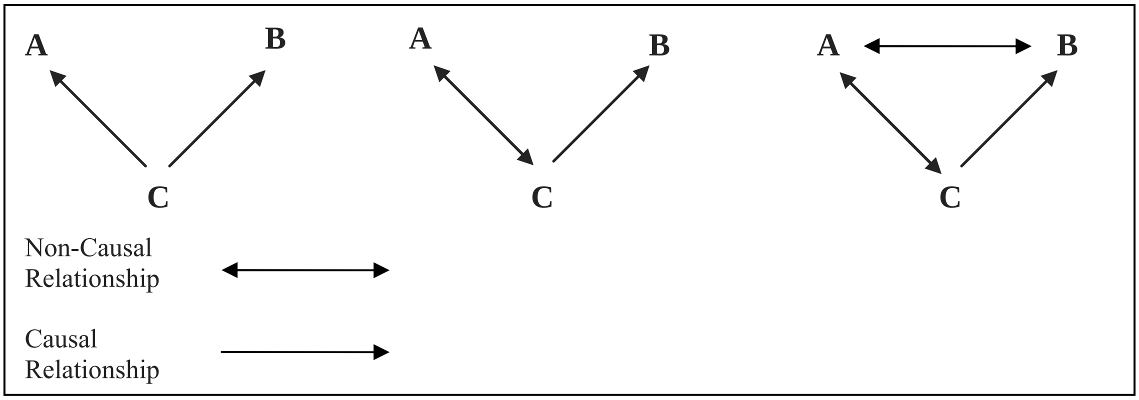

FIGURE 4 Confounding Relationships

As an example of confounding, consider the effect of lane width on crash risk. A potential confounding variable on the true effect of lane width is ADT. Previous studies have shown ADT to be a significant predictor of crash risk and it is likely that ADT is associated with lane width; higher functional class facilities are usually associated with relatively high ADTs and wider lanes. Hypothetically, an increase in lane width may be associated with a decrease in crashes, but this effect may be masked by ignoring the confounding variable (ADT). From previous studies, crashes tend to increase with increasing ADT. Ignoring ADT in the analysis of lane width may incorrectly lead to the conclusion that crashes increase with increasing lane width. In fact, lane width may prove to be insignificant or wider lanes may even reduce the risk of a crash when potential confounders, such as ADT, are accounted for appropriately. Figure 5 indicates potential confounding variables of the effects of lane and shoulder width on crash frequency. Segment length may also be considered as a potential confounder; however, the relationship with lane and shoulder width is less clear and further explored in Section 6.2.

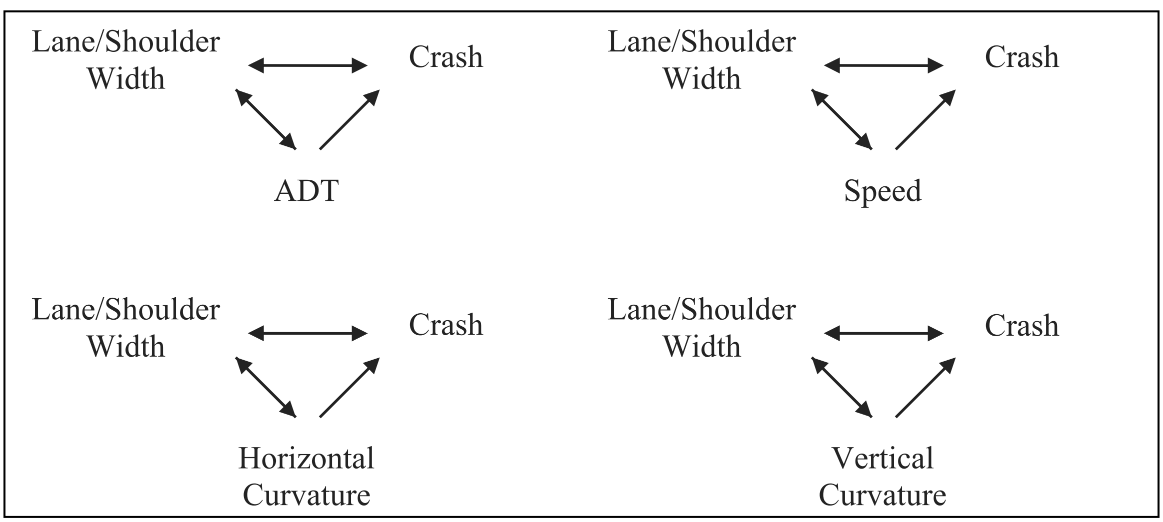

FIGURE 5 Potential Confounders of Lane and Shoulder Width

Matching is accomplished during the purposeful selection of controls. Controls are selected so that each matched pair has identical values for the confounding variables. It is often difficult to match controls with identical values due to limited sample sizes; therefore, controls are often matched based on a range of similar values for the confounders. For example, continuous variables such as ADT may be categorized into increments of 500 vehicles per day and the control must match within the same category. Another technique is to match controls within a set limit on either side of the case (e.g. no more than 250 vehicles per day above or below).

The main advantage of matching during the design stage is direct control of confounders. Matching provides an automatic adjustment of the relationship between the risk factor and outcome. In fact, matching ensures that adjustment is possible. Under rare circumstances, a random sample may result in cases that consist solely of high ADTs while the control group consists of segments with low ADTs. In this case, there would be no way to adjust the results during the analysis phase. Matching may also improve the efficiency of the design requiring smaller sample sizes or resulting in estimates with a narrower confidence interval; however, this only holds when the matching is based on true confounders. Otherwise, the design may be unnecessarily "overmatched". Overmatching may result in loss of efficiency or even biased results (Woodward, 2005).

A disadvantage to the matched design is the increased complexity of data collection and sample selection, especially when there are many matching variables. This may increase the cost and certainly the time for the data collection process. When matching upon multiple variables, the sample sizes within each matching combination often become very small due to the limited number of subjects (sites) that match the criteria exactly. In transportation, this has been stated as a limitation to cross-sectional studies that involve matching (Hauer, 2005a). A matched design also requires a matched analysis, which is often more complex to understand and compute than a similar unmatched study. Further, the effect due to the matching variables cannot be estimated because the probability of being a case or control, given a certain level of the matching variable, is 0.5 for the matched design. The interaction between the matching variable and risk factor, however, may be analyzed. If the investigators wish to analyze the effect of the matching variables individually, then a new sample must be obtained because the adjustment cannot be removed from the matched design.

In chapter six, a matched case-control design is set-up to investigate the effects of lane width and shoulder width (risk factors) in relation to crashes (outcome) on roadway segments. Cases are defined as segments that experience at least one crash during a particular year of the study period. Control segments are matched to each case segment at a one-to-one ratio and matching is completed on several factors to account for potential confounding. The matched case-control design is then evaluated in terms of estimating safety effectiveness and its general application in highway safety.

4.4 Analysis of Matched Case-Control Designs

The analysis of a matched case-control design must account for the matching process. There are several methods that may be applied to analyze a matched design. The simplest case is a 1:1 matched design with a binary risk factor. In this case, the data should be presented in terms of study pairs as shown in Table 2 (Woodward, 2005).

TABLE 2 Example Tabulation of Matched Case-Control Study

Risk Factor Present in Case	Risk Factor Present in Control	
	Yes	No
Yes	c_1	d_1
No	d_2	c_2

Concordant pairs (c_1 and c_2) are of little interest because both the case and control have the same risk factor status. Discordant pairs (d_1 and d_2) are those pairs with different risk factor status, which are of particular interest in the analysis and estimation of effect. The probability that a discordant pair includes a case with the risk factor is estimated by Equation (6).

$$\hat{\phi} = \frac{d_1}{d_1 + d_2} \quad \ldots (6)$$

Under the null hypothesis there is no association between the risk factor and disease and φ is equal to one half. McNemar's test statistic to support or reject the null hypothesis is calculated from Equation (7) and compared to the chi-square value with one degree of freedom (Woodward, 2005).

$$McNemar\,Statistic = \frac{(2\mathrm{d}_1 - \mathrm{d})^2}{d} \quad \ldots (7)$$

Where, $d = d_1 + d_2$

The corresponding estimate of the odds ratio is calculated from Equation (8) and when d is large, a 95 percent confidence interval may be calculated using Equations (9) and (10).

$$\psi = \frac{d_1}{d_2} \quad \dots (8)$$

$$\psi_L = \frac{d_1}{(d_2 + 1)F_L} \quad \dots (9)$$

$$\psi_U = \frac{(d_1 + 1)F_U}{d_2} \quad \dots (10)$$

Where,

F_L is the upper 2.5 percent of F on $2(d_2 + 1)$ and $2d_1$ degrees of freedom, and

F_U is the upper 2.5 percent of F on $2(d_1 + 1)$ and $2d_2$ degrees of freedom

When the risk factor includes more than two levels, analysis is often accomplished through statistical modeling. Conditional binary logistic regression is one such approach that may be applied to matched case-control designs. Conditional binary logistic regression may be used to estimate the relative risk of a binary outcome and account for multi-level risk factors, confounding variables that are not included in the matching process, and interaction terms. Conditional binary logistic regression is applied to a matched case-control design to estimate the effects of lane and shoulder width on crash risk as an empirical example in chapter six. The conditional probability of an outcome associated with the unmatched variables $x_1,\ldots,x_p$ for each member of the jth matched set is given by Equation (11) (Schlesselman, 1982).

$$\Pr(Y = 1) = 1/\{1 + \exp[-(\alpha_j + \sum_{i=1}^{p} \beta_i x_i)]\} \quad (11)$$

Where,

α_j = effect of matching variables for each matched set

β_i = estimated coefficients for explanatory variables

x_i = unmatched explanatory variables included in the model

Estimates of the coefficients for the explanatory variables are obtained by maximizing the likelihood expression in Equation (12).

$$L(\beta) = -\sum_{j=1}^{n} \ln\left[1 + \sum_{k=1}^{c} \exp\left\{\sum_{i=1}^{p} \beta_k \left(x_{jki} - x_{j0i}\right)\right\}\right] \quad (12)$$

Where:

n = number of cases

c = number of controls matched to each of n cases

x_i = unmatched explanatory variables

x_{j0i} = value of x_i for a case in the jth matched set

x_{jki} = value of x_i for the kth matched control in the jth matched set

In this study, the dependent variable is coded as a one or zero to indicate a case and control, respectively. Indicator variables are created for each level of the risk factor (lane and shoulder width) and are represented by x_i in Equations 11 and 12. Confounding variables included in the matching scheme do not appear in the estimation because matching variables have the same value for cases and controls.

In the case where roadway segments may experience multiple crashes per year, a binary logistic regression will not utilize all available information. A multinomial logistic regression model is more appropriate to estimate the relative risk when the response variable may have more than two levels. In the context of this research, a separate binary model is estimated to relate the relative risk of each level of crash experience (i.e. 1, 2, 3, and 3+ crashes) to the baseline (i.e. 0 crashes). The multinomial logit model is used to estimate the relative risk for alternative response models in Section 6.4.4.

4.5 Cohort Study Design

The purpose of a cohort study is to derive an estimate of risk and relative risk. Subjects are enrolled into a particular “cohort” based upon current risk factor status and followed over time to determine outcome status. Cohort studies assess whether the time at risk is disproportionate between cohorts, which indicates the relative risk due to inclusion in a specific cohort. Cohort studies are more powerful than case-control designs because they include some measure of exposure, which makes a stronger case for causality. The application of cohort studies in highway safety as well as advantages and disadvantages are discussed in this section.

Cohort designs are relatively easy to set-up, but more difficult to complete. Subjects are enrolled in a cohort study based upon *current* risk factor status. The enrolled subjects are followed over time to determine the number of outcomes in each cohort and the duration until the outcome occurs. Several cohorts may be enrolled in the same study; however, only measured risk factors may be investigated for any particular cohort design. Table 3 illustrates how cohort data are tabulated for a binary risk factor. In the multi-level variable case, Table 3 is expanded so the number of rows equals the number of cohorts in the study. Continuing with the example of the effect of lane width on crashes, a separate cohort would be created for each particular lane width in question. The lane width cohorts would then be followed throughout the study period to determine the number of segments experiencing a crash and the time between the start of the study and the outcome event. Multiple crashes per segment are not an issue in cohort studies because the analysis is based on the time to the first event relative to the start of the study. The time to first event is then aggregated within each cohort and compared to the baseline cohort to estimate the effect of the risk factor.

TABLE 3 Tabulation for Simple Cohort Analysis

Cohort	Outcomes	Non-Outcomes	Total At-Risk
Exposed	A	B	A+B
Not Exposed	C	D	C+D

Cohort designs are usually set-up to follow a sample forward through time. This is known as a prospective cohort study, which may last months or years depending on the likelihood of the outcome in question. A disadvantage to the prospective cohort design is the high cost and logistics of following a large sample over many months. Another type of cohort design is a retrospective cohort, where past data are used to determine risk factor and outcome status. Long follow-up periods are avoided by using the retrospective study; however, there are a few potential disadvantages as discussed later in this section.

The cohort design proposed for this study is a “retrospective” cohort with concurrent follow-up. In other words, the analysis is based upon past data (retrospective) where all subjects enter the study at the same time (concurrent) and are followed for the same duration or until the time of an event (a crash). Ideally, subjects entering the study are free of the outcome in question (i.e. a crash); however, this is not a relevant issue for roadway segments because crashes are not prevalent or long term. The “outcome-free” issue is more often a concern in epidemiological studies when trying to show causality. For example, in a study to show the affect of smoking on lung cancer, it would not make sense to select subjects who were diagnosed with lung cancer before they smoked. In the highway safety context, it is likely that road segments will experience multiple outcomes (i.e. crashes) in a given year, making it more difficult to show causality.

The time sequence of events is not a question in cohort studies because subjects are enrolled based upon outcome status (i.e. subjects do not currently have the outcome in question) and followed until the event in question occurs, or the end of the study, or loss to follow-up. The risk factors, therefore, are known to be present before the event can occur. Risk factors are, however, subject to change during the study period. If the risk factor for a particular subject changes during the study period then the subject is effectively moving from one cohort to another. The time at risk should then be allocated proportionally between the respective cohorts. For example, roadway segments are enrolled on the first day of the year and followed for a one year period. After five months, a section of roadway is widened from eleven to twelve feet. Assuming that none of these improved segments has experienced a crash, the segments would contribute five months of exposure to the eleven foot cohort and the remaining time to the twelve foot cohort. The analysis then reflects the periods of exposure to different risk factors.

Relative risk is derived as the measure of effect for a cohort study. The risk of an outcome due to a particular factor is calculated as the (number of cases) divided by the (total number at risk) within a particular cohort, as was shown in Equation (4). The relative risk may then be computed for any two levels of a risk factor as the ratio of the two risks, shown in Equation (13). A relative risk greater than 1.0 suggests an increase in the likelihood of an outcome due to the risk factor in the numerator. A value less than 1.0 would suggest a decreased risk.

$$\text{Relative Risk} = \frac{A/(A+B)}{C/(C+D)} = \frac{A(C+D)}{C(A+B)} \quad \ldots (13)$$

Where,

A = number of outcomes in the exposed cohort

B = number of non-outcomes in the exposed cohort (or total time for the exposed cohort)

C = number of outcomes in the unexposed cohort

D = number of non-outcomes in the unexposed cohort (or total time for the unexposed cohort)

Several methods are available to analyze cohort studies including simple tabulation, cohort life tables, subject-years approach, and other statistical models. Table 3 represents simple tabulation, which is the most basic type of analysis for a cohort study. The simple tabulation only accounts for the number of outcomes within each cohort relative to the total number at risk. Other methods include some measure or indication of time at risk to derive a more precise estimate of relative risk. These methods are described further in Section 4.6.

Confounding variables may be accounted for during the design or analysis stage of a cohort study. In either case, it is important to adjust for confounding factors because ignoring true confounding variables may lead to incorrect estimates of the relative risk. Similar to case-control studies, matching is an option in cohort designs to account for potential confounding variables. It is more common, however, to adjust for confounding variables during the analysis of a cohort design and matching is reserved for special situations. A known powerful confounder or one that is difficult to measure precisely may call for a matching scheme. Pair matching is often used to account for confounding variables when a matching scheme is required. Pair matching involves matching each study subject closely with a control subject on the specific confounding factor. Frequency matching is another type of matching scheme where each study subject or group is matched with controls based on a category of a factor (e.g. age or gender). Frequency matching helps to prevent large imbalances between study groups that may reduce the power of the study. The shortcomings of a matching scheme remain the same as in the case-control method; matching requires special statistical analysis to adjust for the confounding effects and the individual effect of the matching variable cannot be estimated for the outcome in question. Therefore, it is recommended to adjust for confounding variables during the analysis when possible.

Advantages

Cohort studies are very powerful from a statistical standpoint and well suited for studying rare risk factors. Subjects are followed over a period of time, which provides evidence of causation between the risk factor and outcome in question. This is a significant advantage over observational studies that are only able to demonstrate association between risk factor and outcome. The cohort design is ideal for studying rare risk factors because the sample is selected based on risk factor status. A pre-specified number of subjects may be enrolled in each cohort to ensure an adequate sample for analysis.

In a cohort design, several outcomes may be assessed for any particular risk factor. For example, a cohort study designed to investigate the effects of seatbelt use on fatality likelihood may also be used to investigate the likelihood of serious injury or minor injury from seatbelt use without obtaining a new sample. This is a particular advantage when the investigator may be interested in exploring the effects of one potential risk factor (countermeasure) on several outcomes.

Disadvantages

While the cohort design is relatively powerful, practical limitations often restrict the application of this method. Cohort studies may last several months or even years to observe the event in question. In addition, large sample sizes are often required to achieve statistical significance, which makes cohort studies relatively expensive when coupled with long follow-up periods. Time and financial constraints are often the deciding factors that limit the use cohort designs.

Long follow-up periods may be eliminated by using the retrospective study; however, there are potential drawbacks to using historical data. The first issue is that the necessary historical data has to be available for analysis. If the data do not exist, then a prospective study is required to collect the information. Another weakness of the retrospective cohort is the potential for loss of follow-up. This is a common problem when using human subjects if the respective subjects are no longer available for follow-up questioning to fill-in missing information. The potential for loss of follow-up is less of an issue when dealing with roadway segments; however, there are other issues related to historical data that need to be addressed. Several points regarding the completeness, consistency and reliability of historical data are presented in Section 4.2 in relation to the retrospective case-control approach. These issues remain a concern for retrospective cohort studies.

Length of follow-up becomes a concern if subjects enter the study at different points in time or if follow-up time differs between subjects. Given the stationary nature of a roadway, segments are easily entered at the same point in time and followed over the same time frame. If enrollment period or length of follow-up differs between subjects, then adjustments must be made during the analysis to account for these differences.

Cohort studies are ranked just below randomized clinical trials in terms of strength and validity when the purpose is to investigate cause and effect. Unfortunately, randomized clinical trials are not a viable alternative to study the safety effects of roadway characteristics and countermeasures. This leaves cohort studies at the top of the list, just above case-control designs, as the most powerful type of observational study. There are, however, limitations to the cohort method such as time and budget constraints that make this an impractical option in many situations.

In chapter six, cohort designs are set-up to evaluate the effects of lane width and shoulder width (risk factors) in relation to roadway crashes (outcome). The study population consists of all rural, two-lane, undivided highway segments in Pennsylvania and Washington. A random sampling method may be used to generate equal sample sizes, but cohorts of equal size are not required for the cohort analysis. This study is designed to make use of all available data and enrolls all segments meeting the risk factor criteria. Segments are followed for one year periods or until the time of the first event (crash). Matching is not used in this cohort study and potential confounding factors are adjusted for during the analysis. Several analytic methods are applied to the cohort design and compared. The cohort method is then evaluated in terms of estimating safety effectiveness and its general application in highway safety.

4.6 Analysis of Cohort Studies

Several methods may be applied to analyze cohort studies including simple tabulation, cohort life tables, subject-years approach, and statistical modeling. Simple tabulation was discussed in Section 4.5, which considers the number of events within each cohort but does not account for the time at risk for each subject. Cohort life tables, subject-years methods and count models are all capable of accounting for time at risk; however, some methods are better suited for deriving relative risk and adjusting for confounders. Cohort life tables are useful to estimate the cumulative survival probability, which represents the probability of survival for each cohort over time. Cohort life tables are not, however, useful for deriving the relative risk between two cohorts and will not be discussed further. The subject-years approach is capable of deriving an estimate of the relative risk, but adjusting for confounding variables can be a bit complex. Statistical models are the most efficient approach to analyzing cohort data when the objective is to derive an estimate of relative risk while accounting for time at risk and adjusting for confounding variables. Statistical models are discussed individually in the following two sections including survival models (Cox Proportional Hazard and Parametric Survival Analysis) and count models (Poisson and Negative Binomial).

4.6.1 Survival Models

Survival models are one option for evaluating cohort data and accounting for an individual's time at risk. For each subject, the time to first event is analyzed rather than the mere fact that the event occurred. Subjects that experience multiple events are only counted once and considered non-survivors after the first event. Subjects that do not experience an event during the study period contribute the full duration to the time at risk and are considered censored at the end of the study. The time to first event for each subject is considered as the dependent variable in the survival model. Independent variables include the risk factor in question and any other potential confounding variables or interaction terms.

The *Cox Proportional Hazard* method and *Parametric Survival* model represent two different types of survival models; semi-parametric and parametric, respectively. Parametric models assume a probability distribution and pre-specify a theoretical probability model for survival time. The semi-parametric models make no assumption of the probability distribution of survival time, but assume a parametric form for the effects of the explanatory variables. Common probability distributions used in parametric modeling include the exponential or Weibull distribution as shown in Equations (14) and (15), respectively (Woodward, 2005).

$$f(t) = \lambda e^{-\lambda t} \quad \ldots (14)$$

$$f(t) = \lambda\gamma(t^{\gamma-1})\exp[-\lambda(t^{\gamma})] \text{ ... (15)}$$

Where,

λ and γ are constants that may be estimated from sample data.

The exponential function is the most basic density function to assume. The Weibull distribution is more flexible and can change depending on the specified shape parameter (γ). In either case, it is important to have an understanding of the distribution of the data. If no a priori knowledge exists on the distribution of the data, the Cox Proportional Hazard model is an appropriate choice. The Cox Proportional Hazard model does not require a particular form for the survival times and also does not specify a baseline hazard function. McCullagh and Nelder (1989), comment that for practical purposes the estimates are relatively indifferent to the assumption of a model structure on the baseline hazard function.

The hazard function is the conditional instantaneous probability of failure within the next small interval of time given survival to the start of the interval (McCullagh and Nelder, 1989). The hazard function may be estimated for each individual or group over time and is derived in Equations (16) to (18).

$$F(t) = \int_{-\infty}^{t} f(s)ds \text{ ... (16)}$$

$$S(t) = 1 - F(t) \text{ ... (17)}$$

$$h(t) = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{S(t)} \text{ ... (18)}$$

Where,

F(t) = fraction of population failing by time t

S(t) = fraction of population surviving at time t (survivor function)

h(t) = hazard function

f(t) = density function for survival time

The hazard ratio is used to compare the hazard functions between two individuals or groups. The hazard ratio represents the relative risk as shown in Equation (19).

$$\phi = \frac{h_1(t)}{h_0(t)} \quad \ldots (19)$$

Where,

φ = hazard ratio

$h_1(t)$ = hazard for group 1 at time t

$h_0(t)$ = hazard for group 2 at time t

An assumption often made in survival analysis is that the ratio of hazards is the same at all possible survival times (Woodward, 2005). This means that the hazard ratio is a constant for any two groups and is referred to as the proportional hazards assumption. A test for the proportional hazards assumption can be completed formally or graphically. The formal test is done by including an interaction term for each covariate with the log(time) variable. A non-significant coefficient for the interaction term indicates that the proportional hazards assumption is satisfied. The graphical test is accomplished by plotting the hazard functions and visually inspecting the plot. Parallel hazard functions indicate that the proportional hazards assumption is satisfied.

Estimates of the hazard ratio are adjusted for any additional covariates in the model. When there are multiple covariates in the model, a multiple proportional hazard regression is defined in Equation (20).

$$\log_e \phi = b_1 x_1 + b_2 x_2 + \ldots + b_k x_k \quad \ldots (20)$$

Where,

$\log_e(\varphi)$ = logarithm of the hazard ratio,

$x_1 \ldots x_k$ = covariates included in the model, and

$b_1 \ldots b_k$ = estimates of the coefficients for each covariate.

Categorical variables are analyzed by creating dummy variables to represent each category and interaction terms are modeled by including appropriate terms in Equation (20). Nested models may be compared using the likelihood ratio test from Equation (21) compared to a chi-square with u degrees of freedom (Woodward, 2005). The likelihood ratio test indicates whether or not the u terms should be included in the model after adjusting for the v terms already included.

$$\Delta = -2\log L_v - (-2\log L_{v+u}) \quad \ldots (21)$$

Where,

Δ= likelihood ratio,

L_v = likelihood for model with v terms, and

L_{v+u} = likelihood for model with v terms plus u additional terms.

4.6.2 Count Models

Count models are another option for evaluating cohort data while accounting for each individual's time at risk. The difference between survival and count models is that count models use the occurrence of an outcome as the dependent variable and adjust for time at risk as an offset on the right hand side. Again, the first event is analyzed so that subjects experiencing multiple events are only counted once and considered non-survivors after the first event. Independent variables include the risk factor in question and any other potential confounding variables or interaction terms.

The Poisson and Negative Binomial models represent two popular distributions for modeling discrete, non-negative count data. In particular, the Poisson and Negative Binomial models are useful for modeling rare events such as the number of crashes on roadway segments. The probability distribution for a Poisson model is given by Equation (22).

$$P(n_{ij}) = \frac{\exp(-\lambda_{ij})\lambda_{ij}^{n_{ij}}}{n_{ij}!} \quad \text{… (22)}$$

Where,

$P(n_{ij})$ = probability of n events for individual i in time period j, and

λ_{ij} = mean occurrence rate or expected value of n_{ij}.

Woodward (2005) shows how Equation (23) may be applied to estimate a multiple Poisson regression model while controlling for confounding variables and interaction terms.

$$\log_e e = \log_e y + b_0 + b_1 x_1 + b_2 x_2 + ... + b_k x_k \quad \text{… (23)}$$

Where,

e = expected number of events,

y = total time at risk,

$x_1 \ldots x_k$ = covariates included in the model, and

$b_1 \ldots b_k$ = parameter estimates for each covariate.

The relative rate may be calculated for a binary risk factor by comparing the two groups or for a risk factor with multiple groups by selecting one group as the baseline for comparison. The relative rate and the corresponding 95 percent confidence interval may be calculated from the estimated parameters in Equation (23) as shown in Equations (24) and (25), respectively.

$$\hat{\omega} = \exp(b_k) \quad \ldots (24)$$

$$95\%\ \text{C.I.} = \exp\{b_k \pm 1.96 s\hat{e}(b_k)\} \quad \ldots (25)$$

Where,

ω = estimated relative rate,

b_k = parameter estimate from Equation (23), and

$se(b_k)$ = standard error for the parameter estimate.

Interaction terms are accounted for by including additional covariates in the model. Similar to a logistic regression, nested models may be compared by comparing the difference in deviance between the two models to a chi-square with degrees of freedom equal to the difference in degrees of freedom between the two models.

The Poisson distribution operates under the assumption that the mean and variance are equal. Over-dispersion refers to the situation where the variance is greater than the mean and when data are over-dispersed the Poisson distribution may not be adequate to model the data. The Negative Binomial distribution is more appropriate to model over-dispersed data because there is no restriction on the mean and variance. The Negative Binomial distribution is identical to the Poisson model from Equation (22); however, a gamma-distributed error term is included to allow for unobserved heterogeneity. The mean occurrence rate for a Negative Binomial model is given in Equation (26).

$$\lambda_{ij} = \exp(\beta X_{ij} + \varepsilon_{ij}) \quad \ldots (26)$$

Where,

λ_{ij} = mean occurrence rate or expected value of n_{ij},

β = vector of unknown regression coefficients, and

$\exp(\varepsilon_{ij})$ = gamma-distributed error term.

Survival models and count models are both viable alternatives for the analysis of cohort data. For the purposes of this research, both methods are applied to the cohort designs for lane and shoulder width. Parametric and semi-parametric models are compared within the survival analysis and Poisson and Negative Binomial models are applied to determine which is more appropriate. Overall comparisons are then made between survival and count models to recommend the most efficient analysis technique to estimate crash modification factors.

4.7 Application of Case-Control and Cohort Methods in Highway Safety

Case-control and cohort methods are used to estimate the odds ratio and relative risk, respectively. The odds ratio and relative risk directly estimate safety effectiveness, which may be a good approximation of crash modification factors. Both measures of effectiveness provide a measure of the percent increase in the chance of an outcome that can be expected for a given risk factor compared to the baseline level of the risk factor. In the case of a binary risk factor (i.e. presence or absence), the baseline is usually the absence of a particular feature and the odds ratio or relative risk indicates the percent increase in the risk of an outcome due to the presence of the risk factor in question. For risk factors with more than two possible categories, the baseline may be selected as any one category to which other categories are compared. Each category may be compared to the baseline, in which case the measure of effectiveness would indicate the percent change in the risk of an outcome due to the specified deviation from the baseline. This lends itself well to the approximation of crash modification factors because the purpose is to provide an estimate of the incremental safety effect of a particular feature in relation to a certain baseline level.

CHAPTER V DATA SETS AND SAMPLING METHOD

5.1 Overview of Datasets

5.1.1 Pennsylvania Overview

Geometric, traffic and crash data were obtained for more than 44,500 miles of highway segments in Pennsylvania from 1997 – 2001. The data were obtained in two parts (1) a crash inventory database extracted from the Pennsylvania Crash Reporting System and (2) a roadway inventory file. Each database identifies segments by County, State Route Number and Segment Number. Crash data were available for each year of the study period; however, only one geometric file was available for the five-year period. The crash data were merged with the geometric data using the three unique identifying features (i.e. county, route number and segment number) and separated by year.

The crash inventory data include all reportable crashes from calendar year 1997-2001 for mid-block locations (i.e. non-intersection crashes). Reportable crashes are defined as those in which at least one vehicle is towed from the scene. This dataset does not contain crashes occurring at or near intersections and any data from "phantom" or "hit-and-run" crashes are excluded. The dataset includes state roads only and does not include turnpike crashes. A list of variables contained in the crash inventory database is shown below.

- Crash Type
- Severity
- Time of Day
- Day of Week
- Weather
- Illumination
- Surface Condition
- Special Location
- Relation to Roadway
- Drug, Alcohol or Medication Usage
- Prime Factor Source
    - E=Environmental/Roadway
    - V=Vehicle Failure
    - P=Pedestrian Action
    - D=Driver Action
- Person Type
- Gender
- Date of Birth
- Seating Position
- Safety Equipment Usage

The roadway inventory file contains geometric and traffic data for all segment types (i.e. rural, sub-urban, small urban, and large urban) for the year 2004. Every state route is divided into segments, which are typically numbered starting with 0010 and increase in increments of 10 from south to north and west to east. Divided sections of highway include an even and odd segment to designate the direction of travel. For example, within the four lane section of SR0322 the eastbound lanes have a segment labeled 0330 and the corresponding westbound lanes are labeled as segment 0331. Segment length varies and a new segment is created whenever there is a change in cross-section or section characteristics. The reliability of the data depends on the accuracy and consistency of the data collectors. Inaccurate measurements may lead to misclassification of roadway segments, which would affect the estimated safety effectiveness for individual geometric elements. A complete list of variables from the roadway inventory file is given below.

- Urban/Rural Code
- Number of Lanes
- Average Daily Traffic
- Posted Speed Limit
- Segment Length
- Surface Type
- Pavement Width
- Left Shoulder Type
- Left Shoulder Paved Width
- Left Shoulder Total Width
- Right Shoulder Type
- Right Shoulder Paved Width
- Right Shoulder Total Width
- Median Type
- Median Width (excluding inside shoulders)
- County
- Route Number
- Segment Number
- Direction

The crash inventory database was merged with the roadway inventory file based on unique identifying variables for each segment (i.e. county, route number, and segment number). Once the crash data were merged with the roadway inventory file, the data were separated by year and segment location (i.e. rural, sub-urban, small urban, and large urban). A summary of crashes, by year and segment location, is provided in Table 4. The majority of highway crashes occur on segments in rural and large urban areas, as might be expected. The numbers in Table 4 represent the total number of crashes occurring on segments with available roadway data. There were relatively few crashes (less than 2 percent) where location data were not available as shown in the "missing" row.

TABLE 4 Crash Segments by Year and Location

Segment Type	1997	1998	1999	2000	2001	Total
Rural	15,930	14,470	15,998	16,568	14,396	77,362
Sub-Urban	3,289	3,281	3,283	3,556	2,889	16,298
Small Urban	2,388	2,477	2,564	2,665	2,285	12,379
Large Urban	16,109	15,691	16,504	16,767	14,442	79,513
Missing	1,056	452	362	354	776	3,000
Total	38,772	36,371	38,711	39,910	34,788	188,552

The database was cleaned to eliminate segments with incomplete geometric data. This was accomplished by sorting the data by segment length, ADT, and speed limit and removing those segments with a value of zero for any of the three variables. Results of the data cleaning are shown in Table 5. Segment length was available for all segments and did not have an effect on missing data. There were 60 segments missing data for ADT and about twice as many without speed limit data. In total, 197 segments were removed from the five years of data due to missing values, representing less than one percent of the total data. There was no recognizable pattern in the segments with missing data and the removal of these segments is not expected to influence the analysis.

TABLE 5 Data Cleaning

	Segments Removed from Sample			
Year	Length	ADT	Speed	Total
1997	0	12	28	40
1998	0	12	28	40
1999	0	12	30	42
2000	0	12	24	36
2001	0	12	27	39
Total	0	60	137	197

The remaining analyses and discussion are focused on rural, two-lane, undivided segments and other segment types are not discussed further. Table 6 indicates the total number of rural crash segments and non-crash segments for each of the five years. This subset is sorted by posted speed limit to categorize segments as low speed (posted speed less than 50 mph) and high speed (posted speed greater than or equal to 50 mph). Data manipulation is performed carefully to reduce the size of the database and assure that later analyses are based on segments with similar characteristics. Tables 7 and 8 indicate the numbers of crash and non-crash segments for both low and high speed rural, two-lane segments with no median. There are slightly more segments in the low speed category and non-crash segments outnumber crash segments in both tables. The data used for the empirical investigation of case-control and cohort designs were sampled from Tables 7 and 8.

TABLE 6 Rural, Two-Lane, Undivided Crash and Non-Crash Segments

Year	Crash Segments	Non-Crash Segments	Total
1997	11,611	14,038	25,649
1998	10,949	14,445	25,394
1999	11,804	13,942	25,746
2000	12,166	13,846	26,012
2001	10,606	14,511	25,117
Total	57,136	70,782	127,918

TABLE 7 Low Speed Rural Crash and Non-Crash Segments

Year	Crash Segments	Non-Crash Segments	Total
1997	6,479	7,242	13,721
1998	6,080	7,481	13,561
1999	6,530	7,212	13,742
2000	6,640	7,208	13,848
2001	5,851	7,539	13,390
Total	31,580	36,682	68,262

TABLE 8 High Speed Rural Crash and Non-Crash Segments

Year	Crash Segments	Non-Crash Segments	Total
1997	5,132	6,796	11,928
1998	4,869	6,964	11,833
1999	5,274	6,730	12,004
2000	5,526	6,638	12,164
2001	4,755	6,972	11,727
Total	25,556	34,100	59,656

5.1.2 Washington Overview

Geometric, traffic and crash data were obtained for more than 8,300 miles of state highway segments in Washington from 1993 – 1996 and 2002 – 2003. The Washington data were obtained in four parts (1) a roadway inventory file, (2) a horizontal curve file, (3) a vertical curve file, and (4) a crash inventory database. The geometric databases (roadway inventory, vertical curve, and horizontal curve files) identify segments by a road inventory number as well as beginning and ending milepost. Crash locations are identified by road inventory number and approximate milepost.

The crash inventory data included all reportable mid-block crashes from calendar year 1993 – 1996 and 2002 – 2003, inclusive. The State of Washington defines the reporting threshold as a crash which involves at least $700 of damage. This dataset does not contain crashes occurring at or near intersections. A list of variables contained in the crash inventory database is shown below.

- Crash Type
- Severity
- Crash Date
- Day of Week
- Weather
- Illumination
- Surface Condition
- Location
- Number of Vehicles

The roadway inventory file contains geometric and traffic data for all segments by location (i.e. rural and urban). Information regarding horizontal and vertical curvature was included in separate files. The data were merged to obtain a single roadway inventory file of homogeneous roadway segments. First, the horizontal curve file was merged with the roadway data file. Segments were merged by road inventory number and beginning and ending milepost; a new segment was created for every curve and any changes in roadway geometry (e.g. number of lanes, lane width, shoulder width, shoulder type, etc.). The vertical curve file was then merged with the roadway/horizontal curve file in a similar fashion; creating a new segment for every vertical curve. A list of variables contained in the complete roadway file is given below.

- Urban/Rural Code
- Number of Lanes
- Average Daily Traffic
- Posted Speed Limit
- Segment Length
- Surface Type
- Pavement Width
- Left Shoulder Type
- Left Shoulder Width
- Right Shoulder Type
- Right Shoulder Width
- Median Type
- Median Width
- Horizontal Curvature
  - Curve Angle
  - Curve Radius
  - Degree of Curve
  - Direction of Curve
- Vertical Curvature
  - Vertical Curve Length
  - Percent Grade
  - Direction of Grade
- Functional Class
- County
- Route Number
- Traffic Control

The crash inventory database was merged with the complete roadway inventory file. Each crash was identified by approximate milepost and matched with the appropriate segment based on the beginning and ending milepost. Once the crash data were merged with the roadway inventory file, the data were separated by segment location (i.e. rural or urban). A summary of crashes, by year and segment location, is shown in Table 9. Urban segments account for the majority of highway crashes similar to the Pennsylvania dataset. Table 9 represents the total number of crashes occurring on segments with available roadway data. There were relatively few crashes (< 1 percent) where location data were not available as indicated in the "missing roadway" row.

TABLE 9 Crashes by Year and Location

Segment Type	1993	1994	1995	1996	2002	2003	Total
Rural	11,388	11,875	12,062	13,406	13,576	12,932	75,239
Urban	22,427	24,868	26,831	28,703	36,471	34,806	174,106
Missing	0	3	1	4	2	3	13
Total	33,815	36,746	38,894	42,113	50,049	47,741	249,358

The database was cleaned to eliminate segments with incomplete data. This was accomplished by sorting the data by segment length, ADT, and speed limit and removing those segments with a value of zero for any of the three variables. Results of the data cleaning are shown in Table 10. Segment length was not available for all segments and 6,487 segments were removed from the dataset. There were 565 segments missing data for ADT and 4,812 without speed limit data. In total, 19,125 segments were removed from the five years of data due to missing values, representing about 15 percent of the total data.

TABLE 10 Data Cleaning

Year	Segments Removed from Sample					
	Rural/ Urban	Length	ADT	Speed	Vertical Curvature	Total
1993	12	1103	85	776	1339	3315
1994	9	1096	94	810	1272	3281
1995	9	1054	64	765	1157	3049
1996	39	1063	0	777	1190	3069
2002	17	1085	160	836	1098	3196
2003	21	1086	162	848	1098	3215
Total	107	6487	565	4812	7154	19,125

The remaining discussion is focused on rural segments. The subset of rural segments was reduced to rural, two-lane segments with no median and separated by crash experience as shown in Table 11. The data from Table 11 were then sorted by posted speed limit to categorize segments as low speed (posted speed less than 50 mph) and high speed (posted speed greater than or equal to 50 mph). Tables 12 and 13 indicate the numbers of crash and non-crash segments for rural, two-lane segments with no median on low and high speed facilities, respectively. The Washington dataset consists mostly of high speed segments and low speed segments account for less than 20 percent of rural facilities. Non-crash segments outnumber crash segments, similar to Pennsylvania; however, the ratio is almost 9:1 (non-crashes to crashes). This ratio is much higher compared to the Pennsylvania dataset and will provide a greater sample of control segments for the case-control study. The data used for the empirical investigation is sampled from Tables 12 and 13.

TABLE 11 Rural, Two-Lane, Undivided Crash and Non-Crash Segments

Year	Crash Segments	Non-Crash Segments	Total
1993	5412	52,352	57,764
1994	5852	51,873	57,725
1995	5690	50,033	55,723
1996	6039	50,165	56,204
2002	5938	50,794	56,732
2003	5867	50,907	56,774
Total	34,798	306,124	340,922

TABLE 12 Low Speed Rural Crash and Non-Crash Segments

Year	Crash Segments	Non-Crash Segments	Total
1993	968	9384	10,352
1994	1120	9463	10,583
1995	1085	9197	10,282
1996	1045	9407	10,452
2002	1173	10,127	11,300
2003	1168	10,024	11,192
Total	6559	57,602	64,161

TABLE 13 High Speed Rural Crash and Non-Crash Segments

Year	Crash Segments	Non-Crash Segments	Total
1993	4444	42,968	47,412
1994	4732	42,410	47,142
1995	4605	40,836	45,441
1996	4994	40,758	45,752
2002	4765	40,667	45,432
2003	4699	40,883	45,582
Total	28,239	248,522	276,761

5.2 Descriptive Statistics

Several variables are available for both crash and non-crash segments; however, only those variables that are consistent across both populations may be used in the analysis. This limits the depth of model estimation because driver- and vehicle-related variables are not available for non-crash segments. The limited amount of data available for non-crash segments does not present a major issue for this research. The objective is to evaluate the use of case-control and cohort studies to develop crash modification factors for lane and shoulder width while controlling for confounding variables. Roadway and traffic characteristics are available for both crash and non-crash segments and are likely to have the most influence as confounding variables. Those available data common to both crash and non-crash segments are discussed in detail in the remainder of this chapter for both Pennsylvania and Washington datasets.

5.2.1 Pennsylvania

Descriptive statistics are provided for segment length, ADT, normalized ADT, posted speed, shoulder width and lane width in Table 14. Segment length is normally distributed as shown in Figure 6 with a mean of approximately 0.5 miles and standard deviation of about 0.125 miles. ADT appears to follow a Poisson distribution (Figure 7) and a cube root transformation is used to normalize the variable (Figure 8). The cube root transformation of ADT ($ADT^{1/3}$) has a mean and standard deviation of 14.4 and 4.4, respectively. Posted speed limits range between 15 mph and 55 mph with a mean and standard deviation of 48 mph and 7.6 mph, respectively. Shoulder width ranges from zero to eighteen feet with a mean of about four feet. Lane width ranges from 6 to 33 feet with a mean of about 11 feet.

TABLE 14 Descriptive Statistics for Pennsylvania Study Population

Variable	N	Mean	S.D.	Min.	Max.
Length (ft)	127,029	2560	680	23	7793
ADT (veh/day)	127,029	3879	3506	95	25844
$ADT^{1/3}$	127,029	14.4	4.4	4.6	29.6
Speed (mph)	127,029	48	7.6	15	55
Shoulder Width (ft)	127,029	4.1	2.2	0	18
Lane Width (ft)	127,029	11.2	1.8	6	33

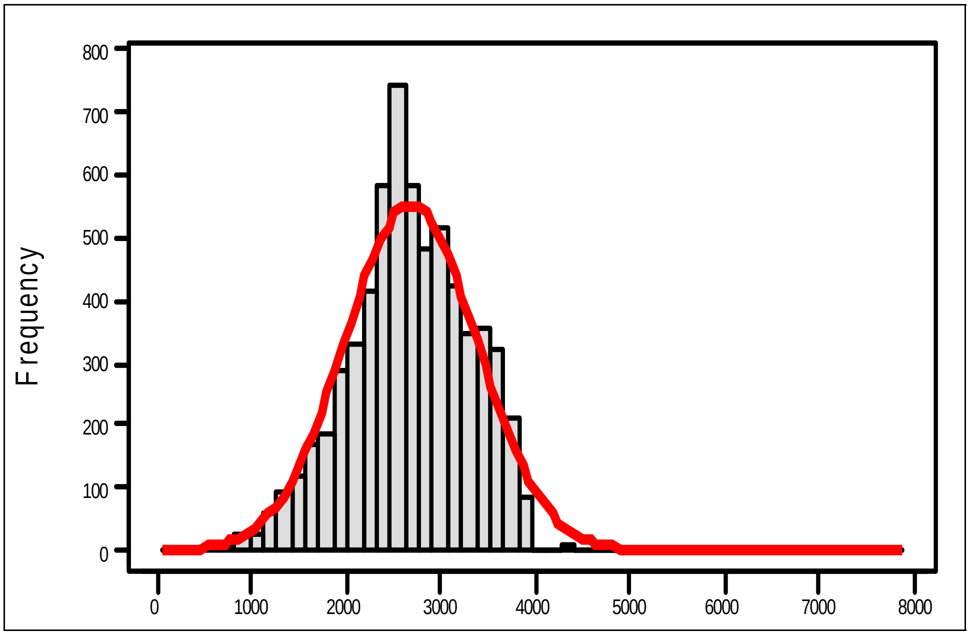

FIGURE 6 Histogram of Segment Length for Pennsylvania

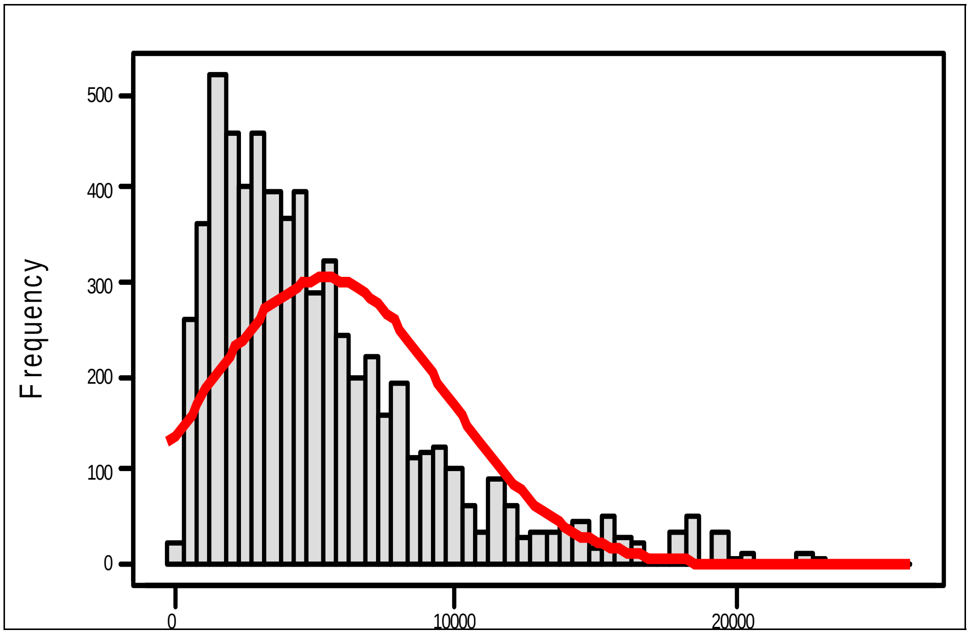

FIGURE 7 Histogram of ADT for Pennsylvania

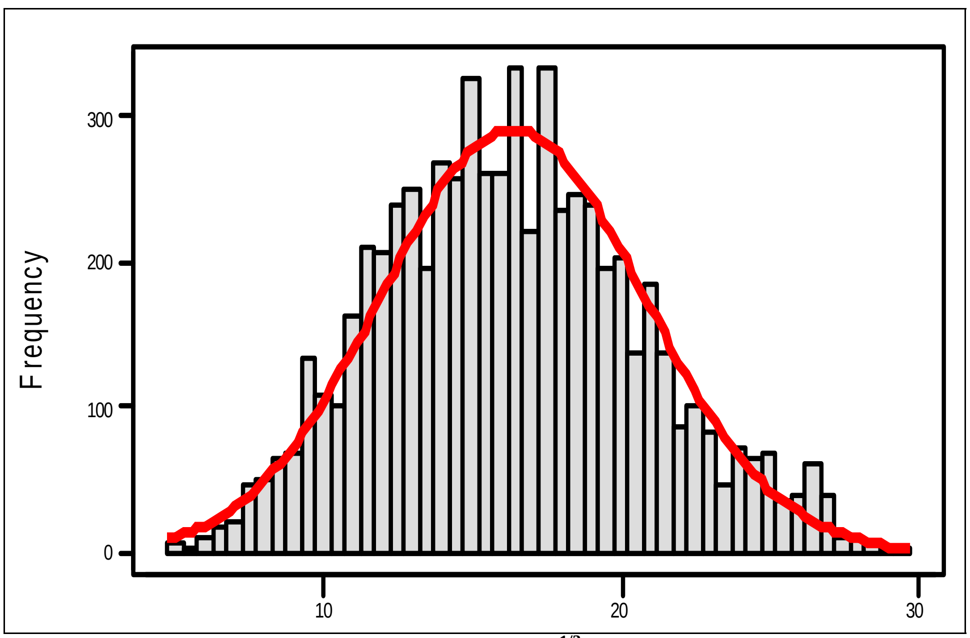

FIGURE 8 Histogram of Normalized ADT ($ADT^{1/3}$) for Pennsylvania

Shoulder width and lane width are the main focus of this study and are examined in more detail. The mean shoulder width and lane width are about 4 and 11 feet, respectively. This does not, however, say much about the sample sizes within each category. Sample sizes are shown in Tables 15 and 16 for shoulder width and lane width, respectively. Shoulder widths are most prevalent in the 2 foot to 6 foot range. There is also a relatively high frequency of zero foot shoulders in the population. Relatively small sample sizes are available for 1, 7, and 9 foot shoulders. For lane width, the most prevalent widths are 10, 11, and 12 feet. The moderate sample sizes for lane widths less than ten feet and greater than thirteen feet are the result of combining several small samples in these ranges. Relatively small sample sizes lead to large confidence intervals in many of the lane width categories. This issue is further discussed in chapter six.

TABLE 15 Sample Size for Shoulder Width

Shoulder Width (ft)	Sample Size	Percent
0	6,512	5.1
1	1,495	1.2
2	21,249	16.7
3	19,683	15.5
4	38,212	30.1
5	9,348	7.4
6	14,484	11.4
7	1,820	1.4
8	9,797	7.7
9	586	0.5
> 9	3,843	3.0
Total	127,029	100.0

TABLE 16 Sample Size for Lane Width

Lane Width (ft)	Sample Size	Percent
< 10.0	8,409	6.6
10.0	32,157	25.3
10.5	4,429	3.5
11.0	46,848	36.9
11.5	1,376	1.1
12.0	25,109	19.8
12.5	486	0.4
13.0	1,074	0.8
> 13.0	7,141	5.6
Total	127,029	100.0

5.2.2 Washington

Descriptive statistics are provided for segment length, ADT, normalized ADT, posted speed, shoulder width, lane width, horizontal curvature and vertical curvature in Table 17. The mean segment length is almost 0.1 miles with a standard deviation of about 0.125 miles. Segment lengths in the Washington dataset are much smaller, on average, than those in Pennsylvania although the standard deviation is about the same. The distribution is, therefore, different for segment length when comparing the two states as shown in Figure 9. ADT is similarly Poisson distributed (Figure 10) and requires a cube root transformation to normalize the distribution (Figure 11). For $ADT^{1/3}$, the mean and standard deviation are 13.4 and 4.4, respectively. Posted speed limits range between 25 mph and 65 mph with a mean and standard deviation of 51 mph and 8.2 mph, respectively. Shoulder width ranges from zero to forty feet with a mean of just over four feet. Lane width ranges from 6 to 40 feet with a mean of 11.7 feet. The Washington dataset also includes information regarding horizontal and vertical curvature. Of the total 340,922 segments, just over one-third include a horizontal curve and more than two-thirds contain a vertical curve.

TABLE 17 Descriptive Statistics for Washington Study Population

Variable	N	Mean	S.D.	Min.	Max.
Length (ft)	340,922	460	659	53	105,178
ADT (veh/day)	340,922	3311	3490	47	42,998
$ADT^{1/3}$	340,922	13.4	4.4	3.6	35.0
Speed (mph)	340,922	51	8.2	25	65
Shoulder Width (ft)	340,922	4.3	2.7	0	40
Lane Width (ft)	340,922	11.7	2.1	6	40
Horizontal Curves	122,155	*	*	*	*
Vertical Curves	239,668	*	*	*	*

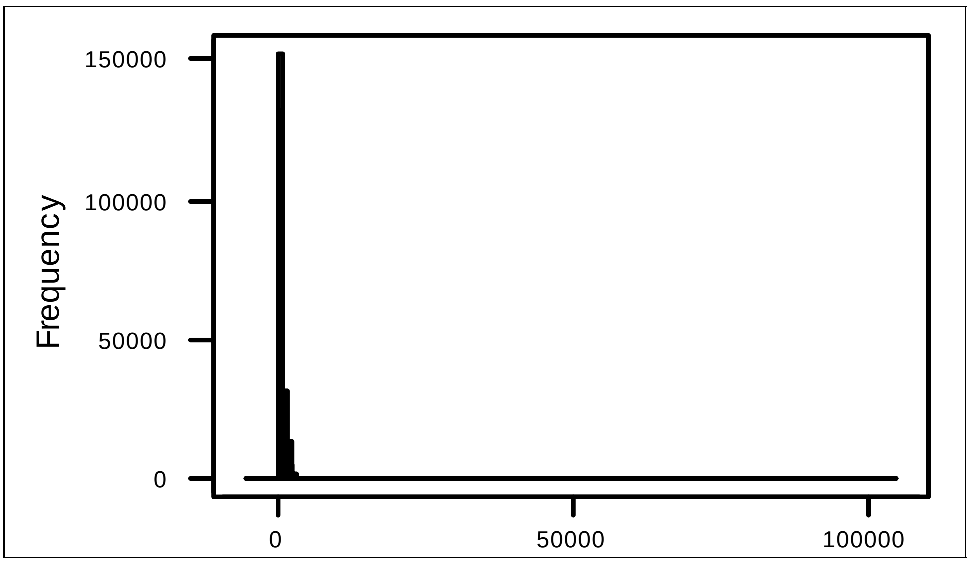

FIGURE 9 Histogram of Segment Length for Washington

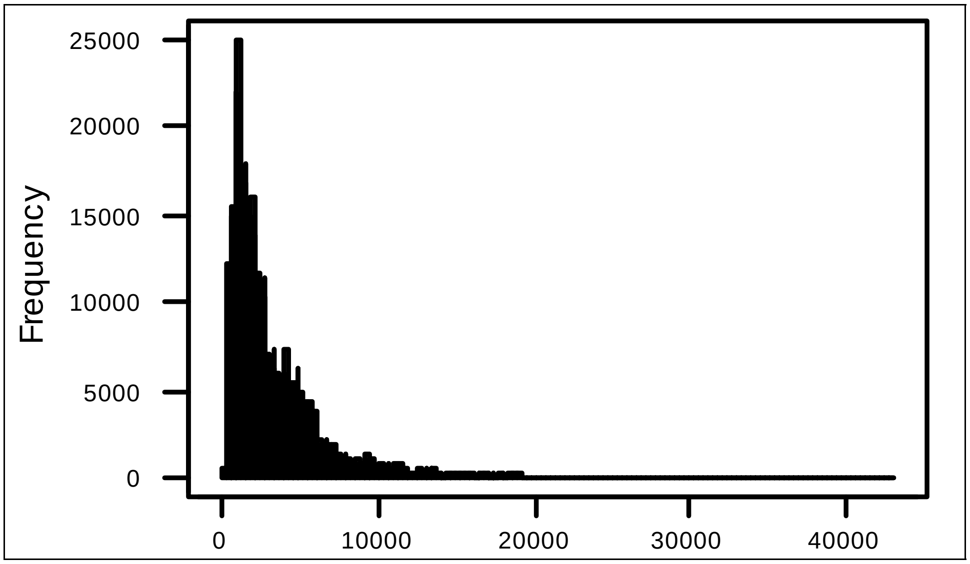

FIGURE 10 Histogram of ADT for Washington

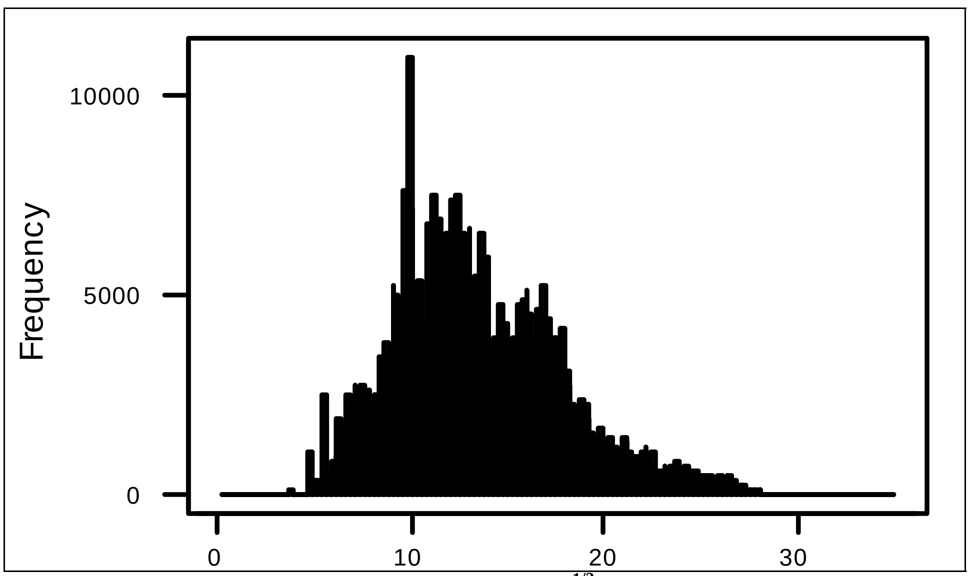

FIGURE 11 Histogram of Normalized ADT ($ADT^{1/3}$) for Washington

The mean shoulder width and lane width are 4.3 and 11.7 feet, respectively, which is slightly greater than Pennsylvania. Sample sizes from the Washington dataset are shown in Tables 18 and 19 for shoulder width and lane width, respectively. Shoulder widths are most prevalent in the 2 to 8 foot range, which is also slightly different from Pennsylvania. Again, there is a relatively high frequency of zero foot shoulders in the population. Relatively small sample sizes are available for shoulder widths greater than eight feet. There is not much variation in lane width for the Washington dataset where 11 and 12 foot lanes account for 75 percent of the study population. Lane widths with the next largest sample sizes are 11.5, 10.0 and 10.5, respectively.

TABLE 18 Sample Size for Shoulder Width

Shoulder Width (ft)	Sample Size	Percent
0	19,816	5.8
1	17,987	5.3
2	58,309	17.1
3	60,861	17.9
4	55,025	16.1
5	19,916	5.8
6	29,700	8.7
7	21,033	6.2
8	43,649	12.8
9	2,862	0.8
> 9	11,764	3.5
Total	340,922	100.0

TABLE 19 Sample Size for Lane Width

Lane Width (ft)	Sample Size	Percent
< 10.0	2,917	0.9
10.0	20,689	6.1
10.5	13,935	4.1
11.0	145,375	42.6
11.5	27,464	8.1
12.0	111,523	32.7
12.5	2,784	0.8
13.0	2,014	0.6
> 13.0	14,221	4.2
Total	340,922	100.0

5.3 Creation of Categorical Variables

Matching is applied within the case-control designs to account for potential confounding effects of ADT, speed limit, segment length, horizontal curvature and vertical curvature. Matching cases and controls by exact values is not practical because it significantly reduces the available sample size. Therefore, categorical variables are created for each of the variables included in the matching schemes and matching is completed by category. Speed, horizontal curvature and vertical curvature are converted into binary variables. Speed limits are divided into two categories (low speed and high speed), where low speed segments are defined as those with a posted speed of 45 mph or less and high speed segments are those with a posted speed greater than 45 mph. Horizontal and vertical curvature are also divided into two categories indicating the presence or absence of a curve. Multiple categories are created for segment length and ADT using the following three steps. Step one: plot histograms and determine the distribution for each variable. Step two: apply normalizing transformation as necessary. Step three: create categories from the normalized distribution by taking the mean plus and minus standard deviations as illustrated in Figure 12.

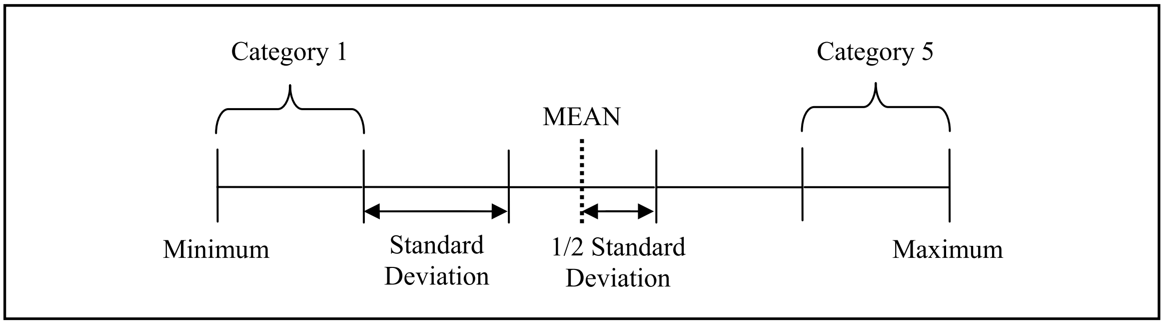

FIGURE 12 Creating an Odd Number of Categories

For Pennsylvania, categories are created for segment length and $ADT^{1/3}$ as shown in Table 20 using the mean and standard deviation from Table 14 above. Similarly, categories are created for Washington for $ADT^{1/3}$ (Table 21); however, the method shown in Figure 12 does not work well for segment length. In the Washington dataset, there are many short segments and a few relatively long segments resulting in a small mean and large variance. In fact, the mean is less than the variance so the data are over-dispersed. Using the method above would only result in the creation of two categories for segment length; segments shorter than the mean and segments longer than the mean. Instead of creating just two categories for segment length, segments are classified by the same categories used for Pennsylvania. The effect of segment length can then be estimated for each category to determine if the categorization was appropriate.

TABLE 20 Categories for Pennsylvania

Segment Length (ft)	$ADT^{1/3}$
< 1320	< 5.6
1320 ~ 1980	5.6 ~ 10.0
1980 ~ 2640	10.0 ~ 14.4
2640 ~ 3300	14.4 ~ 18.8
3300 ~ 3960	18.8 ~ 23.2
≥ 3960	≥ 23.2

TABLE 21 Categories for Washington

Segment Length (ft)	$ADT^{1/3}$
< 1320	< 4.6
1320 ~ 1980	4.6 ~ 9.0
1980 ~ 2640	9.0 ~ 13.4
2640 ~ 3300	13.4 ~ 17.8
3300 ~ 3960	17.8 ~ 22.2
≥ 3960	≥ 22.2

5.4 Selection of Case and Control Segments

5.4.1 Case-Control Design

A matched case-control design is set-up to evaluate the effects of shoulder width and lane width on roadway segment crashes. A sample is selected from the population of all rural, two-lane, undivided highway segments. This study population is used to eliminate the variability between rural and urban segments, multi-lane segments, and those segments with and without a median. In Pennsylvania, the study period continues from 1997 – 2001 and in Washington from 1993 – 1996 and 2002 – 2003. Each year of the study period is analyzed separately as opposed to aggregating the five years of data before selecting cases and controls. If the five years of data were aggregated before case selection, it is likely that many more segments would experience at least one crash in this period, leaving relatively few controls for comparison. Cases are defined as segments that experience at least one crash during a particular year of the study period. Segments experiencing multiple crashes per year are accounted for by creating one crash-roadway data record for each incident. The creation of multiple observations for multiple-crash segments gives each case segment an equal weight for sampling purposes.

Control segments are randomly selected, at a ratio of 1:1, from the same population as each case segment (i.e. rural, two-lane, undivided highway segments in Pennsylvania or Washington). In the event that cases outnumber control segments, a random case is selected to match each available control. The cases and controls are selected without regard to other geometric or traffic characteristics, aside from the matching variables, differentiated only by outcome status (crash or no crash) during a particular year.

The base matching scheme does not control for the effects of confounding through matching whereas the remaining matching schemes do control for confounders. In the base matching scheme, a control is randomly matched to each case by outcome status alone and any adjustment for confounders is applied during model estimation. In the next matching scheme, controls are matched to each case by posted speed and ADT using the categories created in Section 5.3. Additional matching schemes are developed to include segment length, horizontal curvature and vertical curvature.

The number of case-control pairs is given in Tables 22 and 23 for the Pennsylvania and Washington matching schemes, respectively. Comparison of the matching schemes illustrates the effects of matching on sample size. Available sample size decreases as additional matching criteria are applied to the Pennsylvania dataset. For Washington, each of the matched datasets is smaller than the original (Base Match) dataset with no matching. Ideally, controls would be matched to each case so that the case-control pair is identical in all respects; however, this would lead to a sparse data problem and significantly reduce the sample size for model estimation.

TABLE 22 Sample Sizes for PA Matching Schemes

Matching Scheme	Case-Control Pairs
Base Match	56,732
First Match (ADT and Speed)	43,869
Second Match (ADT, Speed and Segment Length)	41,350

TABLE 23 Sample Sizes for WA Matching Schemes

Matching Scheme	Case-Control Pairs
Base Match	47,812
First Match (ADT and Speed)	46,316
Second Match (ADT, Speed and Horizontal Curvature)	47,238
Third Match (ADT, Speed and Vertical Curvature)	47,505

5.4.2 Cohort Design

A cohort design is developed to evaluate the effects of shoulder width and lane width on roadway crashes in Pennsylvania and Washington. Unlike the case-control study, the cohort design does not apply a matching scheme to adjust for confounding variables. Instead, all adjustment for confounders is made during model estimation. The elimination of matching allows a greater sample to be used in the cohort analysis. The entire study population is used as the study sample, which is composed of all rural, two-lane, undivided segments in Pennsylvania (Table 6) and Washington (Table 11). The same years of data are used for the cohort analysis as were used for the case-control study and each year of the study period is analyzed separately.

5.5 Sample Size and Power

5.5.1 Case-Control Design

For a matched case-control design, the required sample size is proportional to the number of discordant pairs (case-control pair with different risk factor status). Specifically, the sample size is equal to the number of discordant pairs divided by the proportion of expected discordant pairs in the sample as shown in Equation (27) (Woodward, 2005). The required number of discordant pairs is based on Equation (28), which is a function of the desired level of significance, power, and detectable difference in risk.

$$n = \frac{2d_p}{\pi_d} \quad \ldots (27)$$

Where,

n = total sample size,

d_p = number of discordant pairs, and

π_d = probability of a discordant pair.

$$d_p = \frac{[z_\alpha(\lambda+1)+2z_\beta\sqrt{\lambda}]^2}{(\lambda-1)^2} \quad \text{… (28)}$$

Where,

z_α = z-statistic for significance level α/2,

z_β = z-statistic for power 1-β,

λ = desired detectable relative risk, and

All other variables as previously defined.

Table 24 illustrates the required sample sizes for various combinations of λ and π_d. In highway safety studies, it is unlikely that geometric elements will have a relative risk greater than 1.5. In this example, the minimum detectable relative risk is set at 1.05 and 1.10 to illustrate the sample size requirements that would be necessary to show relatively small safety effects. The number of discordant pairs was calculated based on a desired power of 90 percent and a significance level of 0.10. The Pennsylvania and Washington data were examined to determine the percent discordant pairs for both lane and shoulder width, which was used as an estimate for the probability of a discordant pair. For Pennsylvania, there were approximately 70 percent discordant pairs for lane width and 80 percent for shoulder width. For Washington, the percent of discordant pairs were similar for lane width (66 percent) and shoulder width (84 percent). Table 24 illustrates how the required sample size changes based on the probability of a discordant pair with values ranging from 0.5 to 0.8.

TABLE 24 Sample Size Calculations

	Lambda	
π_d	1.05	1.10
0.5	57,576	15,094
0.6	47,980	12,578
0.7	41,126	10,782
0.8	35,986	9,434

For Pennsylvania and Washington, the available sample sizes decrease as the matching scheme becomes more complex. The smallest available sample size is 41,350 (for the second matching scheme in Pennsylvania), which is adequate to detect a relative risk of 1.05 while achieving 90 percent power and a significance level of 0.10 with 70 percent discordant pairs.

However, if the probability of a discordant pair is reduced to 0.5, then the available sample sizes for Pennsylvania and Washington will be inadequate for the desired levels of power, significance, and detection.

5.5.2 Cohort Design

For a cohort design, the required sample size may be calculated using Equation (29), where the common proportion over two groups (p_c) is obtained from Equation (30) (Woodward, 2005).

$$n = \frac{r+1}{r(\lambda-1)^2\pi^2}[z_\alpha\sqrt{(r+1)p_c(1-p_c)} + \sqrt{\lambda\pi(1-\lambda\pi)+r\pi(1-\pi)}]^2 \quad \ldots (29)$$

Where,

n = total sample size

p_c = common proportion over 2 groups

π = proportion in the reference group

z_α = z-statistic for confidence level $\alpha/2$

z_β = z-statistic for power $1-\beta$

λ = desired detectable relative risk

r = proportion of risk group to reference group = n_1/n_2

$$p_c = \frac{\pi(r\lambda+1)}{(r+1)} \quad \ldots (30)$$

Where,

z_α = z-statistic for significance level $\alpha/2$,

z_β = z-statistic for power $1-\beta$,

λ = desired detectable relative risk, and

All other variables as previously defined.

Tables 25 and 26 illustrate the required sample sizes for various combinations of λ and π assuming different values of r. Again, the sample size calculations are based on a desired power of 90 percent and a significance level of 0.10. The Pennsylvania and Washington data were examined to determine the proportion in the reference group for lane and shoulder width. The reference group proportion is calculated as the number of crash segments in the reference group divided by the total number of segments in the reference group. For Pennsylvania, the proportions for lane and shoulder width were 0.40 and 0.55, respectively. For Washington, the proportions for lane and shoulder width were 0.22 and 0.13, respectively. Tables 25 and 26 illustrate how the required sample size changes based on the proportion in the reference group and assuming r equals 1.0 and 0.25, respectively.

TABLE 25 Sample Size Calculations (r = 1)

	Lambda	
π	1.05	1.10
0.50	13,692	3,414
0.40	20,714	5,212
0.30	32,420	8,210
0.20	55,832	14,206
0.10	126,064	32,192

TABLE 26 Sample Size Calculations (r = 0.25)

	Lambda	
π	1.05	1.10
0.50	21,392	5,334
0.40	32,346	8,134
0.30	50,602	12,800
0.20	87,114	22,134
0.10	196,648	50,132

For Pennsylvania and Washington, the available sample sizes for the cohort study are much larger than the case-control study. The available sample size for Pennsylvania is 127,029 and 340,922 for Washington. Both datasets are adequate to satisfy the range of required sample sizes in Table 25; however, the Pennsylvania dataset is inadequate to detect a relative risk of 1.05 in Table 26 when the reference group proportion is 0.10.

CHAPTER VI ANALYSIS AND INTERPRETATION OF RESULTS

6.1 Introduction

The applications of case-control and cohort methods for estimating safety effectiveness are presented in this chapter. In particular, safety effectiveness was estimated for both lane and shoulder width using crash and roadway data from Pennsylvania and Washington. Bivariate plots are presented to show the relationships between potential confounding variables, crash frequency, lane width and shoulder width. The structure of the empirical study is introduced in Section 6.3 followed by a presentation of the model estimates and discussion of the results.

6.2 Bivariate Plots

Potential confounding variables were identified in Section 4.3. In this section, the potential confounders are revisited to determine if the variables fit the definition of a true confounder. A confounder is a variable that is a risk factor for the outcome under study, and is associated with, but not a consequence of, the risk factor in question (Collett, 2003). Modeling adjustments should be made for all variables identified as confounders. The following bivariate plots provide a better indication of potential confounders; however, models should be estimated with and without the individual confounders to determine the magnitude of confounding effects.

ADT

There is a clear association between ADT and crash frequency, which may mask the effects of lane and shoulder width on crash risk. Figures 13 and 14 show the average ADT and 95 percent confidence interval for each shoulder width and lane width category. There is a clear increasing trend in ADT as shoulder width and lane width increase. This indicates that ADT is somehow associated with both lane and shoulder width. ADT is also a risk factor for crashes as shown in Figure 15; crashes increase linearly as average ADT increases. ADT is associated with both shoulder and lane width and a risk factor for crash frequency. Thus, ADT is a confounding variable that must be included in the modeling process.

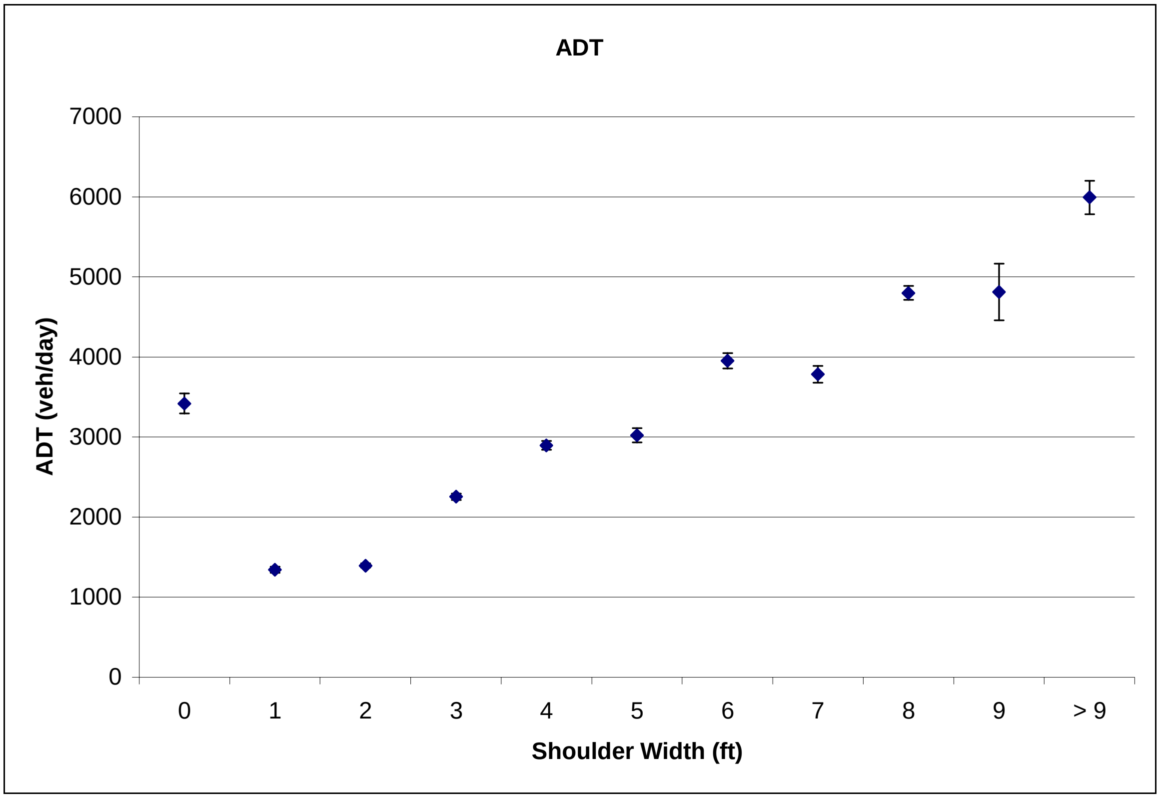

FIGURE 13 Association between Mean ADT and Shoulder Width

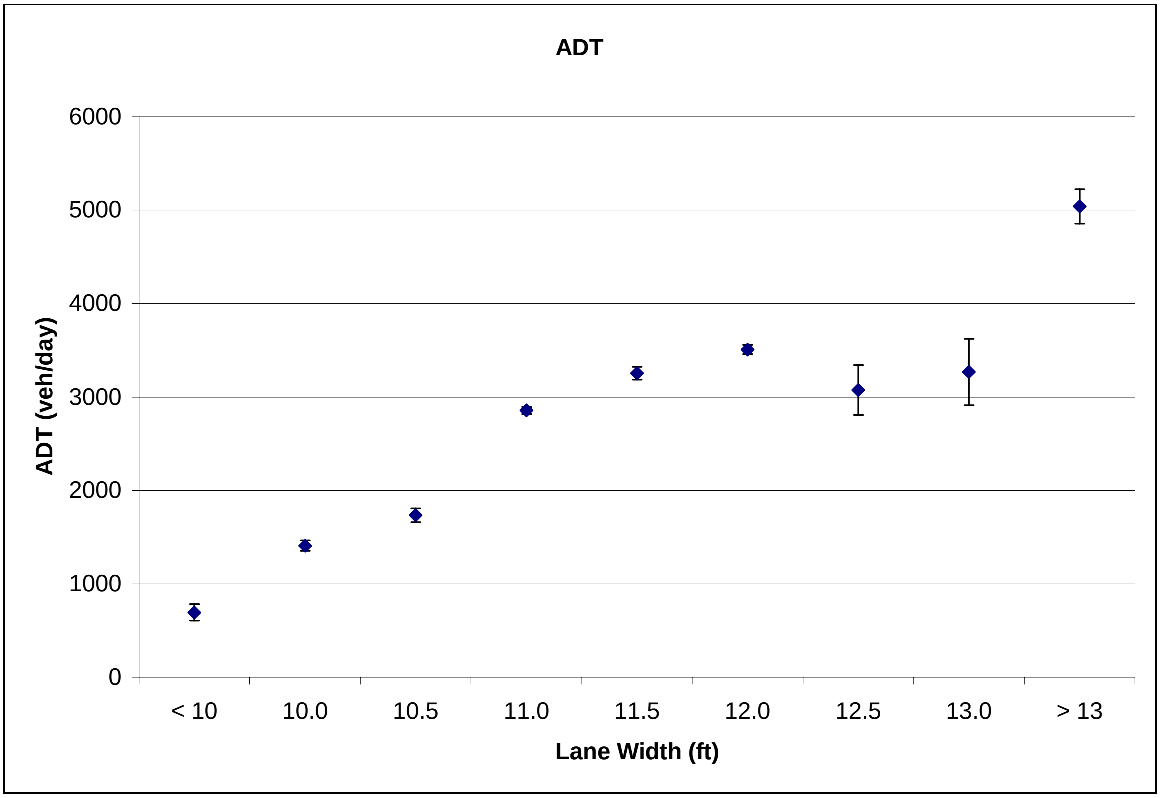

FIGURE 14 Association between Mean ADT and Lane Width

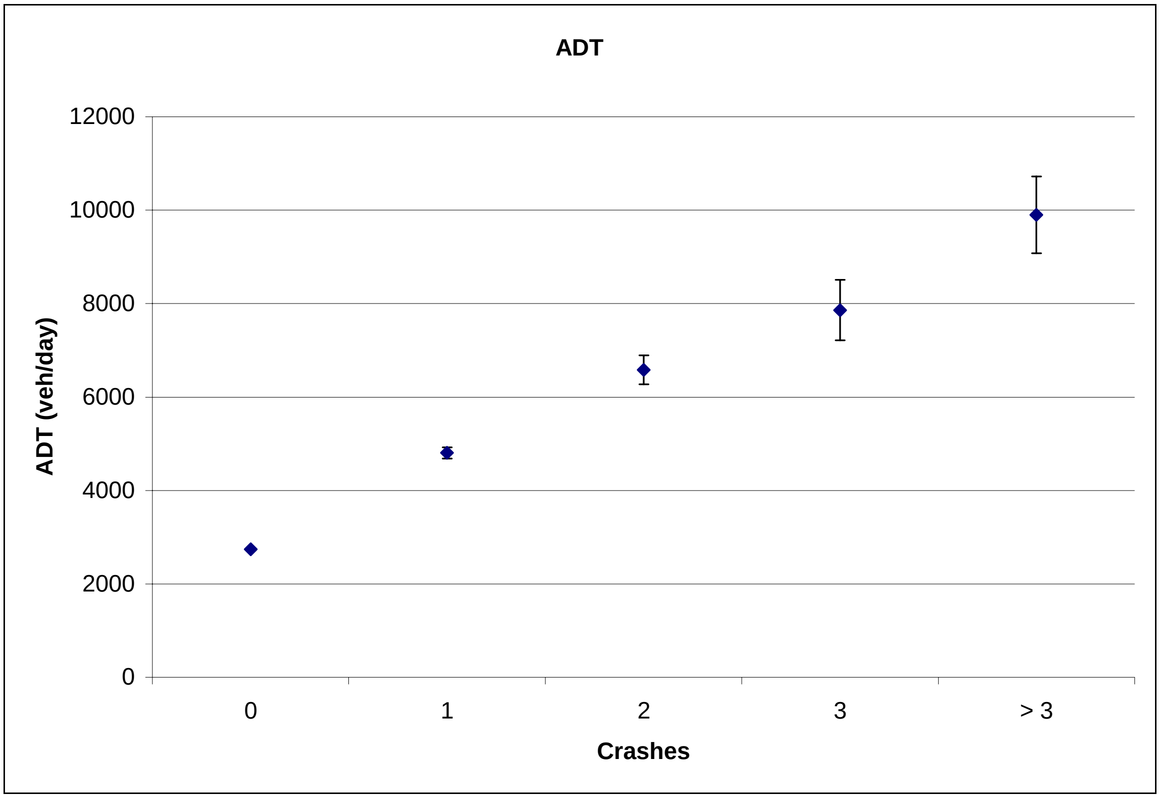

FIGURE 15 Association between Mean ADT and Crash Frequency

Speed

Speed limit appears to be associated with both lane and shoulder width; however, the confounding effects are less clear than for ADT. Figures 16 and 17 show the average posted speed limit plotted against shoulder and lane width, respectively. As lane and shoulder width increase, average speed follows a convex parabolic shape. That is to say, on average, higher speed facilities are more likely to have lane widths between 11.5 and 12.5 feet and shoulder widths between 4.0 and 8.0 feet. Lane and shoulder widths in either extreme are more likely to have lower speed limits. There is also evidence that speed may be a marginal risk factor for crashes. Figure 18 is a bit counterintuitive, but shows that crashes tend to decrease as the average speed limit increases. Speed appears to be associated with both shoulder and lane width and a possible risk factor for crash frequency. Therefore, it is necessary to include model adjustments for the possible confounding effects of speed limit.

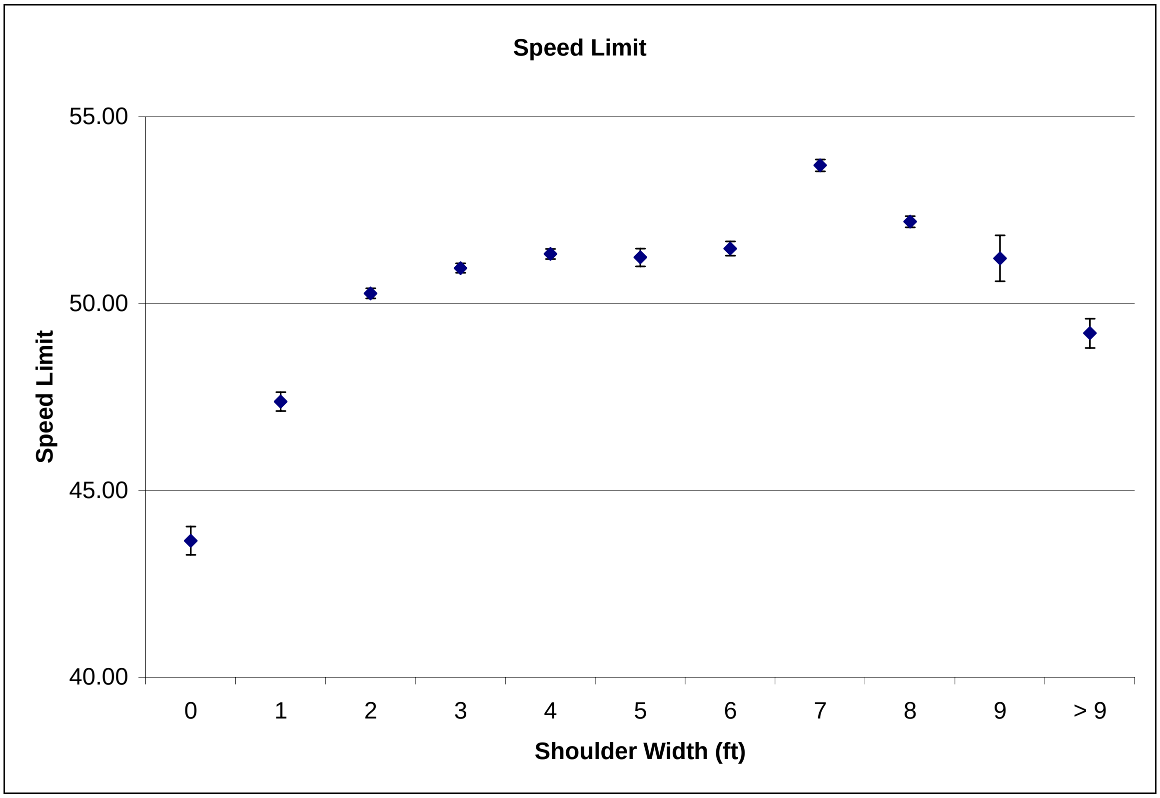

FIGURE 16 Association between Mean Posted Speed and Shoulder Width

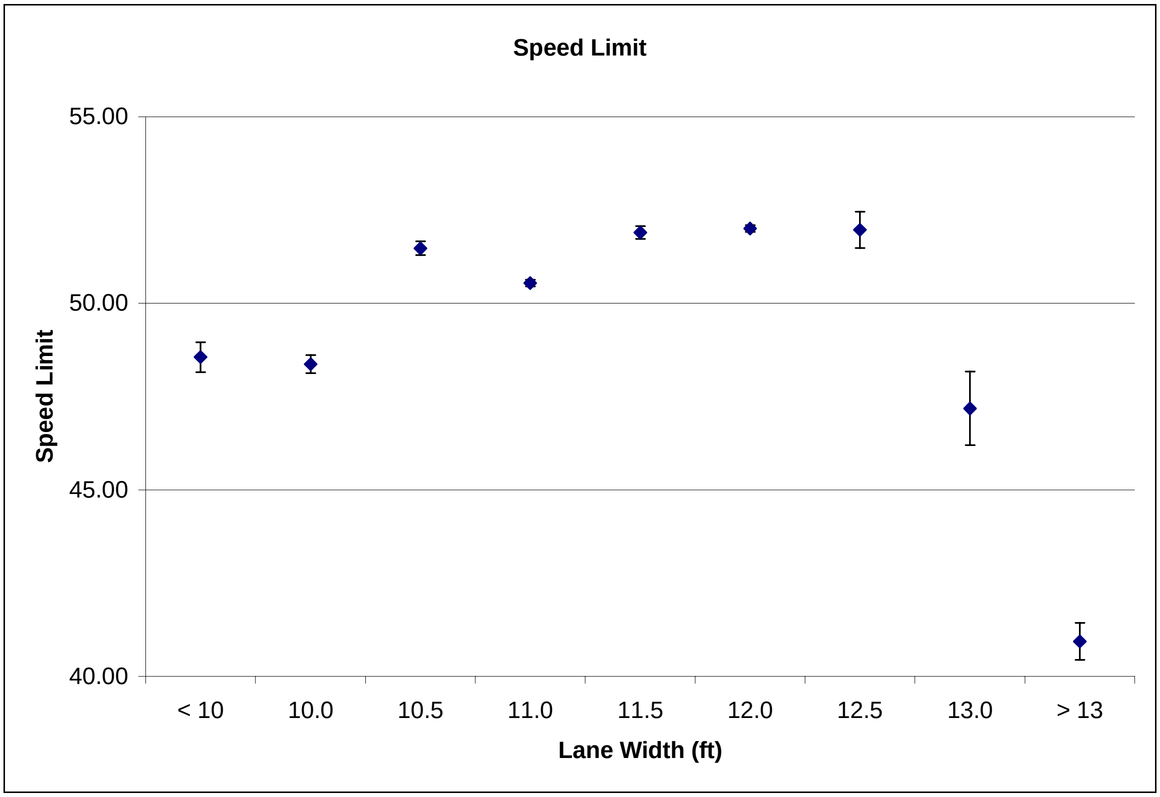

FIGURE 17 Association between Mean Posted Speed and Lane Width

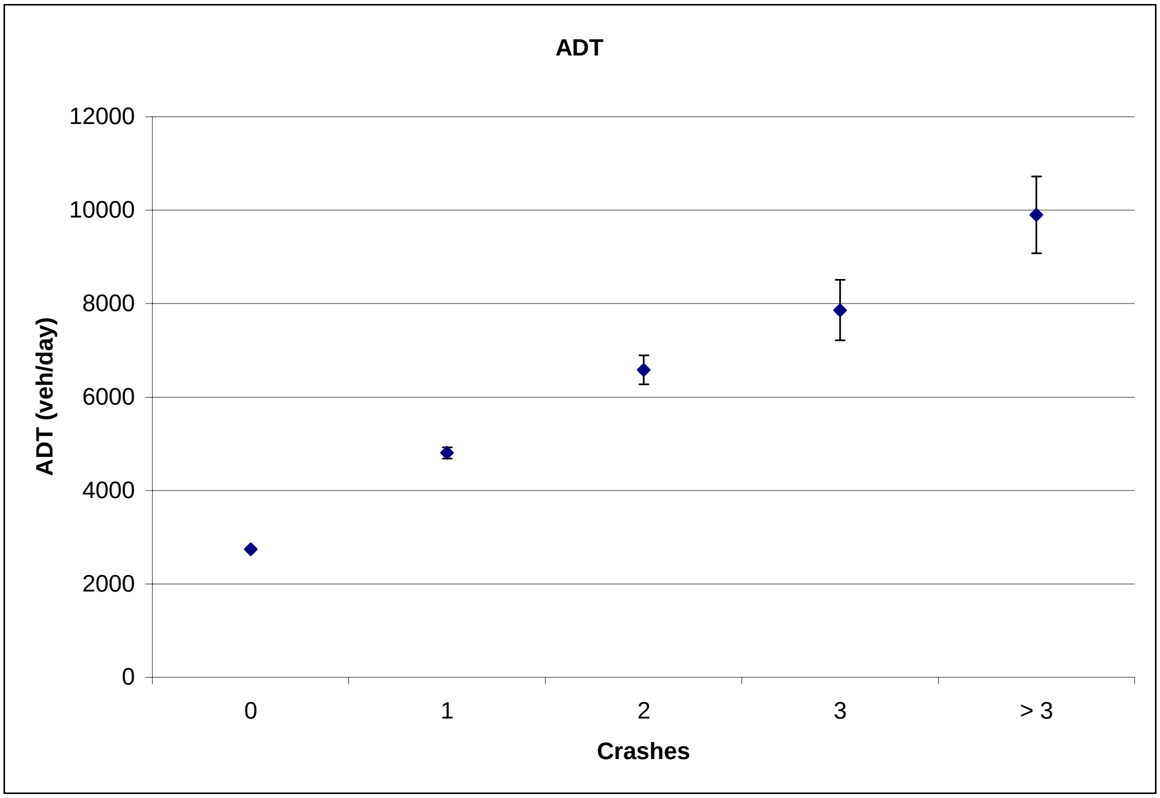

FIGURE 18 Association between Mean Posted Speed and Crash Frequency

Segment Length

The effects of both lane and shoulder width on crash risk may be masked by the association between segment length and crash frequency. Figure 19 shows a clear increasing trend in average segment length as shoulder width increases. The same is generally true for lane width; however, average segment length decreases slightly for lane widths greater than 12.5 feet (Figure 20). It is also apparent that segment length is a risk factor for crashes; crashes increase, at a decreasing rate, as average segment length increases (Figure 21). Segment length is associated with both shoulder and lane width and is a risk factor for crash frequency. Thus, segment length is an obvious confounding variable that must be included in the modeling process.

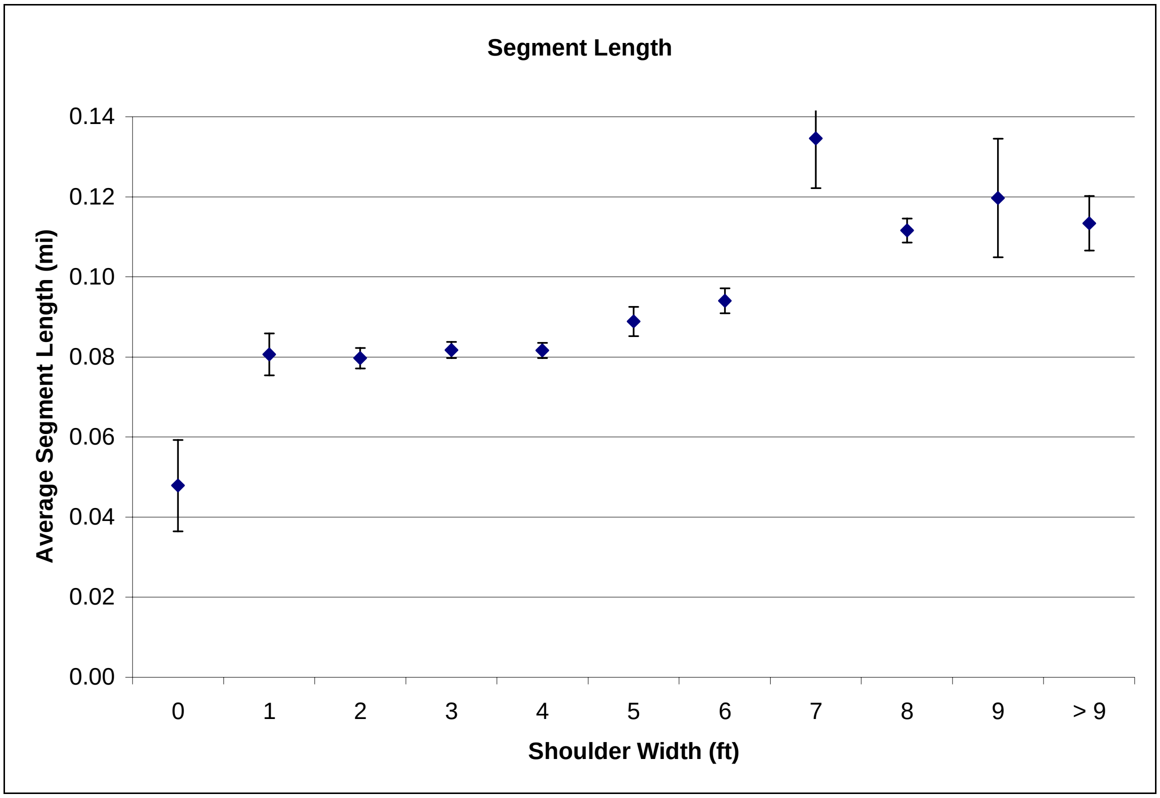

FIGURE 19 Association between Mean Segment Length and Shoulder Width

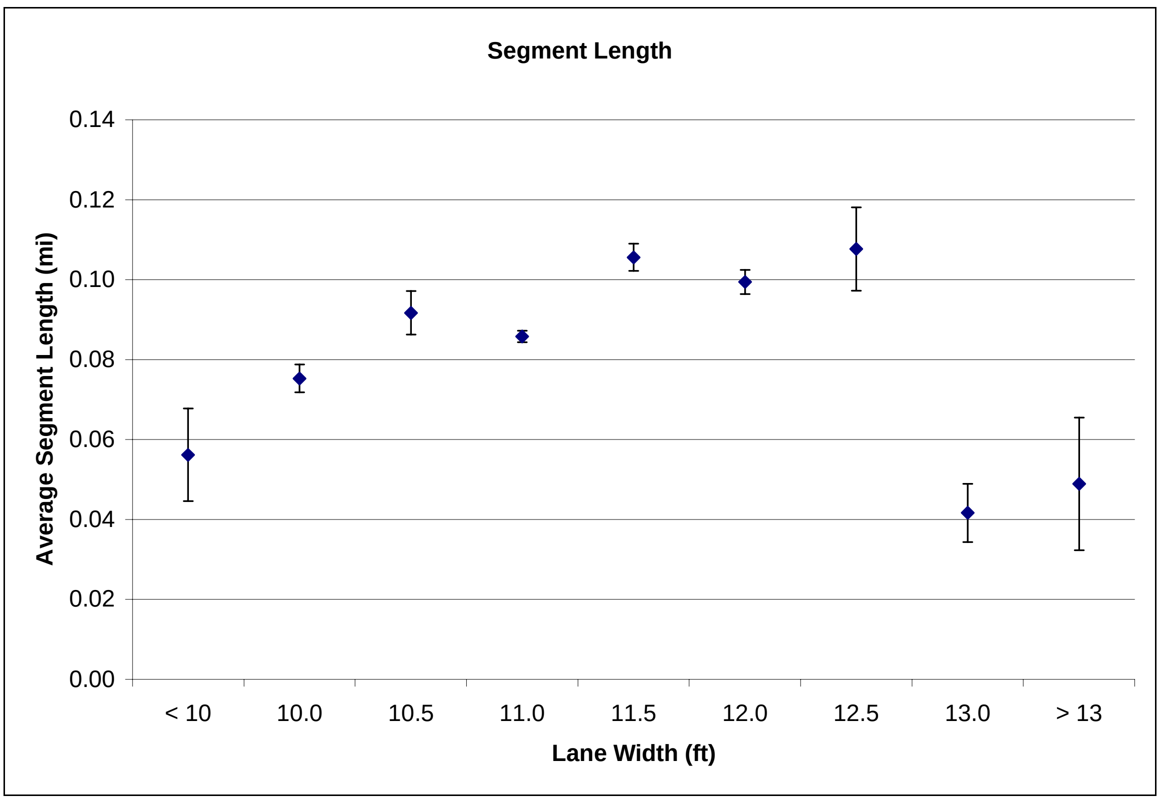

FIGURE 20 Association between Mean Segment Length and Lane Width

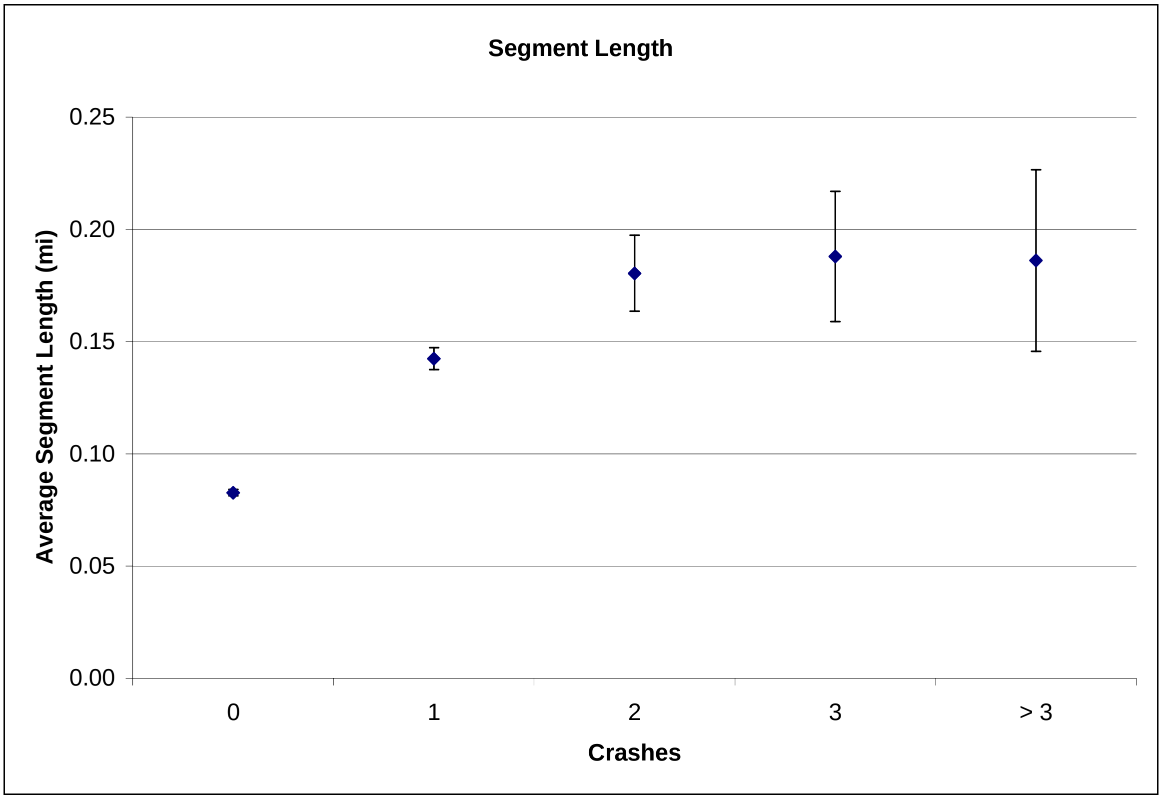

FIGURE 21 Association between Mean Segment Length and Crash Frequency

Horizontal Curvature

There is a clear association between horizontal curvature and crash frequency, which may mask the effects of lane and shoulder width on crash risk. Figures 22 and 23 show the percentage of segments with horizontal curvature plotted against shoulder and lane width. There is a decreasing trend in the percentage of horizontal curves as shoulder width and lane width increase. This indicates that horizontal curves are more prevalent on roadways with narrower lanes and shoulders. These results are consistent with the expectation that higher-type facilities are designed to have wider lanes and shoulders with fewer horizontal curves. Also, crashes increase linearly as the percentage of curves decreases (Figure 24). Although the trend is counterintuitive, horizontal curvature is strongly associated with crash frequency. Horizontal curvature is associated with both shoulder and lane width and a risk factor for crash frequency. It is apparent that horizontal curvature is a confounding variable that should be included in the modeling process.

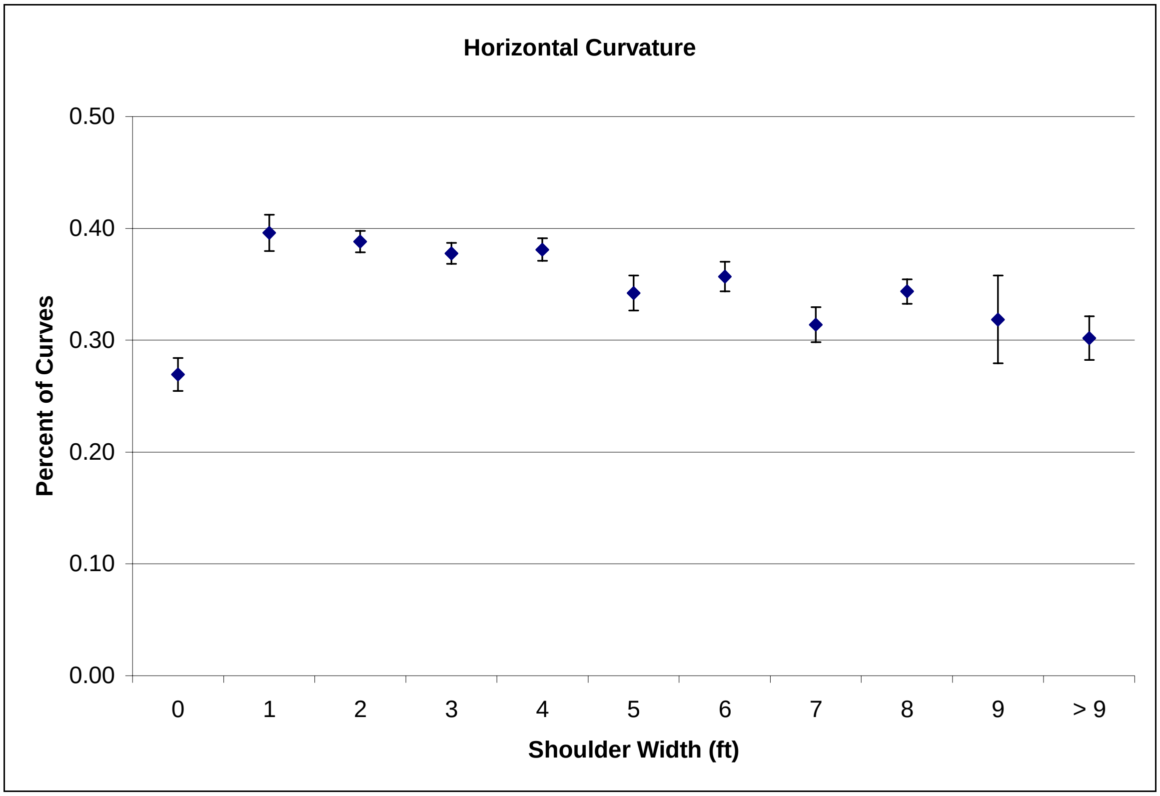

FIGURE 22 Percentage of Segments with Horizontal Curvature versus Shoulder Width

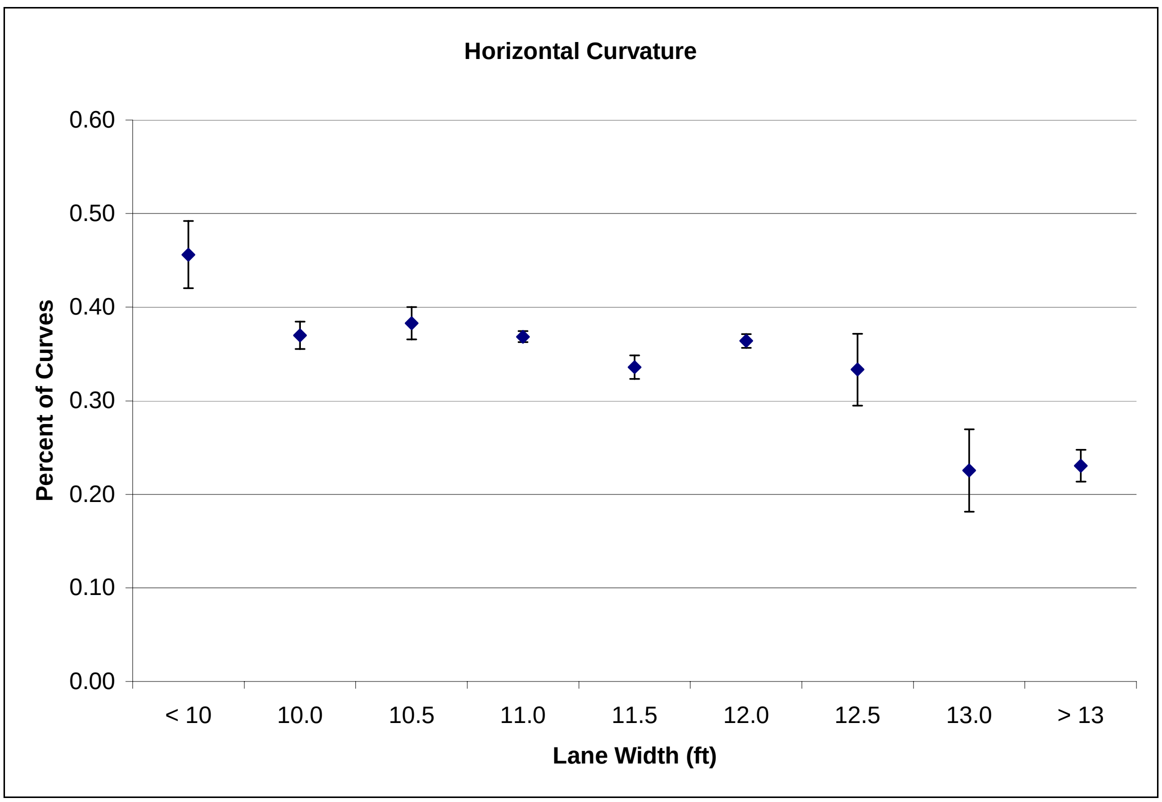

FIGURE 23 Percentage of Segments with Horizontal Curvature versus Lane Width

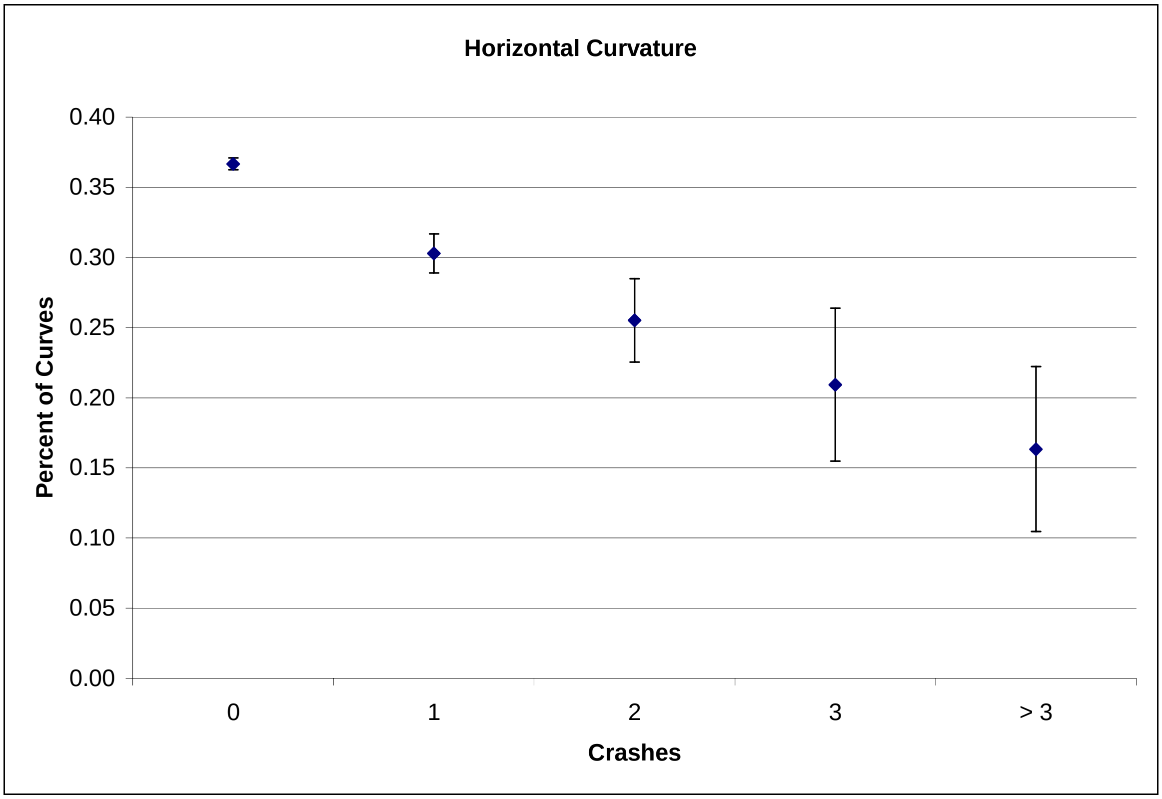

FIGURE 24 Percentage of Segments with Horizontal Curvature versus Crash Frequency

Vertical Curvature

The confounding effects of vertical curvature are less clear than horizontal curvature. Figures 25 and 26 illustrate the association between the percentage of segments with vertical curvature and shoulder and lane width, respectively. The percentage of vertical curves tends to increase as shoulder width increases. This indicates that roadways with a higher percentage of vertical curves are more likely to have wider shoulders. Figure 26 suggests no association between lane width and vertical curvature. In addition, vertical curvature is only weakly associated with crash frequency (Figure 27). Crashes increase linearly as the percentage of curves decrease; however, the trend is relatively flat. Vertical curvature is associated with shoulder width and weakly related to crash frequency. Therefore, vertical curvature should be included in the models to estimate safety effectiveness for shoulder width, but may not be necessary to include in the lane width models.

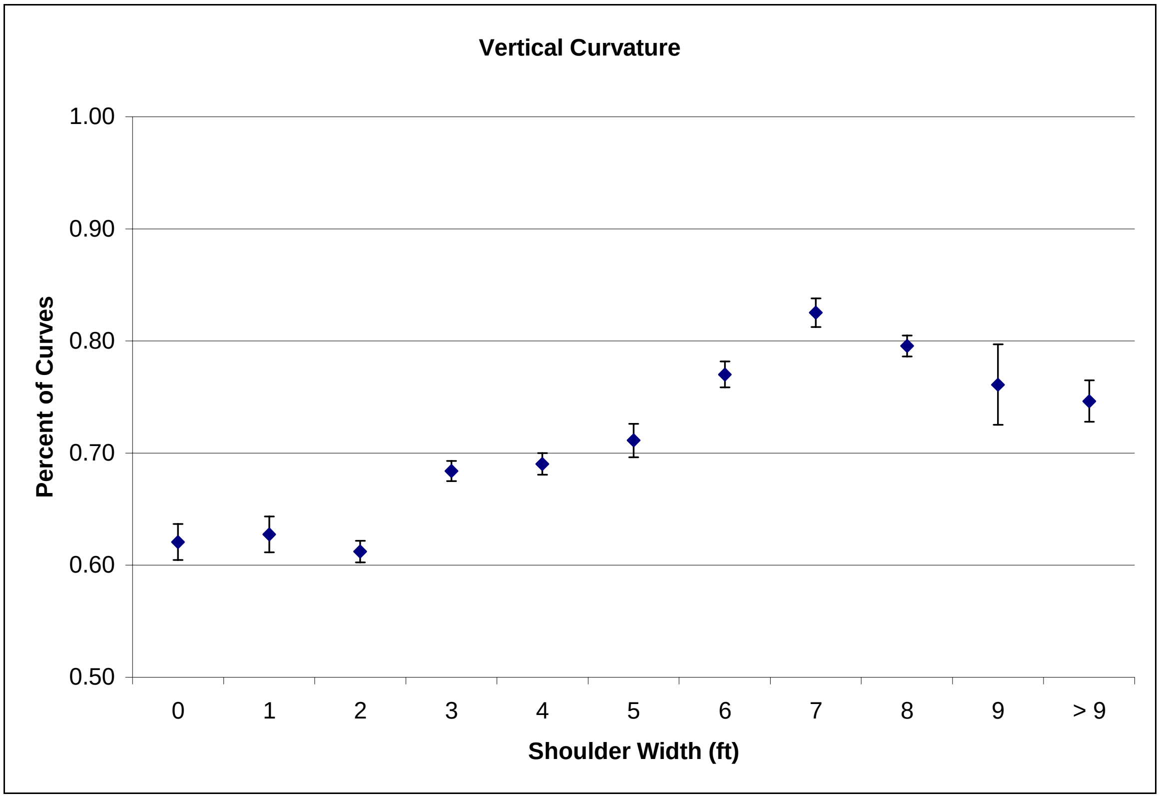

FIGURE 25 Percentage of Segments with Vertical Curvature versus Shoulder Width

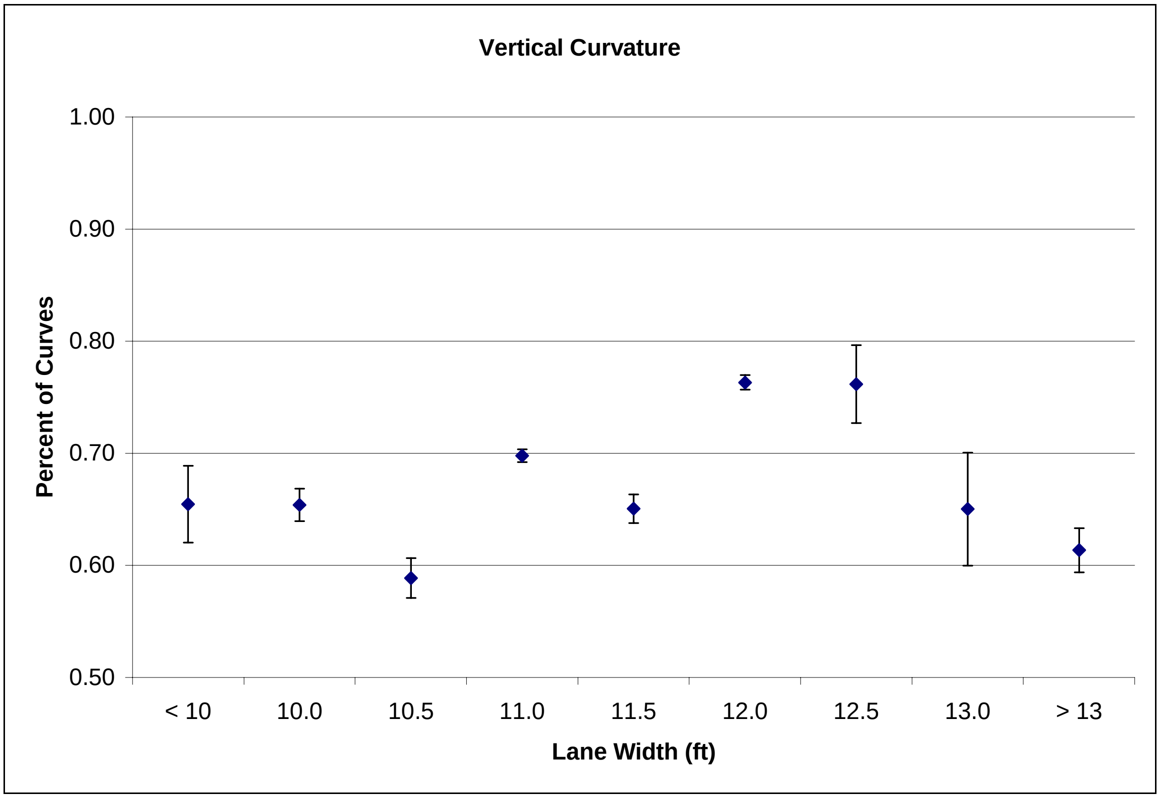

FIGURE 26 Percentage of Segments with Vertical Curvature versus Lane Width

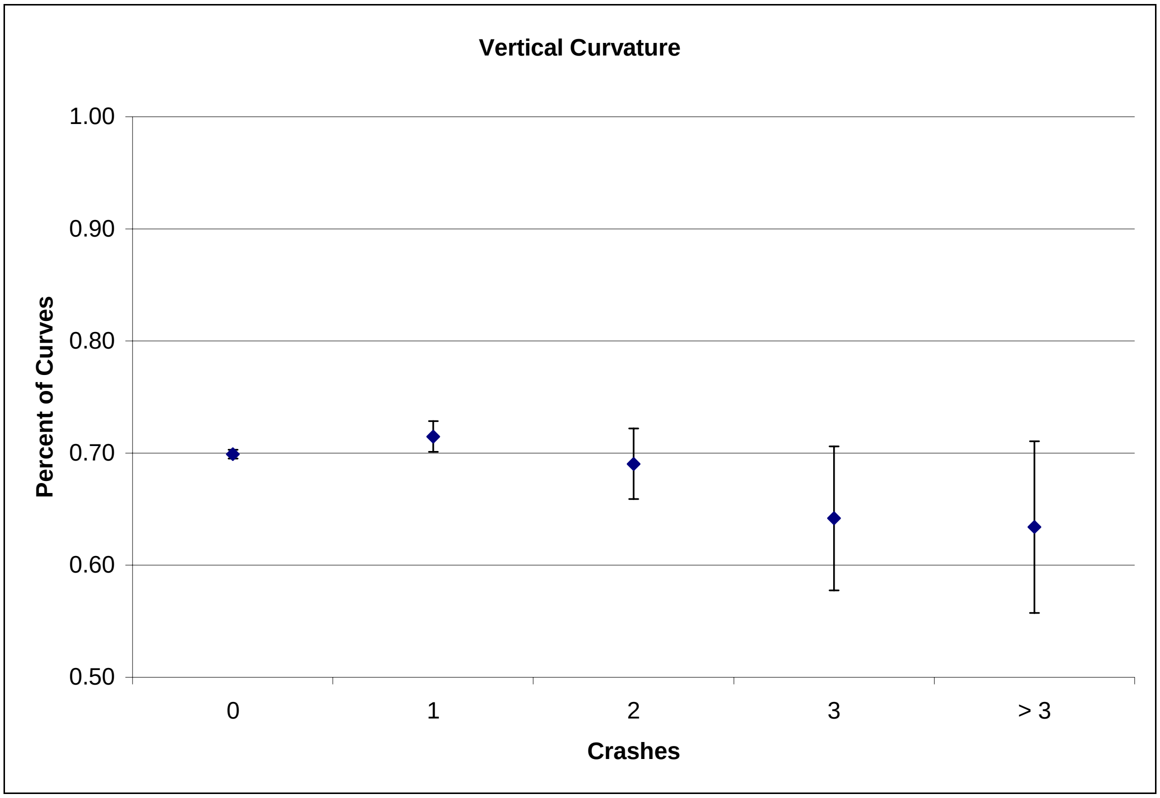

FIGURE 27 Percentage of Segments with Vertical Curvature versus Crash Frequency

6.3 Structure of Empirical Design

The case-control and cohort models are estimated separately and their structure is shown in Figures 28 and 29, respectively. Base models are first estimated for the case-control study in which there is no adjustment for potential confounding variables through matching or covariates. Base models for Pennsylvania and Washington include only one variable (either lane or shoulder width) to demonstrate the naïve estimation of safety effectiveness. Enhanced models are then estimated while making adjustments for several potential confounding variables. Comparison of the base models and enhanced models indicate those variables which confound the estimation of safety effectiveness. Potential confounding affects of ADT, speed, segment length, horizontal curvature and vertical curvature are explored using two alternatives; segment matching and using confounders as covariates. Several case-control designs are set-up to represent each enhanced modeling scheme and the results are presented. Comparisons are made between the matching and covariate approaches; strengths and weaknesses are discussed. Finally, the response variable is analyzed using different scales (binary and ordinal). The initial analyses are completed using a binary response scale (i.e. 1 = case and 0 = control); however, this does not provide information on those segments that experience multiple crashes in a given year. An ordinal response scale is evaluated as an alternative approach and the results are compared to the binary outcome models.

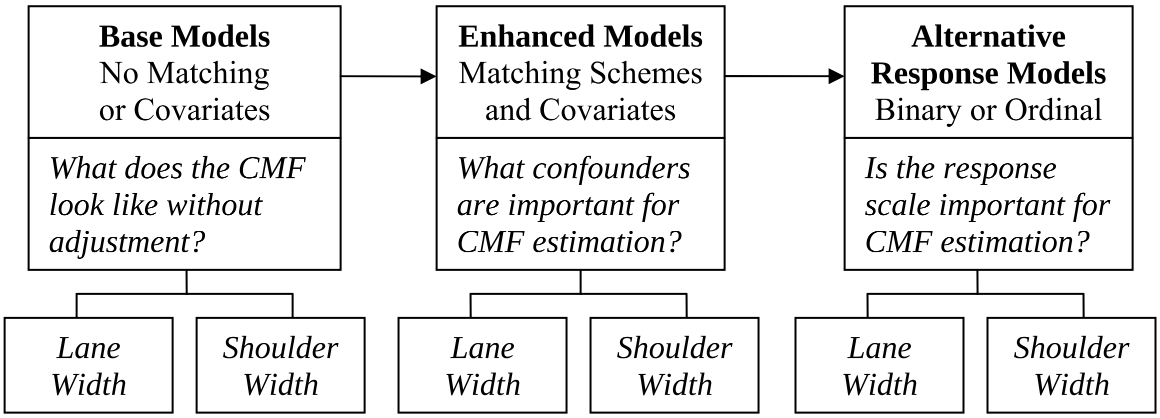

FIGURE 28 Case-Control Model Estimation Process

The cohort design is divided into three sequential steps similar to the case-control structure. Base models are first constructed to illustrate the naïve approach to estimating safety effectiveness using the cohort method. Enhanced models are then estimated to account for confounding variables by including potential confounders as covariates in the model. The cohort design does not include matching as an adjustment option. For the analysis, two different modeling approaches are applied: 1) survival models and 2) count models, as explained in Section 4.6. Finally, the exposure variable is explored using segment-days and segment-length-days as two alternatives.

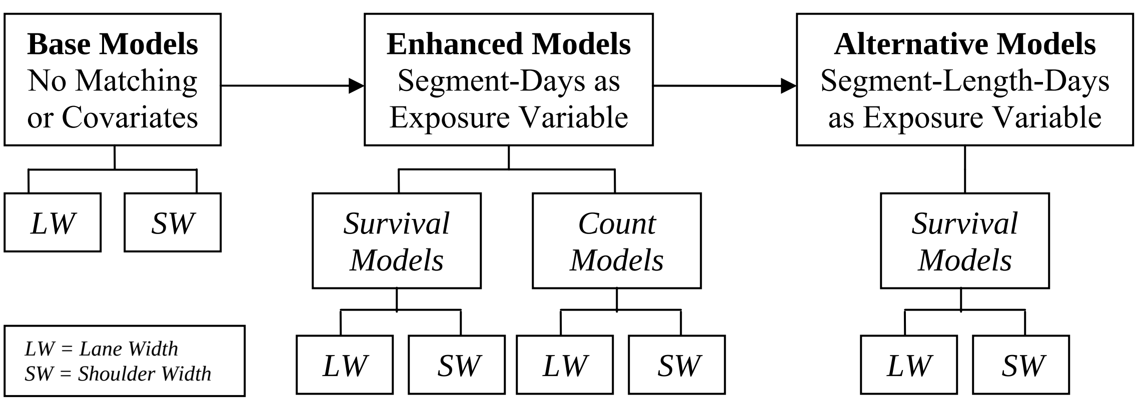

FIGURE 29 Cohort Model Estimation Process

6.4 Estimating Safety Effectiveness: The Case-Control Method

This section presents the results of several case-control models as summarized in Figure 30. Results are presented in progression from base models to enhanced models as was discussed in the model estimation structure in Figure 28. Both Pennsylvania and Washington datasets are analyzed and results are presented separately for lane and shoulder width. Comparisons are made between the results from Pennsylvania and Washington where applicable and results are also compared to the CMFs presented in the Highway Safety Manual. While the definition of safety effectiveness and CMFs are slightly different, results from the case-control and cohort models are used to approximate CMFs. Plots of safety effectiveness are, therefore, referred to as CMFs for the remainder of this chapter.

Results from the proposed case-control and cohort studies are based on all crash types while the CMFs presented in the Highway Safety Manual are based on "related" crash types (i.e. head-on, run-off-the-road, and sideswipes in either direction). Therefore, the results cannot be directly compared without some type of adjustment. CMFs from the Highway Safety Manual may be adjusted to reflect the effect on total crashes using Equation (31) (Harwood et al., 2000).

$$CMF_{all} = (CMF_{rc} - 1.0) * P_{rc} + 1.0 \quad \ldots (31)$$

Where,

CMF_{all} = CMF for all crash types

CMF_{rc} = CMF for relevant crashes

P_{rc} = proportion of total crashes constituted by relevant crashes

The HSM assumes a default value of 0.35 as the proportion of total crashes constituted by relevant crashes (P_{rc}). A summary analysis of the Pennsylvania data, however, reveals that the proportion of relevant crashes is approximately 70 percent (P_{rc} = 0.70). A similar breakdown of crashes for Washington shows that relevant crashes represent about 35 percent of the total, which is consistent with the default value. Tables 27 and 28 show the CMFs for shoulder and lane width based on relevant crashes and for all crash types after adjustment. Results from the initial case-control models are compared to the adjusted CMFs from the Highway Safety Manual. In Section 6.4.4, the case-control models are revisited to estimate the effects of lane and shoulder width on related crashes. At this point, the model results are directly compared to the unadjusted CMFs from the Highway Safety Manual.

TABLE 27 CMFs for Shoulder Width (Adjusted and Unadjusted)

Shoulder Width (feet)	HSM CMF Relevant Crashes	HSM Adjusted CMF (PA Conditions) $P_{rc} = 0.70$	HSM Adjusted CMF (WA Conditions) $P_{rc} = 0.35$
0	1.50	1.35	1.18
1	1.40	1.28	1.14
2	1.30	1.21	1.11
3	1.23	1.16	1.08
4	1.15	1.11	1.05
5	1.08	1.06	1.03
6	1.00	1.00	1.00
7	0.94	0.96	0.98
8	0.87	0.91	0.95

Note: Estimates apply to average daily traffic volumes of 2000 vehicles per day or greater.

TABLE 28 CMFs for Lane Width (Adjusted and Unadjusted)

Lane Width (feet)	HSM CMF Relevant Crashes	HSM Adjusted CMF (PA Conditions) $P_{rc} = 0.70$	HSM Adjusted CMF (WA Conditions) $P_{rc} = 0.35$
< 10	1.50	1.35	1.18
10.0	1.30	1.21	1.11
10.5	1.18	1.13	1.06
11.0	1.05	1.04	1.02
11.5	1.03	1.02	1.01
12.0	1.00	1.00	1.00

Note: Estimates apply to average daily traffic volumes of 2000 vehicles per day or greater.

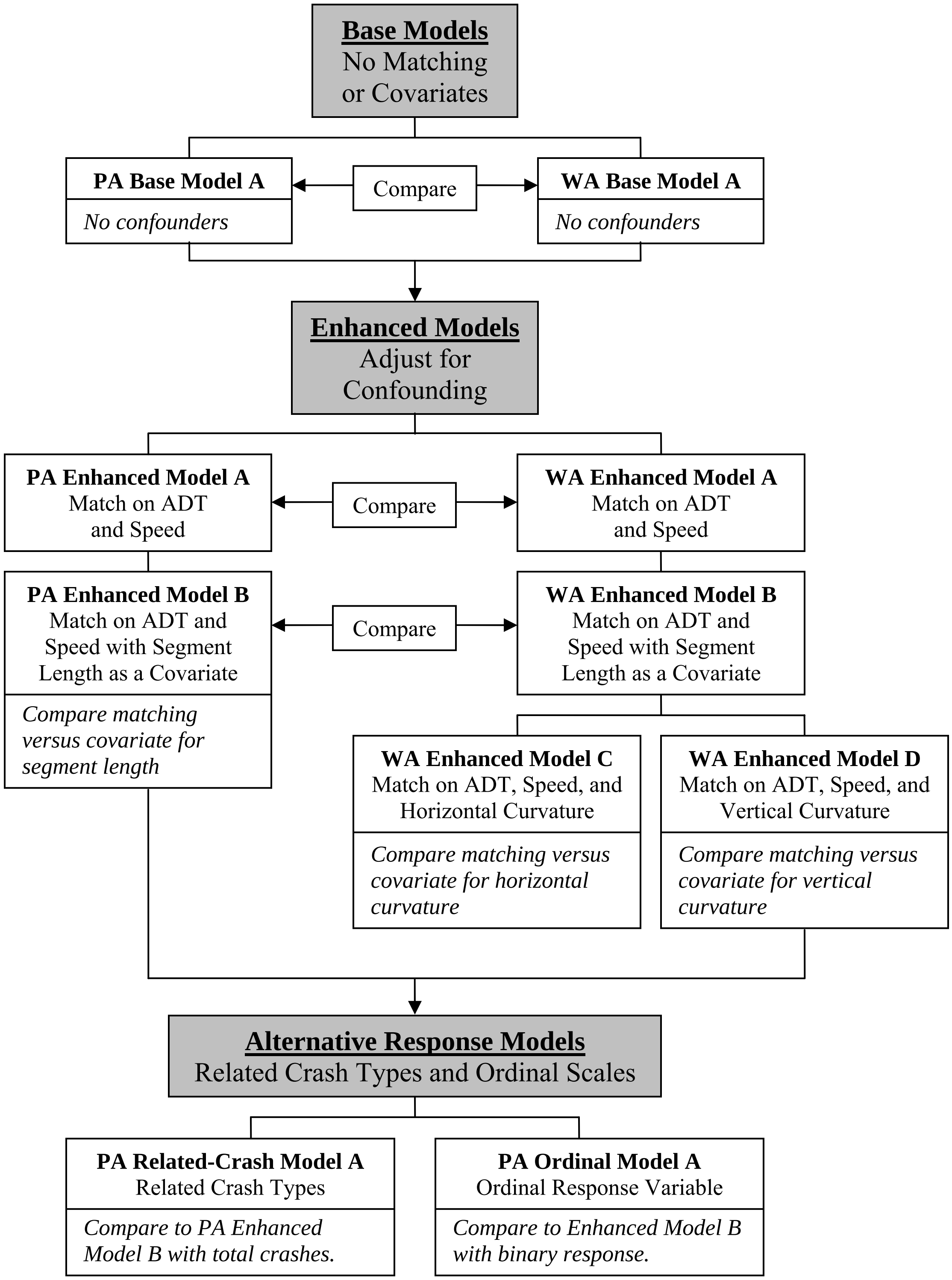

FIGURE 30 Overview of Case-Control Models

6.4.1 Base Models

Shoulder Width Model

The estimated shoulder width results for PA Base Model A and WA Base Model A are shown in Tables 29 and 30, respectively. Odds ratios and 95 percent confidence limits are presented for each shoulder width in comparison to a baseline shoulder width of six feet. The estimated CMF for shoulder width is equivalent to the odds ratio and is shown in Figures 31 and 32 for Pennsylvania and Washington, respectively.

The base model for shoulder width is very similar for both states showing an initial decrease in risk (i.e. odds ratio less than 1.0) as shoulder width increases from zero to two feet. Crash risk increases steadily as shoulder width increases from three to six feet; however, the odds ratio remains below one. Beyond six feet, the results for Pennsylvania and Washington are slightly different. For Washington, crash risk continues to increase as shoulder width increases beyond six feet. This indicates that the risk of a crash is higher for wider shoulders when compared to a six foot shoulder. For Pennsylvania, there is an elevated risk for shoulder widths of seven and eight feet compared to a six foot shoulder. The crash risk then drops below one for shoulder widths greater than eight feet. Also evident in the base models for Washington and Pennsylvania are the wider confidence intervals around nine feet. The wider confidence intervals are associated with relatively high standard errors and smaller sample sizes.

The safety effectiveness estimates show a significant difference in crash risk for almost all shoulder widths when compared to a six foot shoulder. This is apparent from the p-values in Tables 29 and 30 and also from the confidence intervals in Figures 31 and 32. The only shoulder width that is not significantly different is the zero foot shoulder in the Pennsylvania model. The confidence interval for the zero foot shoulder includes 1.0 and the p-value (0.729) is highly insignificant. The p-value for all other shoulder widths is highly significant and the respective confidence intervals do not include 1.0.

Results from the shoulder width models indicate a counterintuitive trend. The base models for Pennsylvania and Washington indicate that the risk of a crash generally increases as shoulder width increases. The CMF for Pennsylvania increases from 0.53 to 1.14 and the CMF for Washington increases from 0.36 to 1.35 for shoulder widths between two and eight feet. The question remains whether or not this counterintuitive result is correct. According to the CMFs provided in the Highway Safety Manual, these results are counterintuitive. The shoulder width

CMF from the Highway Safety Manual (Table 27) shows a steady decrease in crash risk as shoulder width increases from zero (CMF = 1.50) to eight feet (CMF = 0.87). The adjusted CMF is closer to unity, but the general trend remains the same.

This discrepancy deserves further exploration. One potential reason for this large difference is the lack of control for confounding variables in the base models. In Section 6.2, several variables were shown to be associated with both shoulder width and crash frequency. Results may be reflecting the trend in crash frequency due to confounding variables rather than the actual effect of shoulder width. Several models are presented in Section 6.4.2 that are adjusted for potential confounding variables and illustrate how the results change after the adjustment.

TABLE 29 PA Base Model A: Shoulder Width Only

Shoulder Width	Odds Ratio	SE	z	P-value	Lower	Upper
0	0.989	0.032	-0.350	0.729	0.929	1.053
1	0.555	0.033	-9.940	0.000	0.494	0.623
2	0.526	0.012	-27.520	0.000	0.502	0.550
3	0.585	0.014	-22.680	0.000	0.558	0.613
4	0.778	0.016	-12.050	0.000	0.747	0.810
5	0.894	0.025	-3.980	0.000	0.845	0.945
6	1.000	*	*	*	1.000	1.000
7	1.176	0.063	3.03	0.002	1.059	1.307
8	1.136	0.032	4.540	0.000	1.075	1.200
9	0.752	0.068	-3.160	0.002	0.630	0.897
> 9	0.758	0.029	-7.160	0.000	0.702	0.817

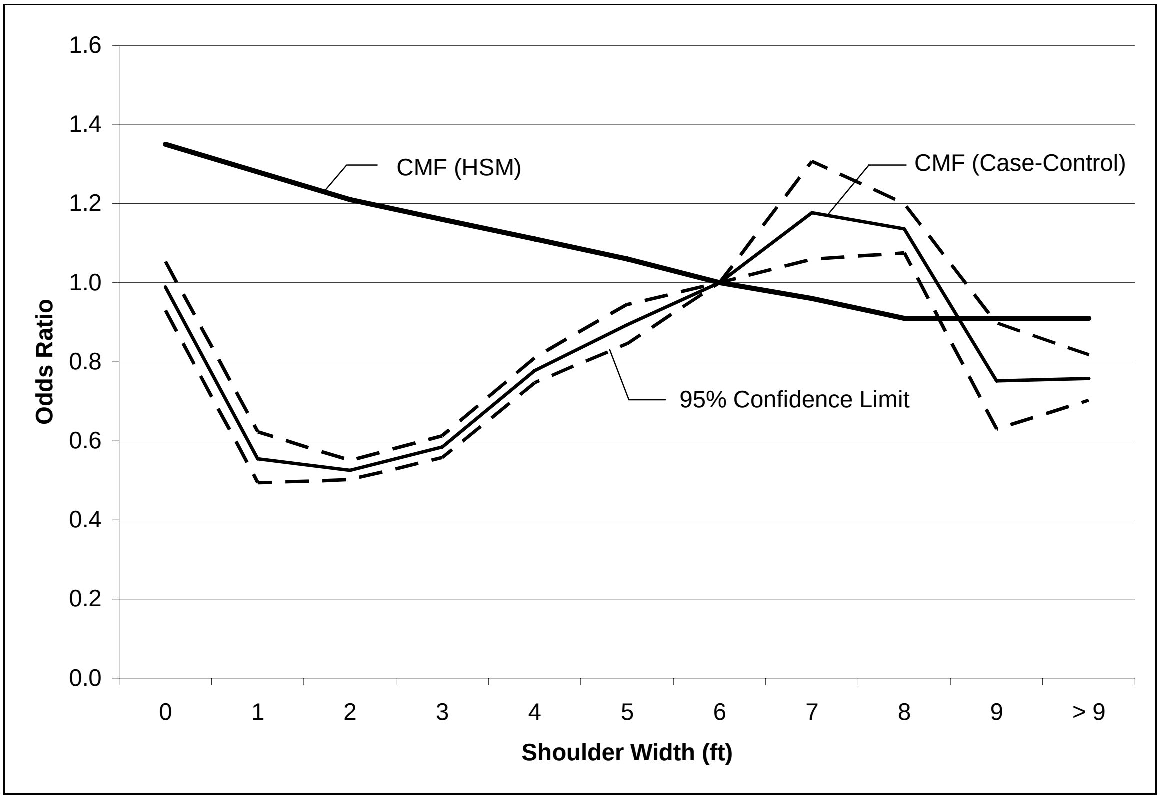

FIGURE 31 CMF for PA Base Model A: Shoulder Width Only

TABLE 30 WA Base Model A: Shoulder Width Only

Shoulder Width	Odds Ratio	SE	z	P-value	Lower	Upper
0	0.808	0.028	-6.200	0.000	0.755	0.864
1	0.372	0.015	-24.150	0.000	0.344	0.403
2	0.364	0.011	-34.790	0.000	0.344	0.385
3	0.565	0.015	-20.950	0.000	0.536	0.596
4	0.745	0.020	-10.900	0.000	0.707	0.786
5	0.760	0.027	-7.830	0.000	0.709	0.814
6	1	*	*	*	1	1
7	1.082	0.036	2.390	0.017	1.014	1.154
8	1.348	0.037	11.010	0.000	1.279	1.422
9	1.271	0.089	3.430	0.001	1.108	1.459
> 9	1.555	0.060	11.480	0.000	1.442	1.677

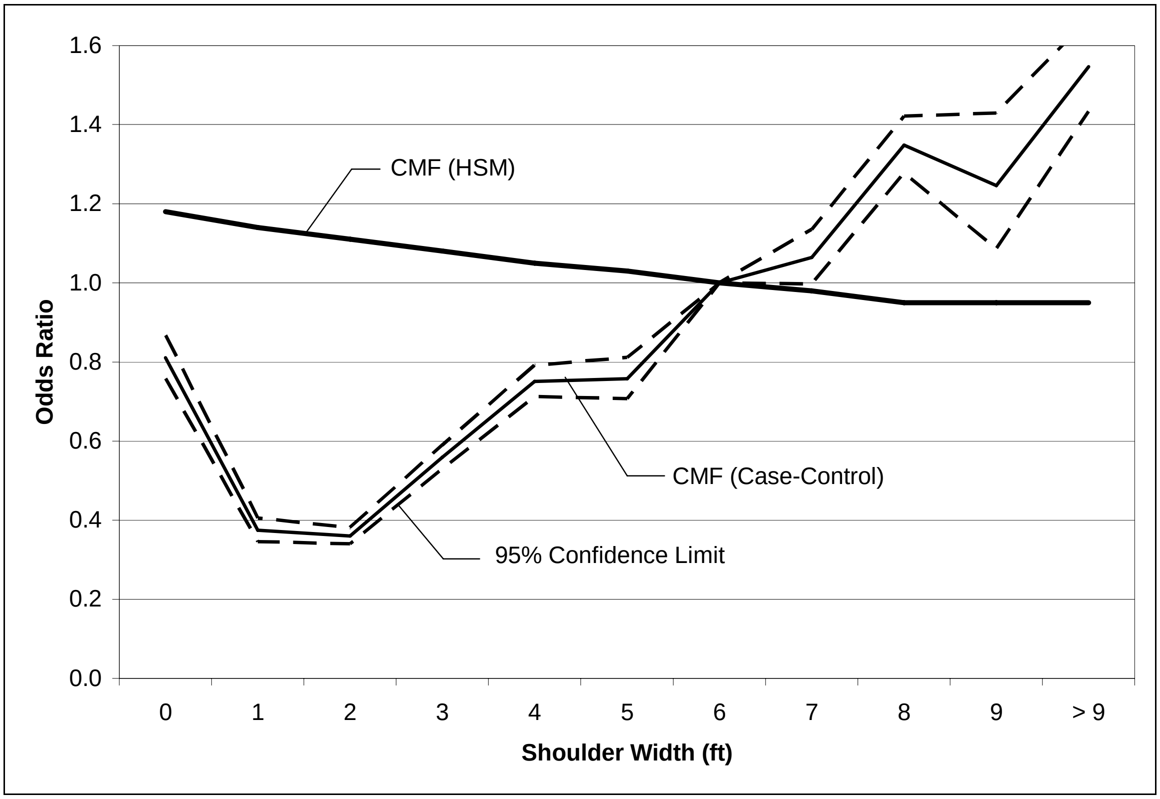

FIGURE 32 CMF for WA Base Model A: Shoulder Width Only

Lane Width Model

The estimated lane width results for PA Base Model A and WA Base Model A are shown in Tables 31 and 32, respectively. The approximated CMFs and corresponding 95 percent confidence limits are shown in Figures 33 and 34 for Pennsylvania and Washington, respectively. The estimates of safety effectiveness for lane width are in comparison to a baseline of twelve feet.

The base model for lane width is similar for both states showing a general increase in expected crash risk as lane width increases. Estimates from the Pennsylvania and Washington models indicate that lane widths less than ten feet are less likely to experience a crash than lane widths of twelve feet. Crash risk increases at a relatively consistent rate between ten and twelve feet with the only major difference occurring between twelve and thirteen feet. The Pennsylvania model indicates a decrease in crash risk for lane widths of 12.5 feet and then a slight increase in risk for thirteen foot lanes. The CMF remains below 1.0, however, indicating a lower risk when compared to lane widths of twelve feet. The Washington data suggest a slightly different trend where crash risk levels out from 11.5 to 13.0 feet and the risk is not significantly different from twelve foot lanes. The estimates of safety effectiveness from Pennsylvania and Washington are again similar for lane widths greater than thirteen feet; both indicate an increase in crash risk. Wider confidence intervals are evident in Figures 33 and 34 for lane widths of 12.5 and 13.0 feet. The wider confidence intervals are again associated with relatively small sample sizes for these categories.

The resulting estimates of safety effectiveness show a significant difference in crash risk for almost all lane widths when compared to the twelve foot baseline. This is apparent from the p-values in Tables 31 and 32 as well as the confidence intervals in Figures 33 and 34. The p-values for all but three lane widths are highly significant and the respective confidence intervals do not include 1.0. As discussed above, the only lane widths that are not significantly different from 12.0 feet are 11.5, 12.5 and 13.0 feet in the Washington model.

Model results for lane width are counterintuitive; crash risk increases as lane width increases. Estimates increase from 0.26 to 1.45 for Pennsylvania and 0.15 to 1.33 for Washington. The base models for lane width are also inconsistent with the CMF provided in the Highway Safety Manual, which shows a steady decrease in crash risk as lane width increases from nine feet (CMF = 1.50) to twelve feet (CMF = 1.00). Again, the CMF from the HSM can be adjusted to reflect total crashes; however, the general comparison is still the same. Lane width models are further explored in the following sections after adjustments are made for several potential confounding variables.

TABLE 31 PA Base Model A: Lane Width Only

Lane Width	Odds Ratio	SE	z	P-value	Lower	Upper
< 10	0.263	0.008	-42.740	0.000	0.247	0.279
10.0	0.580	0.011	-29.670	0.000	0.559	0.601
10.5	0.593	0.021	-14.600	0.000	0.553	0.636
11.0	0.956	0.016	-2.660	0.008	0.925	0.988
11.5	0.816	0.049	-3.420	0.001	0.726	0.917
12.0	1	*	*	*	1	1
12.5	0.585	0.058	-5.370	0.000	0.481	0.712
13.0	0.847	0.057	-2.480	0.013	0.743	0.966
>13	1.445	0.043	12.490	0.000	1.364	1.531

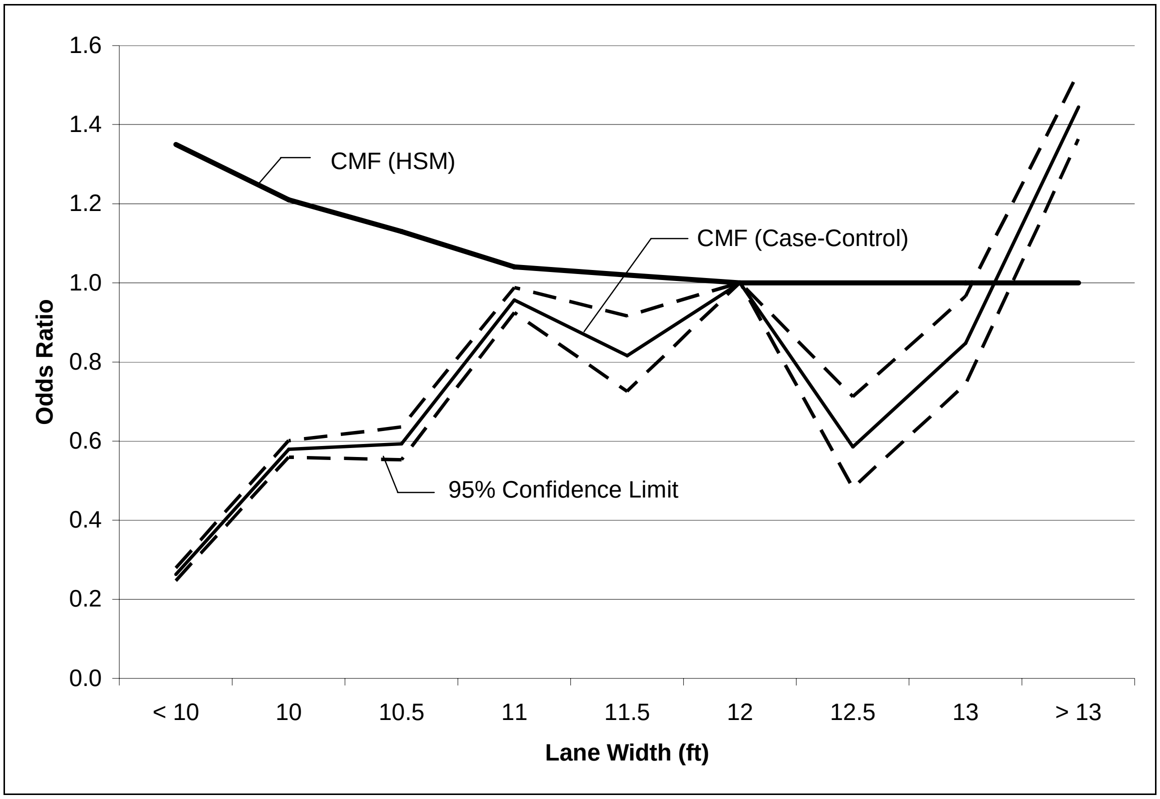

FIGURE 33 CMF for PA Base Model A: Lane Width Only

TABLE 32 WA Base Model A: Lane Width Only

Lane Width	Odds Ratio	SE	z	P-value	Lower	Upper
< 10	0.154	0.019	-15.060	0.000	0.120	0.196
10.0	0.389	0.014	-27.100	0.000	0.363	0.416
10.5	0.456	0.018	-19.680	0.000	0.421	0.493
11.0	0.830	0.013	-12.360	0.000	0.806	0.855
11.5	1.000	0.025	-0.010	0.992	0.951	1.051
12.0	1.000	*	*	*	1.000	1.000
12.5	1.095	0.079	1.260	0.209	0.950	1.261
13.0	1.008	0.080	0.100	0.921	0.863	1.178
>13	1.325	0.042	8.900	0.000	1.245	1.410

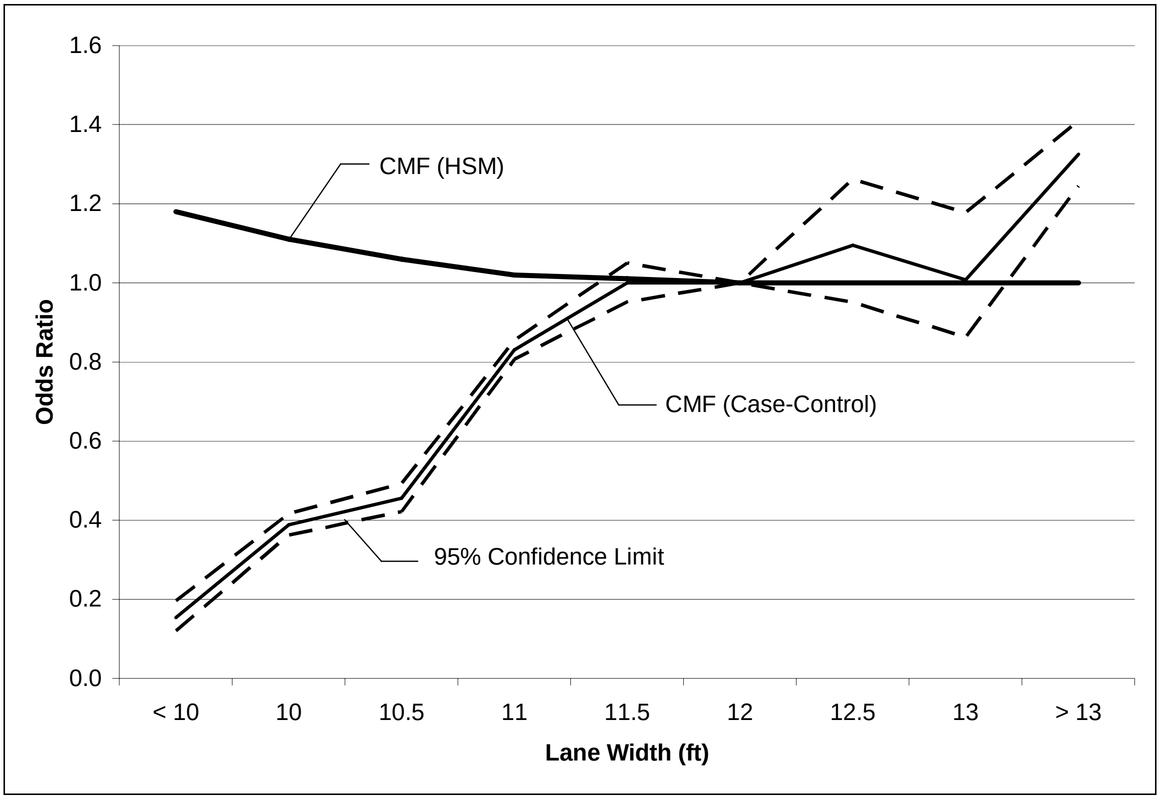

FIGURE 34 CMF for WA Base Model A: Lane Width Only

Combined Model: Shoulder and Lane Width

A combined model is estimated including both shoulder and lane width as covariates. This model represents the effects of lane and shoulder width on crash risk after adjusting for the effects of the other variable in the model. The estimated results for Base Model B are shown in Tables 33 and 34 for Pennsylvania and Washington, respectively.

The estimated coefficients and corresponding CMF change very little after adjusting for lane and shoulder width together. This indicates that lane width does not significantly affect the safety effectiveness of shoulder width and vice-versa. In other words, shoulder widening will have similar affects on narrow lanes and wide lanes while lane widening is expected to have similar affects across various shoulder widths. For completeness, the remaining models are estimated with both lane and shoulder width included as covariates in addition to potential confounders.

TABLE 33 PA Base Model A: Shoulder Width and Lane Width

Width (ft)	Odds Ratio	SE	z	P-value	Lower	Upper
Shoulder Width						
0	0.940	0.032	-1.810	0.070	0.880	1.005
1	0.688	0.042	-6.120	0.000	0.611	0.776
2	0.695	0.017	-14.850	0.000	0.663	0.729
3	0.712	0.017	-13.870	0.000	0.679	0.747
4	0.866	0.019	-6.730	0.000	0.830	0.903
5	0.944	0.027	-2.000	0.046	0.892	0.999
6	1.000	*	*	*	1.000	1.000
7	1.128	0.062	2.210	0.027	1.014	1.256
8	1.055	0.030	1.860	0.063	0.997	1.116
9	0.685	0.063	-4.120	0.000	0.573	0.820
> 9	0.692	0.027	-9.290	0.000	0.640	0.748
Lane Width						
< 10	0.299	0.010	-37.450	0.000	0.281	0.318
10.0	0.630	0.012	-23.960	0.000	0.606	0.654
10.5	0.623	0.023	-13.030	0.000	0.580	0.669
11.0	0.973	0.017	-1.600	0.109	0.941	1.006
11.5	0.836	0.050	-2.970	0.003	0.743	0.941
12.0	1.000	*	*	*	1.000	1.000
12.5	0.569	0.057	-5.630	0.000	0.467	0.692
13.0	0.880	0.060	-1.870	0.061	0.771	1.006
>13	1.370	0.042	10.220	0.000	1.290	1.455

TABLE 34 WA Base Model A: Shoulder Width and Lane Width

Width (ft)	Odds Ratio	SE	z	P-value	Lower	Upper
Shoulder Width						
0	0.494	0.025	-14.110	0.000	0.448	0.545
1	0.434	0.018	-19.770	0.000	0.399	0.471
2	0.383	0.011	-32.210	0.000	0.361	0.406
3	0.560	0.016	-20.840	0.000	0.531	0.592
4	0.755	0.021	-10.290	0.000	0.716	0.797
5	0.756	0.027	-7.940	0.000	0.705	0.810
6	1.000	*	*	*	1.000	1.000
7	1.045	0.035	1.330	0.183	0.979	1.115
8	1.333	0.036	10.510	0.000	1.264	1.407
9	1.225	0.087	2.880	0.004	1.067	1.407
> 9	1.502	0.058	10.450	0.000	1.392	1.621
Lane Width						
< 10	0.318	0.041	-8.970	0.000	0.248	0.409
10.0	0.658	0.025	-11.220	0.000	0.611	0.708
10.5	0.760	0.033	-6.420	0.000	0.699	0.827
11.0	1.076	0.018	4.430	0.000	1.042	1.111
11.5	1.152	0.031	5.320	0.000	1.094	1.214
12.0	1.000	*	*	*	1.000	1.000
12.5	1.166	0.088	2.040	0.042	1.006	1.352
13.0	1.441	0.128	4.110	0.000	1.210	1.715
>13	2.168	0.107	15.700	0.000	1.968	2.387

6.4.2 Enhanced Models with Confounder-Adjustment Schemes

6.4.2.1 Enhanced Model A: Match on ADT and Speed

Estimated CMFs and corresponding 95 percent confidence limits are presented for shoulder width in Figures 35 and 36 and lane width in Figures 37 and 38 for Pennsylvania and Washington, respectively. Detailed model results for PA Enhanced Model A and WA Enhanced Model A are shown in Appendix A.1. These models represent the safety effectiveness for lane and shoulder width after adjusting for the effects of ADT and speed. The adjustment is accomplished by randomly matching a control segment to each case segment with similar values of ADT and speed. Estimates for ADT and speed are not included because these variables were used as matching criteria. Again, all estimates for shoulder width are in comparison to a baseline of six feet and lane widths are compared to a baseline of twelve feet.

Shoulder Width Results

The CMF for shoulder width is not equivalent between the two states after adjustments are made for ADT and speed. The Pennsylvania CMF indicates a general decreasing trend as shoulder width increases while the Washington CMF shows a somewhat level, if not increasing, trend as shoulder width increases. For Pennsylvania, crash risk decreases steadily as shoulder width increases, but the risk is not significantly different than 1.0 for shoulder widths zero, three, five, and seven feet. For Washington, there is a significant decrease in crash risk for shoulder widths of zero, three, four, five, and nine feet when compared to the six foot baseline. The crash risk is not significantly different from six feet for the remaining shoulder widths.

While the resulting CMFs for shoulder width appear to be quite different between the two states, there are two noteworthy similarities. Both similarities appear in the extremes of the CMF plots. In each state, the crash risk for a zero foot shoulder is less than that for a one foot shoulder. This result is counterintuitive, but it is possible that the visual queue of no shoulder causes drivers to proceed with greater caution compared to the presence of a shoulder. At the other extreme, there is a significant decrease in the CMF for nine foot shoulders and then a sharp upturn in crash risk for shoulder widths beyond nine feet. The result is illogical because additional shoulder width should provide more protection against driver error; however, wider shoulders may provide higher levels of driver comfort and induce more aggressive driving. One explanation for this result may be the lack of control for additional confounding variables.

Relatively small sample sizes and inconsistent data coding of wide shoulders may also attribute to the counterintuitive trend.

Results from the enhanced Pennsylvania model are more intuitive than the base models. One would expect a decreasing trend in risk as shoulder width increases because the room for vehicle recovery increases. The Pennsylvania model more closely resembles the CMF from the Highway Safety Manual after making adjustments for ADT and speed. The CMF for Pennsylvania decreases from 1.26 to 0.92 as shoulder widths increases from one to eight feet while the adjusted CMF from the Highway Safety Manual decreases from 1.28 to 0.91. The CMF for Pennsylvania continues to decrease to 0.65 for a nine foot shoulder. The Highway Safety Manual, however, draws a cut-off line at eight feet and notes that the CMF may be assumed to be equal for shoulder widths greater than or equal to eight feet. It appears that the CMF for Pennsylvania is greatly improved after making adjustments for ADT and speed.

Results from the enhanced Washington model also show dramatic improvements over the base model, however, the CMF is still very different from the Highway Safety Manual. Model estimates indicate little change in risk as lane width increases and the question remains why the CMF from Washington is so flat. One answer could be that important confounding variables are still missing from the model. Another possibility is that shoulder width does not have much of an effect on crash risk in Washington and the CMF should therefore remain flat. This question is explored further in the following sections.

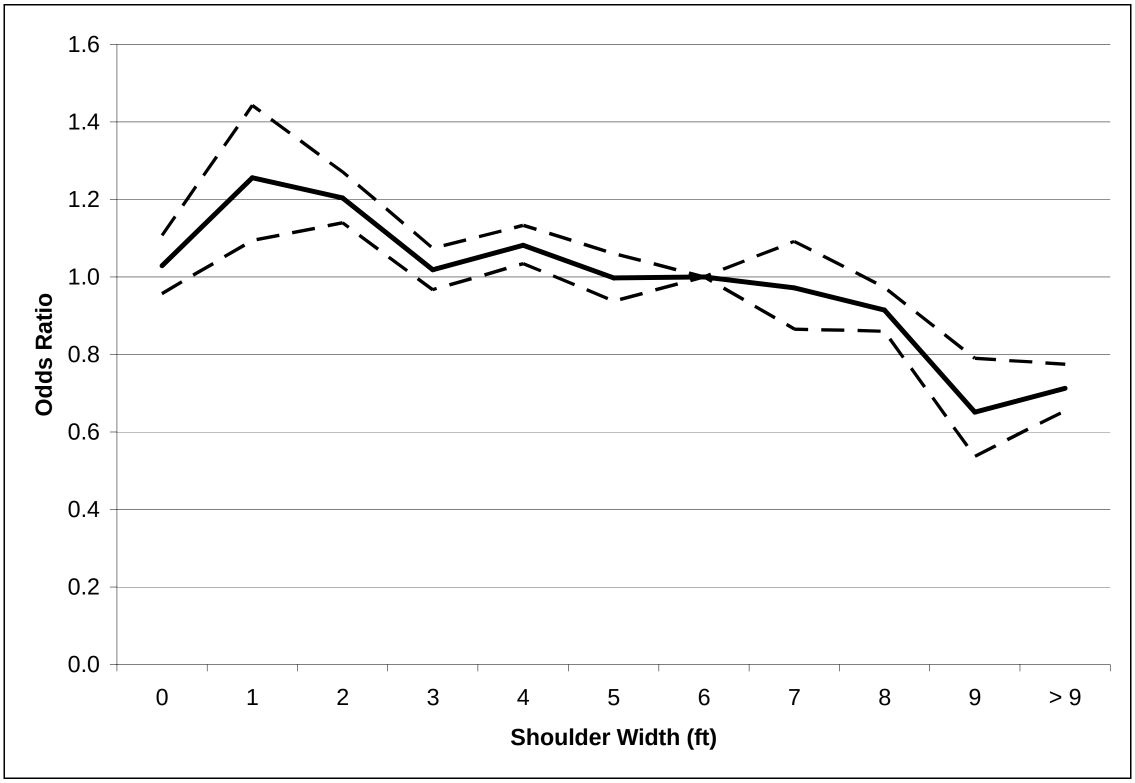

FIGURE 35 CMF for PA Enhanced Model A: Shoulder Width Adjusted for Lane Width, ADT and Speed (Matching)

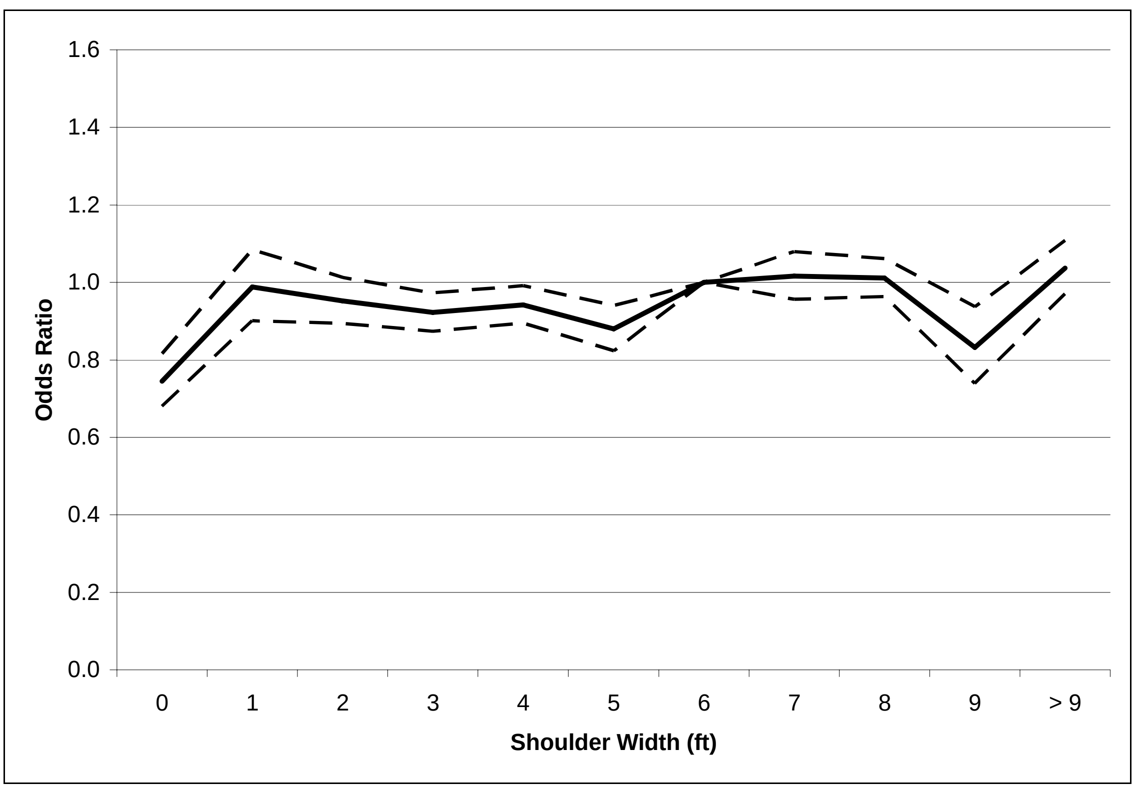

FIGURE 36 CMF for WA Enhanced Model A: Shoulder Width Adjusted for Lane Width, ADT and Speed (Matching)

Lane Width Results

The CMFs for lane width have remarkable similarities, but are not completely comparable between the two states. Crash risk is lower for lane widths less than ten feet when compared to twelve foot lanes in both states. Crash risk then increases sharply and remains significantly greater than 1.0 for Pennsylvania. Washington shows a more gradual increase in crash risk and the results are not significantly different from 1.0 for 10.0 and 10.5 foot lanes. For Pennsylvania, the risk decreases steadily as lane width increases from 10.5 to 12.5 feet. At this point, the CMF turns up and the crash risk is higher for lane widths beyond 12.5 feet; however, the risk remains below one indicating an overall reduced risk for wider lanes. The trend is a little less clear for Washington; risk decreases between eleven and twelve feet, but increases significantly for 12.5 foot lanes. Crash risk remains above one for lanes greater than 12.0 feet; however, the confidence intervals are relatively wide and results are questionable for the wider lane widths. The large standard errors for 12.5 and 13.0 foot lanes are consistent in both Pennsylvania and Washington. This is largely due to smaller sample sizes produced by the limited use of cart ways beyond 24.0 feet on two-lane, rural roads.

Results from the enhanced Pennsylvania model appear to be fairly consistent with the Highway Safety Manual. Although results in the extremes are a bit questionable, the general trend between 10.0 and 12.5 feet is intuitive after adjusting for ADT and speed. As lane width increases from 10.0 to 12.0 feet, the CMF for Pennsylvania decreases from 1.11 to 1.00 and the comparable risks from the Highway Safety Manual decrease from 1.21 to 1.00 after adjusting for total crashes. The CMF for Pennsylvania continues to decrease to 0.72 for a 12.5 foot lane. The Highway Safety Manual, however, draws the cut-off at twelve feet and notes that the crash risk is assumed to be equal for lane widths greater than twelve feet. In Pennsylvania, the CMF for lane width is significantly improved after adjusting for ADT and speed. The anomalies in the extremes are further discussed in Section 6.7.

Results from the enhanced Washington model appear to improve slightly after adjusting for ADT and speed; however, the general trend is still increasing as lane width increases. After initial adjustments, the CMF for Washington remains quite different from the one presented in the Highway Safety Manual and also from the Pennsylvania model. The question is whether or not additional confounding variables are missing from the model. This question is explored in detail in the following sections.

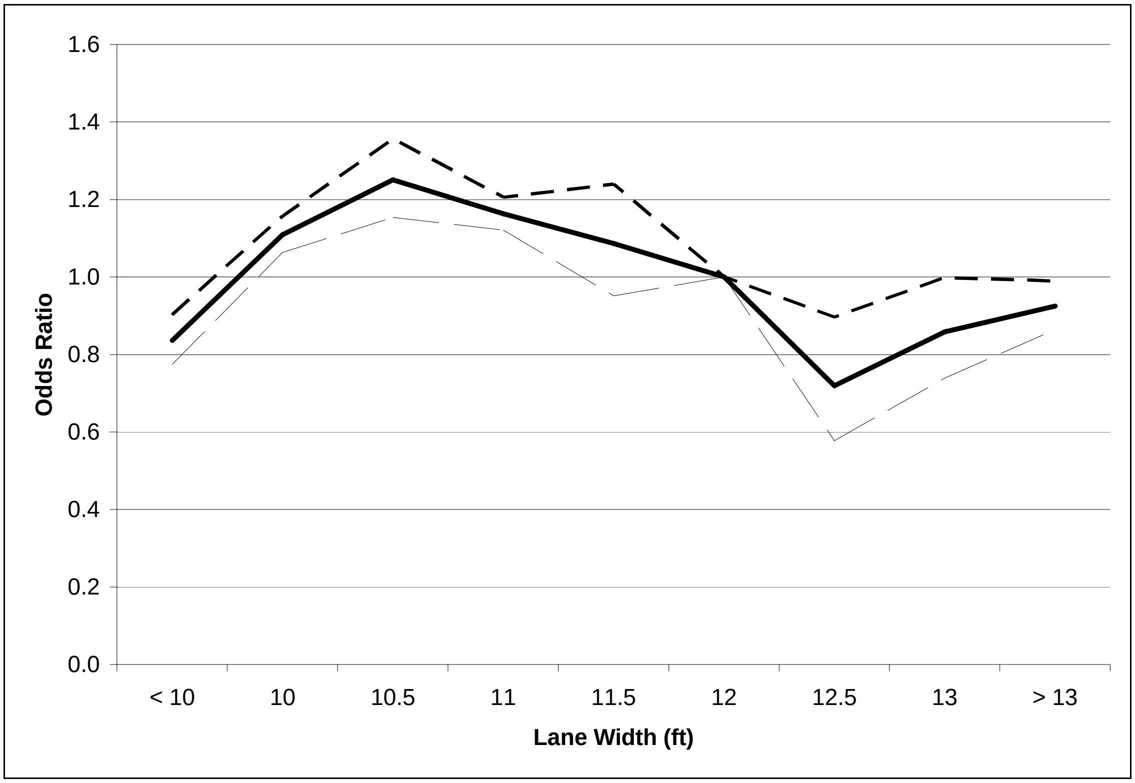

FIGURE 37 CMF for PA Enhanced Model A: Lane Width Adjusted for Shoulder Width, ADT and Speed (Matching)

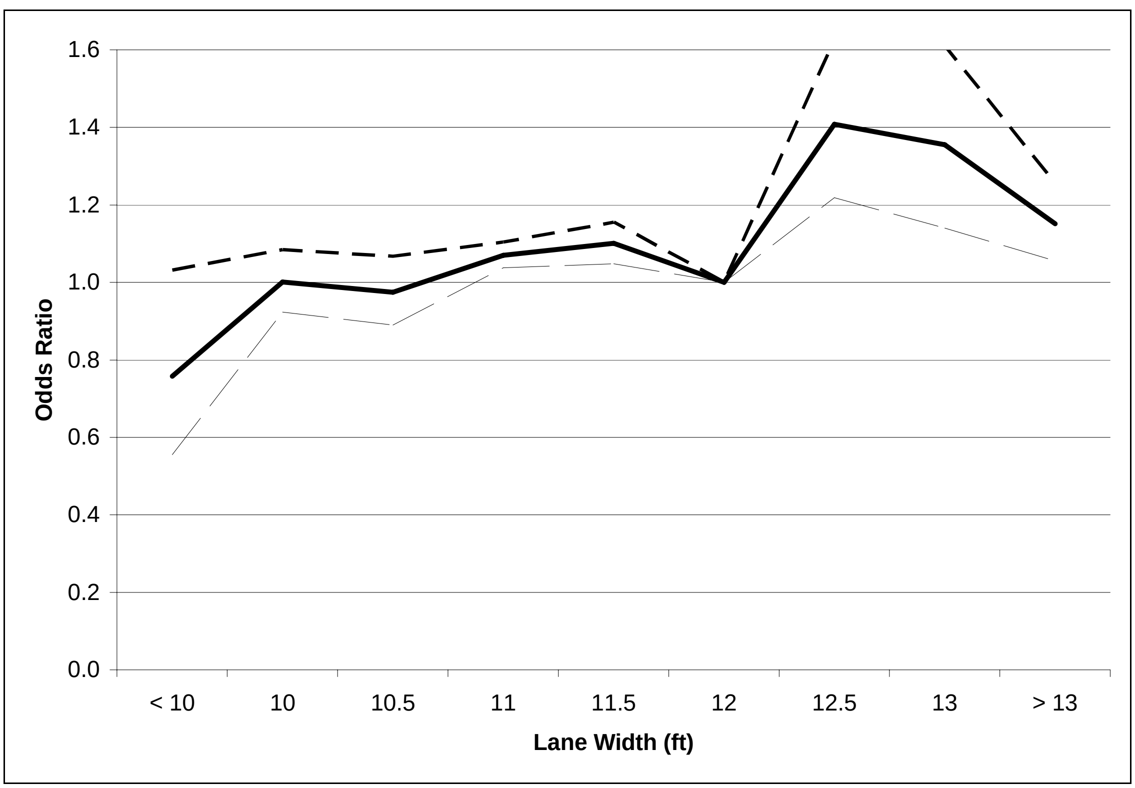

FIGURE 38 CMF for WA Enhanced Model A: Lane Width Adjusted for Shoulder Width, ADT and Speed (Matching)

6.4.2.2 Enhanced Model B: Match on ADT and Speed with Segment Length as a Covariate

Estimated CMFs and corresponding 95 percent confidence limits are presented for shoulder width in Figures 39 and 40 and lane width in Figures 41 and 42 for Pennsylvania and Washington, respectively. Detailed model results for PA Enhanced Model B and WA Enhanced Model B are shown in Appendix A.2. These models represent the effect of lane and shoulder width on crash risk after adjusting for the effects of ADT, speed and segment length. The adjustment is accomplished by randomly matching a control to each case with similar ADT and speed attributes and including segment length as a categorical covariate in the model. Coefficients are estimated and presented for the effects of segment length on crash risk; however, the objective of this research is focused on the effects of shoulder and lane width.

Shoulder Width

The CMF for shoulder width appears to improve after adjusting for segment length. Both states show a general decreasing trend in crash risk as shoulder width increases; however, the trend is more pronounced in the Pennsylvania model. The Pennsylvania model shows a higher crash risk for narrow shoulders (zero to five feet) when compared to the baseline (six feet), but the difference is not significant at three and five feet. Crash risk continues to decrease for shoulder widths greater than six feet, but there is a slight upturn in risk for shoulders greater than nine feet. In this model, the crash risk for zero foot shoulders is greater than one foot shoulders. This is a more intuitive result and perhaps the previous trend was the result of an unaccounted confounding variable (i.e. segment length). For Washington, the crash risk is generally higher for shoulder widths one to five feet compared to those greater than six feet. The change in risk is often not significant when compared to a six foot shoulder; however, there is a significant decrease in risk for nine foot shoulders. There is also a significant decrease in crash risk for zero foot shoulders, but this may be due to a number of factors as previously discussed. A similar upturn in risk is apparent in the Washington model for shoulder widths greater than nine feet, but the risk remains below 1.0. It appears that the models better reflect the actual effects of shoulder width on crash risk after adjusting for ADT, speed and segment length.

The resulting CMFs for shoulder width appear to improve after adjusting for segment length and are compared to the CMF presented in the Highway Safety Manual. The Pennsylvania model still closely resembles the CMF from the Highway Safety Manual after adjusting for

ADT, speed and segment length. Considering shoulder widths between one and eight feet, the CMF for Pennsylvania decreases from 1.19 to 0.95 and the adjusted CMF from the Highway Safety Manual decreases from 1.28 to 0.91.

Results from the Washington model follow the same general trend as the CMF from the Highway Safety Manual, but the change in risk is not as pronounced for various shoulder widths. The Washington results do, however, appear to be improved after adjusting for segment length. Previously, the general trend in the CMF increased as shoulder width increased. Now, the trend is more intuitive and the crash risk decreases slightly as shoulder width increases. The fact that segment length has such a dramatic impact on the shape of the Washington CMF is important to note. This means that results from Washington models that do not adjust for segment length may be misleading. The adjustment for segment length does not appear to be as critical for the Pennsylvania model, but does change the estimate for zero foot shoulders.

To this point, it appears that ADT, speed and segment length are important confounding variables when estimating the effects of shoulder width on crash risk. Base Models A and B for Pennsylvania and Washington illustrate the danger in estimating a model without adjusting for potential confounding variables. Enhanced Models A and B illustrate the effects of ADT, speed and segment length on the resulting CMF for shoulder width. The question remains whether or not additional variables will help to improve the estimated shoulder width CMF for Pennsylvania and Washington.

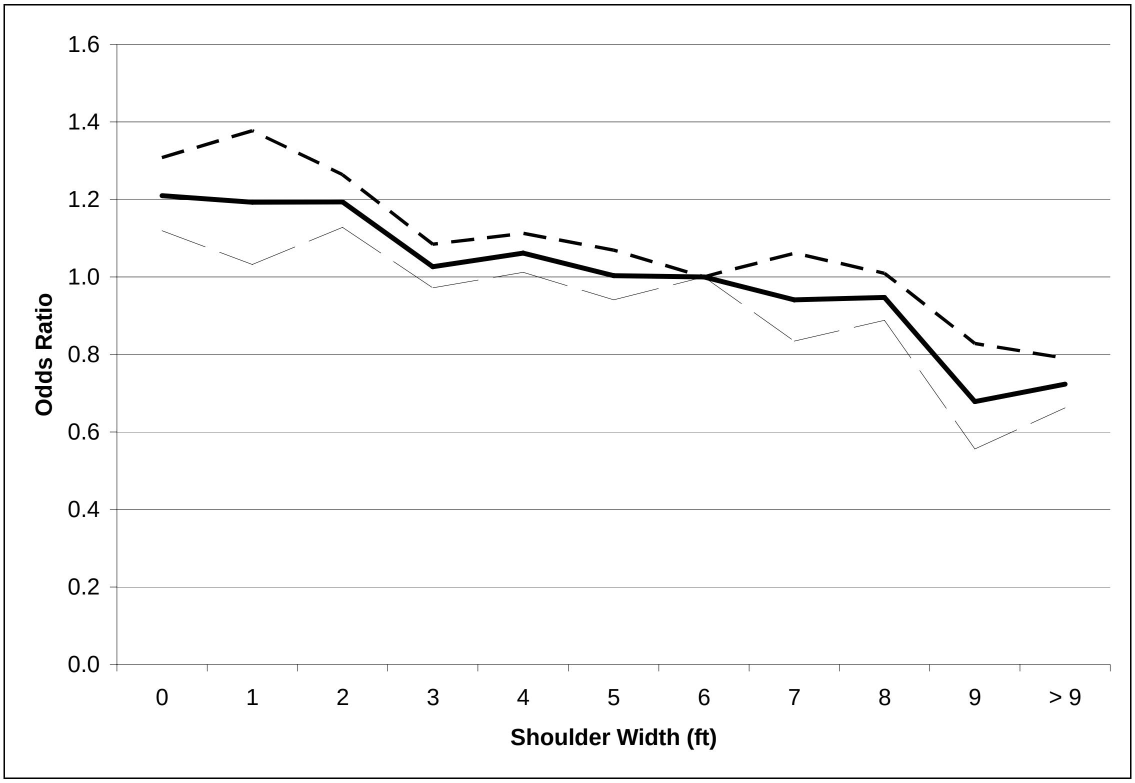

FIGURE 39 CMF for PA Enhanced Model B: Shoulder Width Adjusted for Lane Width, ADT, Speed and Segment Length (Covariate)

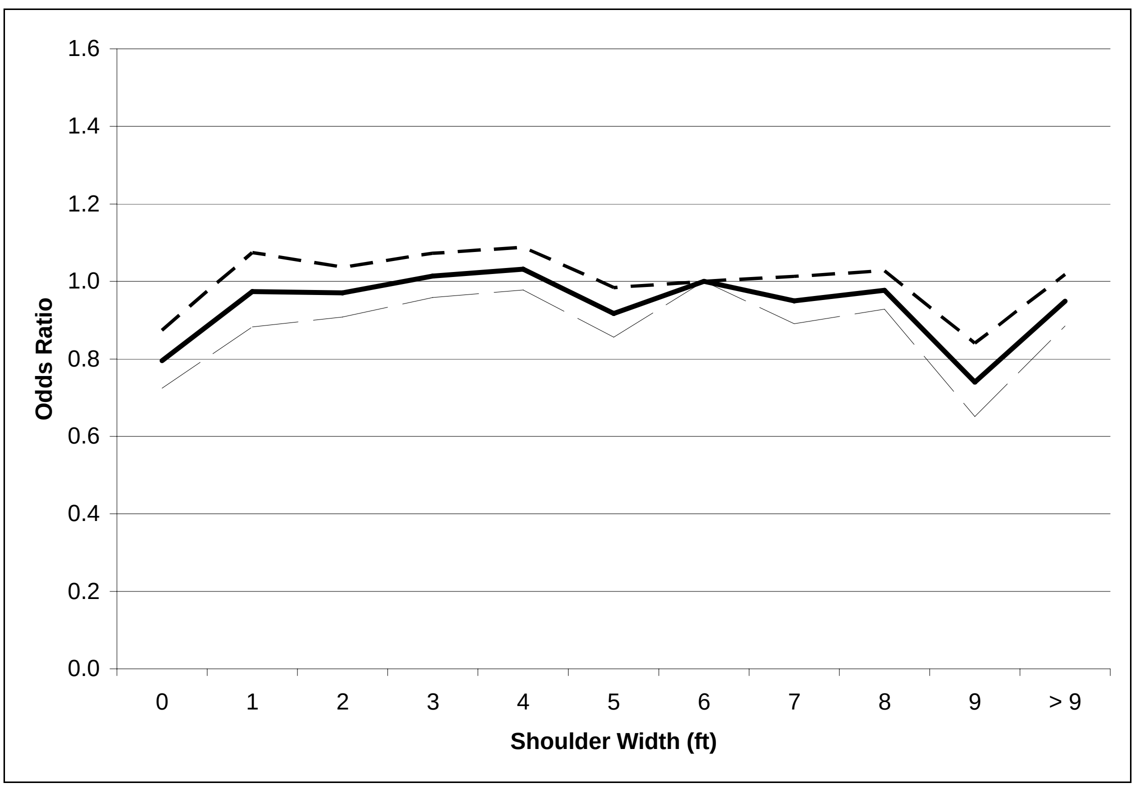

FIGURE 40 CMF for WA Enhanced Model B: Shoulder Width Adjusted for Lane Width, ADT, Speed and Segment Length (Covariate)

Lane Width

The lane width CMFs for Pennsylvania and Washington do not look alike in general, but they have remarkable similarities for specific lane widths. Comparing the Pennsylvania and Washington models, the crash risk is almost identical for lane widths less than 10.5 feet and 11.0 to 12.0 feet. The CMF for Pennsylvania Enhanced Model B looks much the same as Enhanced Model A with one notable difference, the right tail. In the previous Pennsylvania model, the risk turned up after 12.5 feet but remained below one. The risk turns up again in Model B, but increases above one for lane widths greater than 13.0 feet. The remaining aspects of Pennsylvania Models A and B are similar and have already been discussed in detail.

The CMF for Washington Enhanced Model B is quite similar to the previous model (Enhanced Model A). Crash risk decreases slightly as lane width increases from eleven feet to twelve feet with a significant increase in crash risk for lane widths greater than twelve feet. The crash risk for lane widths less than eleven feet is not significantly different from the six foot baseline.

Results from the enhanced Pennsylvania model appear to be fairly consistent with the Highway Safety Manual. Although results in the extremes are a bit questionable, the crash risk is consistent with the Highway Safety Manual for common lane widths (10.0 to 12.0 feet). As lane width increases from 10.0 to 12.0 feet, the CMF for Pennsylvania decreases from 1.06 to 1.00 and the comparable risks from the Highway Safety Manual decrease from 1.21 to 1.00. The CMF for lane width is significantly improved after adjusting for ADT and speed; however, there is little change after adjusting for segment length in the Pennsylvania model. Results from the adjusted Washington model appear to improve slightly after adjusting for segment length, but crash risks in the extremes are questionable considering the relatively large confidence limits.

ADT, speed and segment length appear to be important confounding variables when estimating the effects of lane width on crash risk. Enhanced Model B is a significant improvement over Base Model A for Pennsylvania and Washington, which illustrates the importance of adjustment for confounders. Segment length appears to be an important confounder in the Washington models, but is not as critical in the Pennsylvania models. Whether or not additional variables will help to improve the estimated lane width CMF for Pennsylvania and Washington remains to be tested.

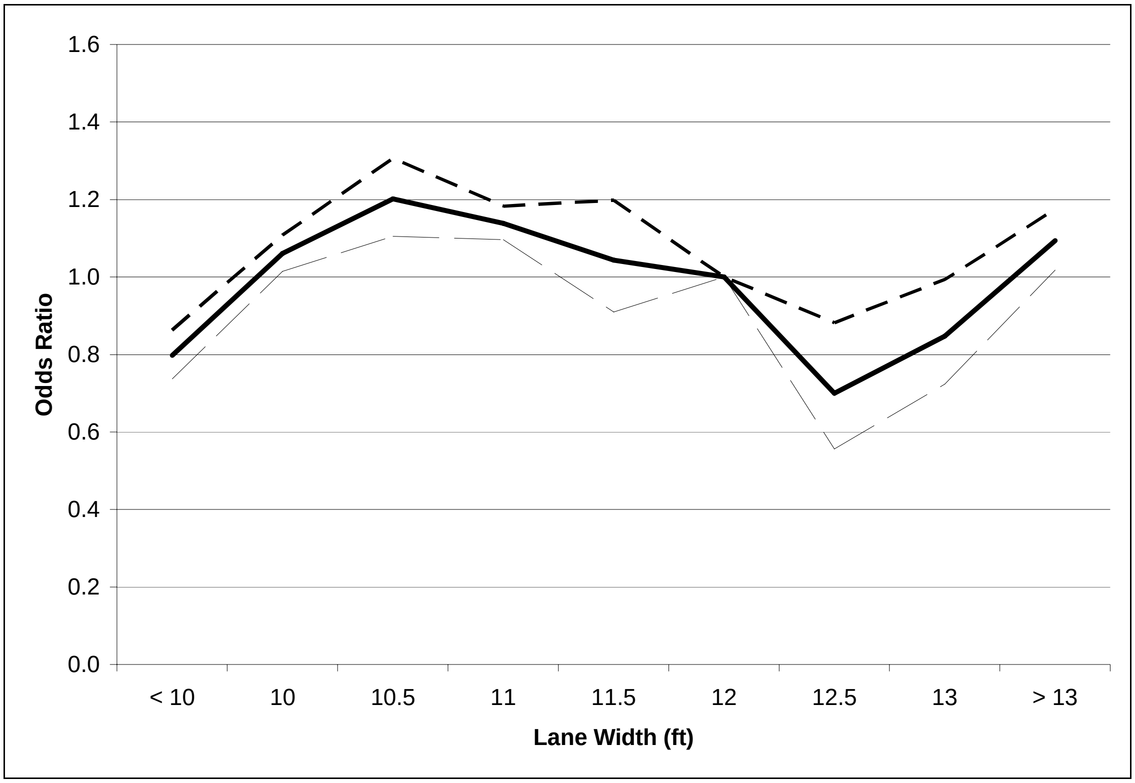

FIGURE 41 CMF for PA Enhanced Model B: Lane Width Adjusted for Shoulder Width, ADT, Speed and Segment Length (Covariate)

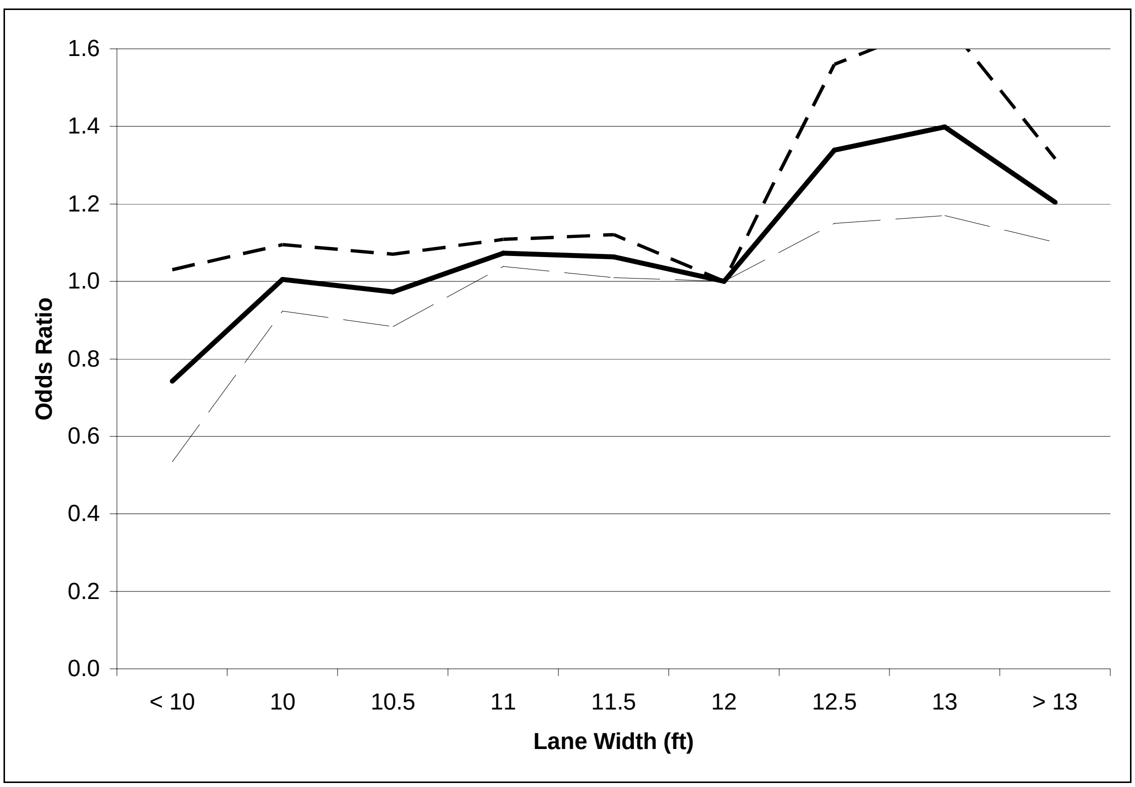

FIGURE 42 CMF for WA Enhanced Model B: Lane Width Adjusted for Shoulder Width, ADT, Speed and Segment Length (Covariate)

6.4.2.3 Enhanced Model C: Match on ADT, Speed and Horizontal Curvature

Estimated CMFs and 95 percent confidence limits are presented for shoulder and lane width in Figures 43 and 44, respectively. Detailed model results for WA Enhanced Model C are shown in Appendix A.3. This model represents the effect of lane and shoulder width on crash risk after adjusting for the effects of ADT, speed and horizontal curvature. The adjustment is accomplished as before by matching a control to each case with similar ADT and speed attributes but now including horizontal curvature as an additional matching criterion. Pennsylvania does not include horizontal curvature information in the roadway inventory file; therefore, horizontal curvature is only evaluated for the Washington data.

Shoulder Width

The shoulder width CMF remains very similar to Enhanced Model A after adjusting for horizontal curvature. The CMF is relatively flat, as before, with the major difference being that the CMF from Enhanced Model C is shifted upwards (estimates of risk are slightly greater). The upward shift in crash risk also affects the significance of the estimates relative to the baseline. A noticeable difference occurs for one foot shoulders where the odds ratio increases above 1.0 after accounting for horizontal curvature.

The resulting CMF for shoulder width is quite similar to Enhanced Model A and the comparison to the Highway Safety Manual remains the same. Results are significantly improved when compared to the base model, but horizontal curvature is relatively insignificant after adjusting for ADT and speed. Comparing Enhanced Models B and C, segment length appears to be more important than the adjustment for horizontal curvature. The fact that horizontal curvature has such a minimal impact on the magnitude and shape of the Washington CMF is important to note. This may indicate that the estimation of a CMF for shoulder width is still valid even if horizontal curvature data are unavailable. Results from Pennsylvania models do not adjust for horizontal curvature, but the results may still be suitable. At this point, it is more appropriate to conclude that the presence of curvature does not affect the CMF for Washington, but remains to be tested for Pennsylvania. In addition, these models include curvature as a binary variable (1 = curve and 0 = no curve). Results may be slightly different if detailed curve information (e.g. degree of curvature, curve length, etc.) are represented in the model rather than the simple presence or absence of curvature.

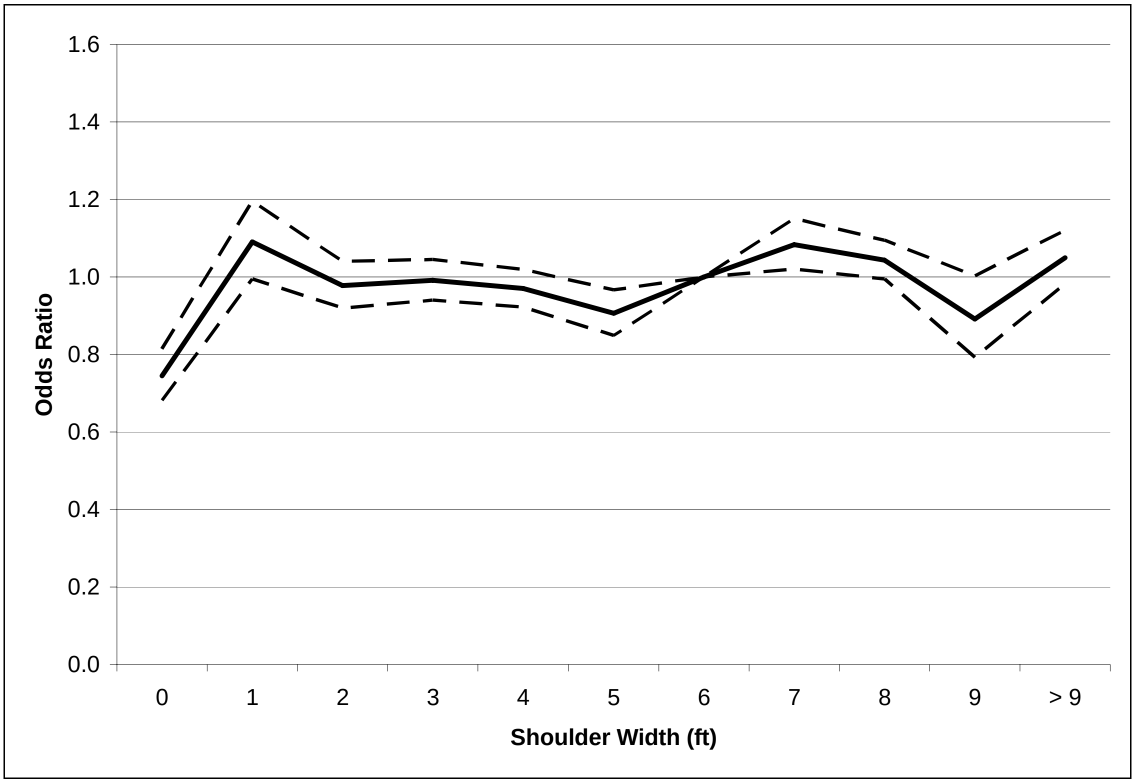

FIGURE 43 CMF for WA Enhanced Model C:
Shoulder Width Adjusted for Lane Width, ADT, Speed and Horizontal Curvature (Matching)

Lane Width

The lane width CMF is comparable to Enhanced Model A after accounting for horizontal curvature. There is a general increasing trend in crash risk as lane width increases, which has been discussed as counterintuitive in Section 6.4.2.1. Many of the lane widths remain significantly different from the twelve foot baseline and there is not a noticeable difference through much of the CMF aside from the general downward shift in crash risk. There is, however, a noticeable difference in risk for 12.5 foot lanes. In Enhanced Model A there is a significant increase in crash risk for lane widths of 12.5 feet. In Enhanced Model C, there remains a significant increase in risk for 12.5 foot lanes, but the odds ratio is 14 percent less than Model A. This is a significant reduction in crash risk after adjusting for horizontal curvature. While horizontal curvature appears to have a significant impact on the risk of 12.5 foot lanes, this category also has a relatively high standard error. Therefore, results may be expected to fluctuate more than other lane widths.

The resulting CMF for lane width is similar to Enhanced Model A and the comparison to the Highway Safety Manual remains the same. Results are improved when compared to the base model, but remain counterintuitive after adjusting for horizontal curvature. Results from the Washington model are more intuitive and more closely resemble the CMF from the Highway Safety Manual after adjusting for segment length. Therefore, it appears that horizontal curvature is not as critical as ADT, speed and segment length. Again, the fact that horizontal curvature has a minimal impact on the CMF for lane width may indicate that the estimation is still valid when horizontal curvature data are unavailable.

To this point, it appears that ADT, speed and segment length are important confounding variables when estimating the effects of shoulder width and lane width on crash risk. Horizontal curvature may be an important variable to include when predicting crash frequency; however, it does not appear to be as critical for CMF estimation. Results from models that do not include horizontal curvature, therefore, may be adequate.

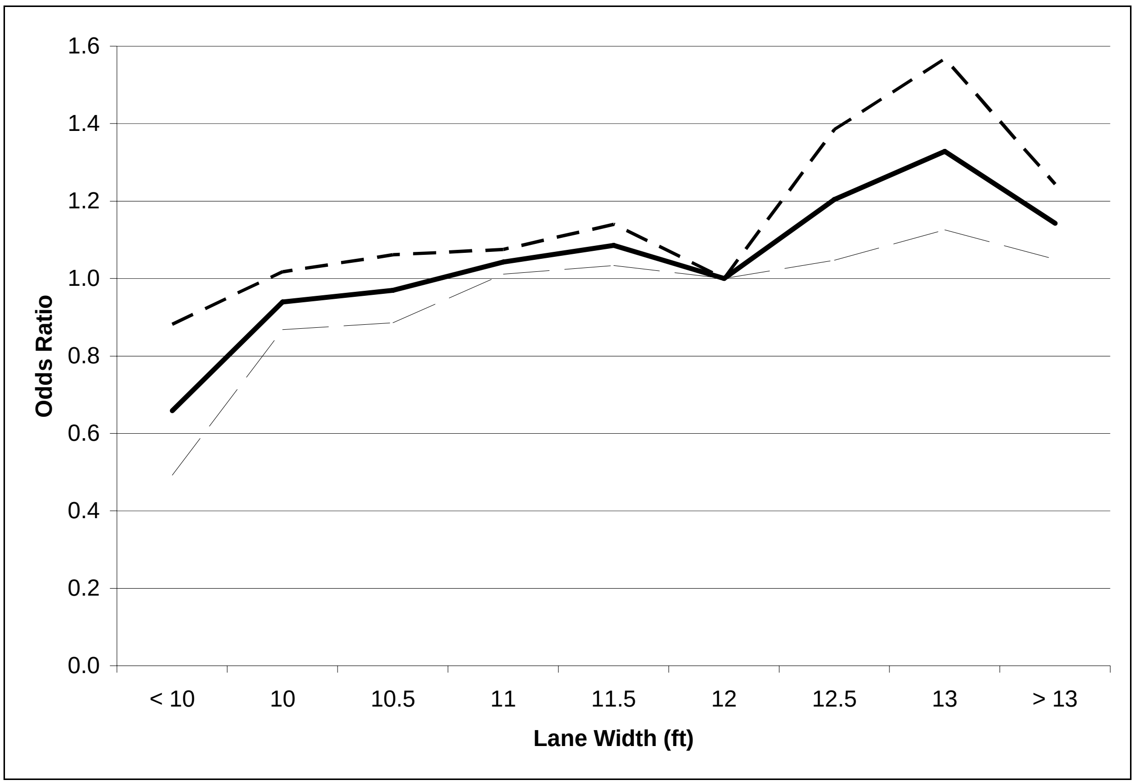

FIGURE 44 CMF for WA Enhanced Model C:
Lane Width Adjusted for Shoulder Width, ADT, Speed and Horizontal Curvature (Matching)

6.4.2.4 Enhanced Model D: Match on ADT, Speed and Vertical Curvature

Estimated CMFs and corresponding 95 percent confidence limits are presented for shoulder width and lane width in Figures 45 and 46, respectively. Detailed model results for WA Enhanced Model D are shown in Appendix A.4. This model represents the effect of lane and shoulder width on crash risk after adjusting for the effects of ADT, speed and vertical curvature. The adjustment is accomplished as before by randomly matching a control to each case with similar ADT, speed and vertical curvature attributes. Pennsylvania does not include vertical curvature information in the roadway inventory file; therefore, vertical curvature is only evaluated for the Washington data.

Shoulder Width

The shoulder width CMF is very similar to Enhanced Model A after adjusting for vertical curvature. The CMF remains relatively flat as shoulder width increases and many of the shoulder widths are not significantly different from the baseline. While many of the shoulder widths are not significant, there is a general upward shift in crash risk similar to that of Enhanced Model C. Most of the odds ratios are comparable to Enhanced Model A with the greatest differences in the seven and nine foot categories. After adjusting for vertical curvature, crash risk increases in both categories; the seven foot shoulder becomes significant and the nine foot shoulder becomes marginally insignificant.

Enhanced Model C is inconsistent with the Highway Safety Manual and the comparison remains the same as before. Results are significantly improved when compared to the base model, but vertical curvature is relatively unimportant after adjusting for ADT, speed and segment length. The minimal impact of vertical curvature relative to ADT, speed and segment length implies that the estimated CMFs may be sufficient without further adjustment. This has significant implications for the Pennsylvania results because vertical curvature data are unavailable.

Several potential confounding variables have been examined during the estimation of CMFs for shoulder width. Confounders were adjusted through various combinations of matching and covariates. ADT, speed and segment length were consistently found to be important confounding variables when estimating the effects of shoulder width on crash risk. Horizontal curvature and vertical curvature were both shown to shift the level of crash risk, but changes were not substantial. Results from models that do not include curvature as an adjustment may be adequate; however, there are considerable differences in results that do not adjust for ADT, speed and segment length.

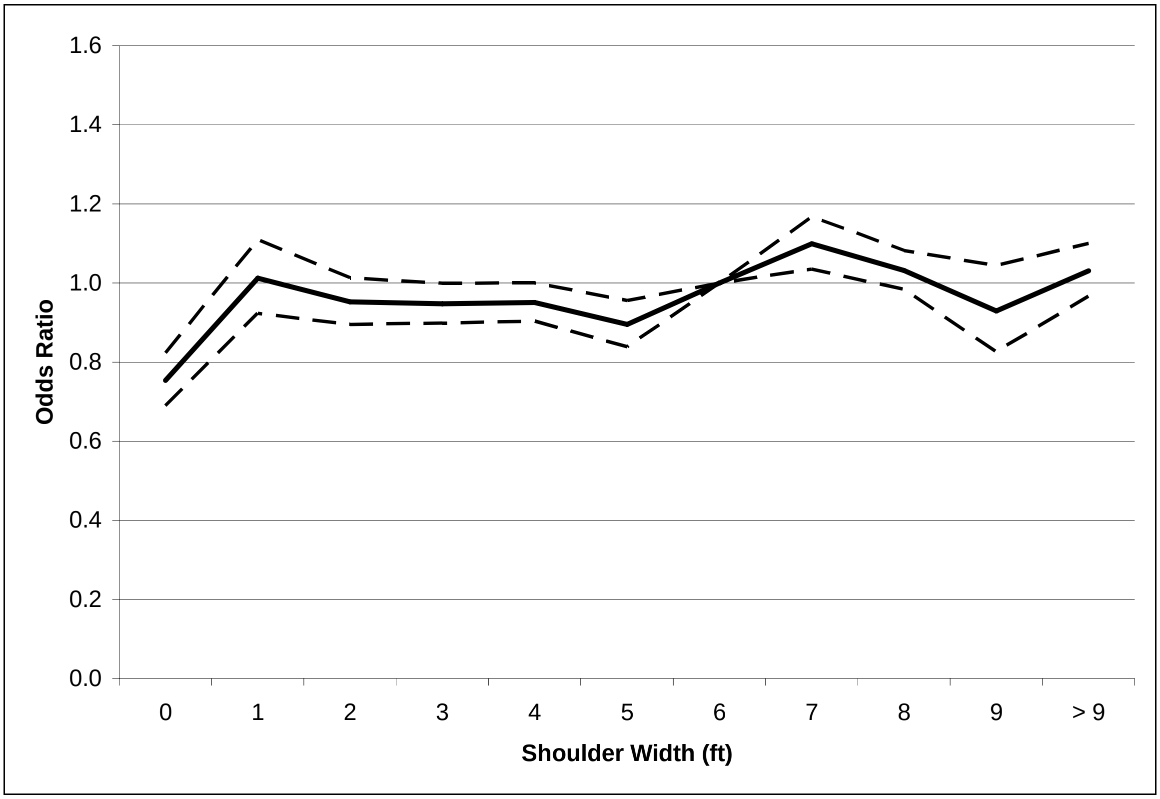

FIGURE 45 CMF for WA Enhanced Model D:
Shoulder Width Adjusted for Lane Width, ADT, Speed and Vertical Curvature (Matching)

Lane Width

The CMF for lane width is similar to WA Enhanced Model A after adjusting for vertical curvature. The general trend in crash risk increases as lane width increases up to 12.5 feet where risk begins to decrease. There is no clear shift up or down in the risk of a crash after adjusting for vertical curvature and the significance of the estimated coefficients is relatively unchanged.

Comparison of Enhanced Model C to the Highway Safety Manual remains the same where results from Washington are mostly counterintuitive. Adjustment for vertical curvature does not significantly improve the results after adjusting for ADT and speed, which is consistent with the findings for shoulder width. Segment length again proves to be a more critical adjustment factor than vertical curvature in the Washington models. The minimal impact of vertical curvature on the estimated CMFs once again suggests that results are probably sufficient after adjusting for ADT, speed and segment length. It may be beneficial to include vertical curvature when possible, but CMFs for lane width appear to be satisfactory when vertical curvature is omitted.

Several potential confounding variables have been examined during the estimation of CMFs for lane width. The effect of these variables has been adjusted through various combinations of matching and covariates as was done for shoulder width. ADT, speed and segment length were consistently observed as important confounding variables when estimating the effects of lane width on crash risk; however, horizontal curvature and vertical curvature were relatively unimportant. It is probably not cost-effective to collect data for curvature and grade, if not readily available, because effects on the CMFs are relatively small.

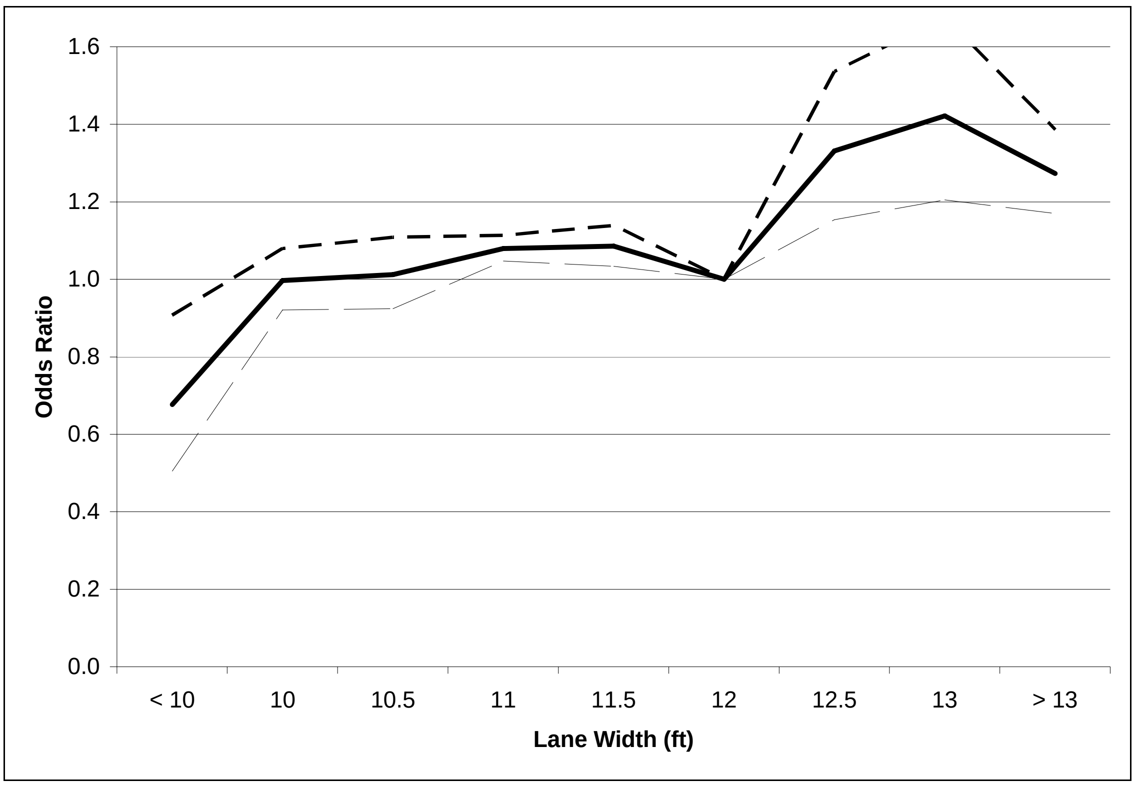

FIGURE 46 CMF for WA Enhanced Model D:
Lane Width Adjusted for Shoulder Width, ADT, Speed and Vertical Curvature (Matching)

6.4.3 Matching Scheme versus Covariates

In case-control studies, matching is the preferred method for adjustment compared to the use of covariates. Although matching is more complex and time consuming than using covariates, it assures that adjustment is possible. In some instances, the use of covariates may not properly adjust for the confounding factor. As an example, consider the affects of ADT on crash frequency. If the sample of cases (crash segments) is mostly composed of high ADT values while the control segments are associated with low ADT values then the model will not properly adjust for the effects of ADT. In this case, matching case and control segments with similar ADT values will allow for proper adjustment.

There are other practical reasons why covariates may be used rather than matching to adjust for confounding variables. Adjustment for confounding variables is automatic in the analysis when using a matching scheme; however, the effects of the confounders cannot be estimated separately. Therefore, covariates are used rather than matching when the effects of the confounding variables are of interest.

Additional case-control studies are set-up to test the difference between matching and the use of covariates. The base models are revisited and covariates are included in the models in place of the matching scheme. Using the covariate-adjusted models, the individual effects of each confounding variable may be estimated to determine if the effect on crash risk is consistent with previous studies. The full models for Pennsylvania and Washington are presented in Appendix A.11 with all variables included as covariates.

6.4.3.1 ADT and Speed: Matching versus Covariates

Estimated results from matching and covariate schemes for ADT and speed are compared in this section. Both models represent the effect of shoulder width and lane width on crash risk after adjusting for the effects of ADT and speed. The results for PA Enhanced Model A are copied from Section 6.4.2.1 and represent the effects of adjustment by matching. Enhanced Model A-1 includes ADT and speed as variables in the model and represents the effects of adjustment by use of covariates. Detailed model results are shown in Appendix A.5 and CMFs are compared for shoulder and lane width in Figures 47 and 48, respectively.

Shoulder Width

The CMFs for Pennsylvania have similar shapes, but slightly different crash risks for certain shoulder widths (Figure 47). In most cases, the direction of the effect is consistent across methods. The estimated crash risk is contradictory for five and seven foot shoulders when comparing the two methods; however, the estimates are not significantly different from the six foot baseline and the interpretation remains the same. The two methods produce consistent results and adjustment through covariates may be satisfactory when developing CMFs for shoulder width.

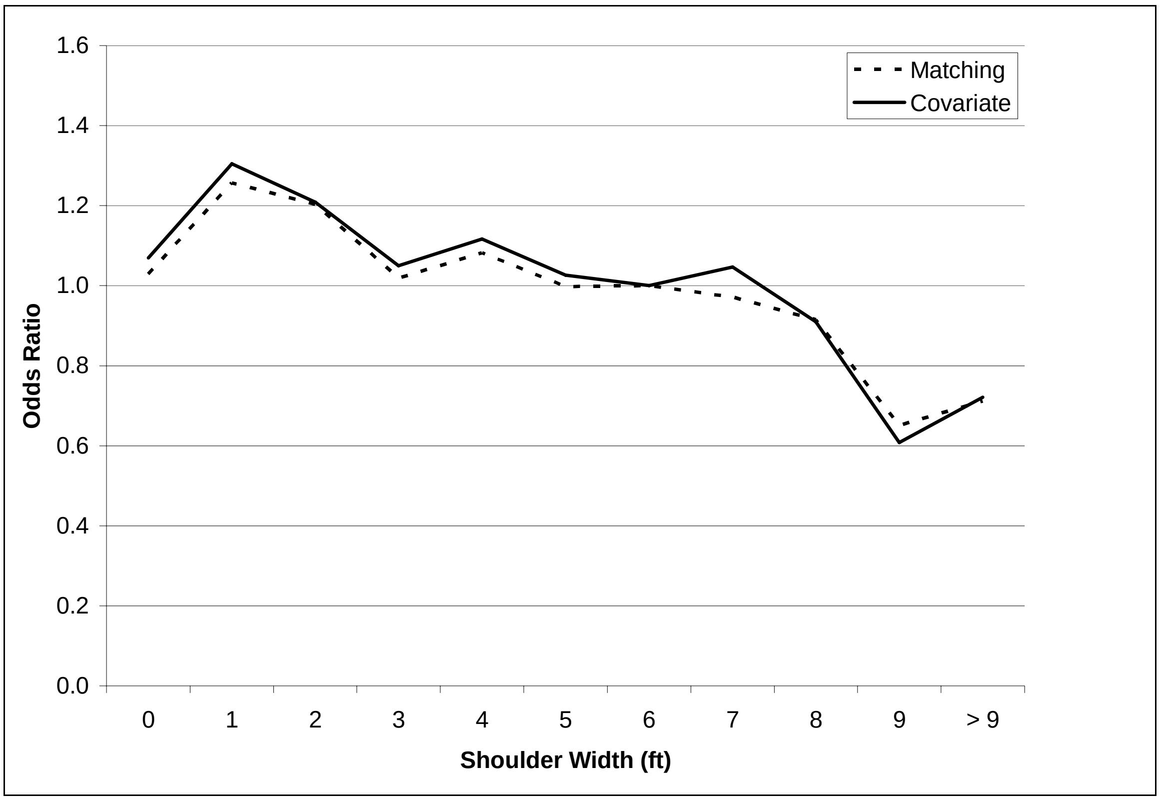

FIGURE 47 CMF comparison of PA Enhanced Models A and A-1:
Shoulder Width Adjusted for Lane Width, ADT and Speed

Lane Width

The CMFs for lane width have similar shapes and comparable crash risks when matching or using covariates (Figure 48). The significance (p-values) of the effects of lane width is also consistent when comparing results from the two adjustment methods. The biggest differences occur for 10.5 and 11.0 foot lane widths. In these two cases, the estimated crash risk is slightly higher when applying a matching scheme. Although the odds ratios are slightly different, the difference is not significant for practical purposes, especially when considering the standard errors. From previous models, it appears that adjusting for ADT and speed has a significant effect on the CMF; however, the method of adjustment may not be as critical.

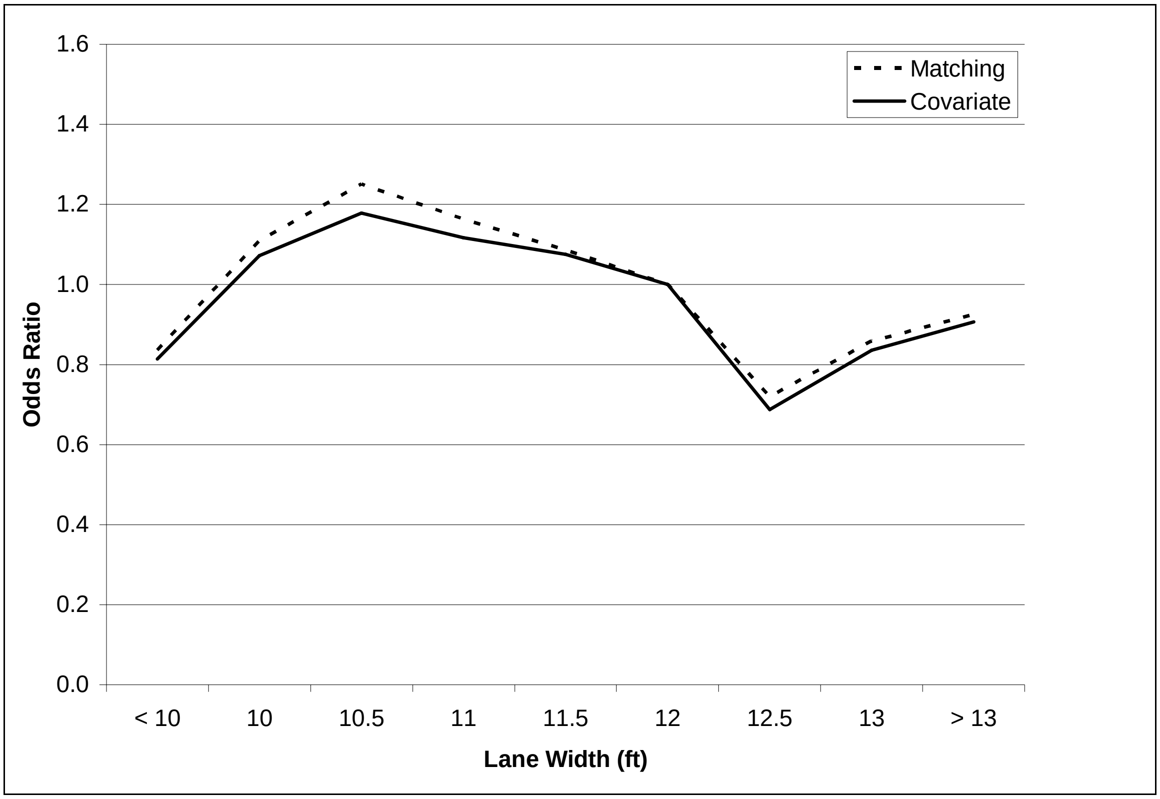

FIGURE 48 CMF comparison of PA Enhanced Models A and A-1: Lane Width Adjusted for Shoulder Width, ADT and Speed

6.4.3.2 Segment Length: Matching versus Covariate

Estimated results from matching and covariate schemes for segment length are compared. Both models represent the effect of lane and shoulder width on crash risk after adjusting for the effects of ADT, speed and segment length. These models adjust for ADT and speed by matching and compare the use of segment length as both a covariate and matching criterion. The results for PA Enhanced Model B are copied from Section 6.4.2.2 and represent the effects of adjustment by covariate. Enhanced Model B-1 includes segment length as a matching criterion and represents the effects of adjustment by matching. Detailed model results are shown in Appendix A.6 and CMFs are compared in Figures 49 and 50 for shoulder and lane width, respectively.

Shoulder Width

The shoulder width CMF is very similar for Pennsylvania regardless of the adjustment method for segment length (Figure 49). While the odds ratios are slightly different when comparing the two adjustment methods, the differences are insignificant for practical purposes and the general shape of the CMF remains the same. The only major difference occurs for shoulder widths of eight feet. The change is not dramatic, but could influence the interpretation of the results depending on the level of significance chosen by the investigator. For a strict 0.05 level of significance, the p-value is significant when adjusting with a covariate, but becomes insignificant when matching. It appears that adjusting for segment length has a significant effect on the CMF; however, the method of adjustment may not be as critical.

FIGURE 49 CMF comparison of PA Enhanced Models B and B-1:
Shoulder Width Adjusted for Lane Width, ADT, Speed and Segment Length

Lane Width

The lane width CMF for Pennsylvania is only slightly different when comparing the results from the two adjustment methods (Figure 50). While the odds ratios are slightly different, the differences are insignificant for practical purposes, especially when considering the standard errors. The greatest difference occurs for lane widths greater than 13.0 feet. Although the odds ratio is similar using both methods, the p-value is highly significant when matching and just marginally significant when adjusting with a covariate. Again, the interpretation is different depending on the chosen level of significance. The safety effect of lane widths greater than 13.0 feet is significant at a 0.10 level of significance for both methods of adjustment. While segment length is a critical adjustment factor when estimating CMFs for lane width, the method of adjustment does not appear to be as critical.

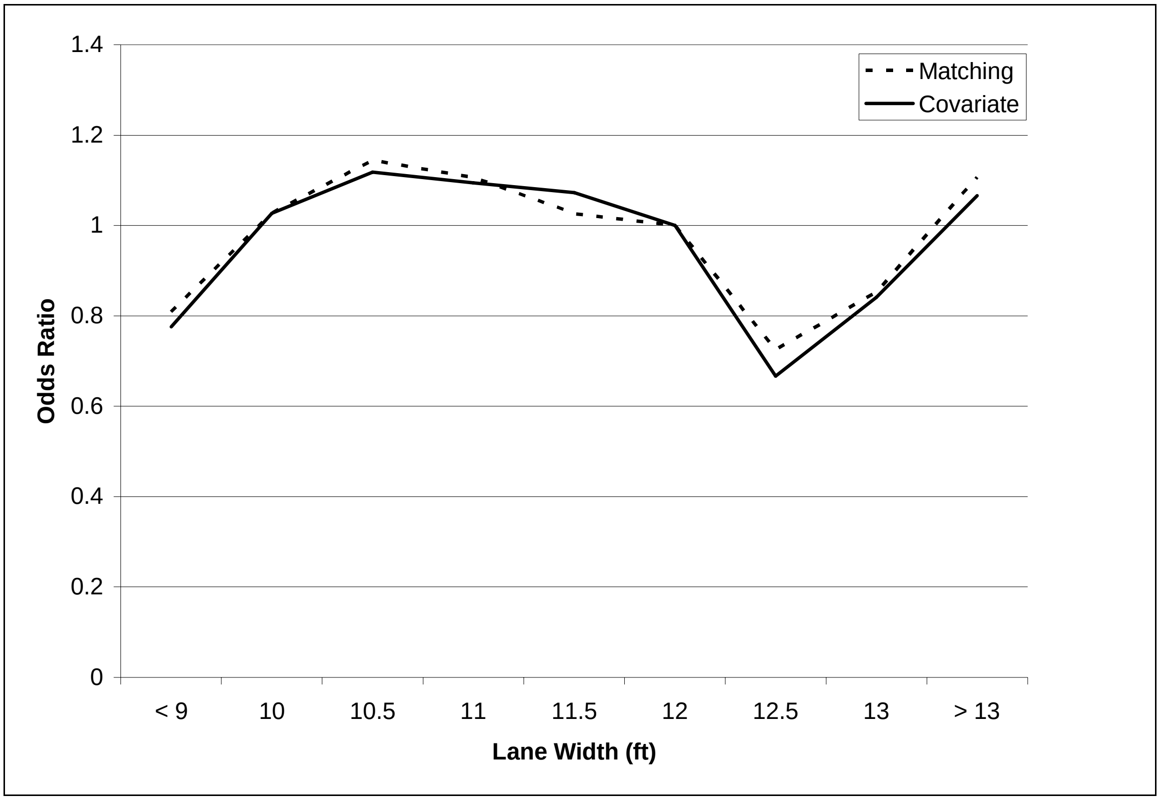

FIGURE 50 CMF comparison of PA Enhanced Models B and B-1:
Lane Width Adjusted for Shoulder Width, ADT, Speed and Segment Length

6.4.3.3 Horizontal Curvature: Matching versus Covariate

Estimated results from matching and covariate schemes for horizontal curvature are compared. Both models represent the safety effectiveness of shoulder width and lane width after adjusting for the effects of ADT, speed and horizontal curvature. These models adjust for ADT and speed by matching and compare the use of horizontal curvature as both a covariate and matching criterion. Results are based on Washington data only because Pennsylvania does not maintain information on horizontal curvature. Estimates from WA Enhanced Model C are copied from Section 6.4.2.3 and represent adjustment by use of a covariate. Enhanced Model C-1 includes horizontal curvature as a matching criterion and represents the effects of adjustment by matching. Detailed model results are shown in Appendix A.7 and CMFs are compared in Figures 51 and 52 for shoulder width and lane width, respectively.

Shoulder Width

The shape of the CMF for shoulder width is very similar regardless of the adjustment method for horizontal curvature (Figure 51). There does, however, appear to be a shift in the magnitude of the estimates for a portion of the CMF. The estimates from the matching scheme are consistently higher than those from the covariate scheme for shoulders less than nine feet. While the difference in odds ratio is insignificant for many of the shoulder widths, there are instances where the results would appear statistically significant from one method and not the other. For example, seven and eight foot shoulders are significantly different (higher risk) compared to the baseline six foot shoulder using the matching scheme, but highly insignificant when using the covariate scheme.

For practical purposes, the general shape of the CMF remains the same; however, the interpretation of results may vary between the two methods. Due to differences in the two methods, matching is recommended as the more appropriate method to adjust for the confounding effects of horizontal curvature. As discussed previously, matching assures that adjustment is possible. In either case, it appears that horizontal curvature has a negligible effect on the CMF and adjusting for horizontal curvature may not be necessary after adjusting for ADT and speed.

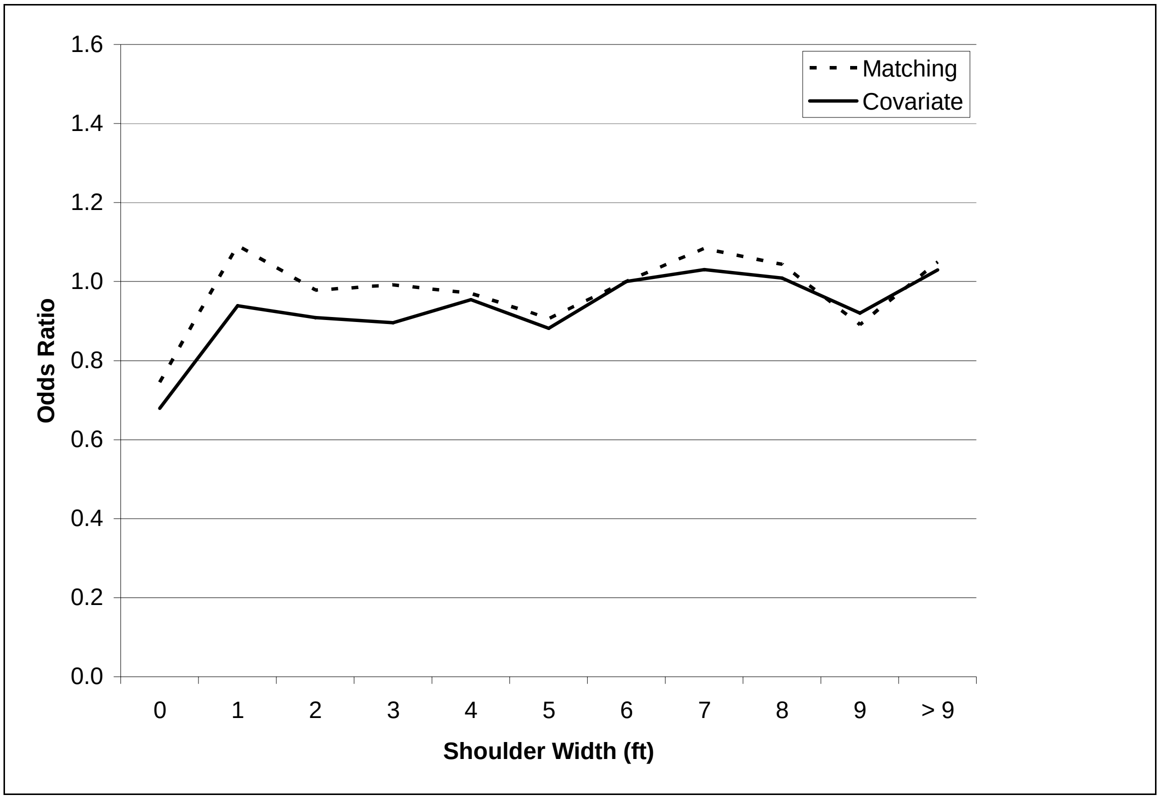

FIGURE 51 CMF comparison of WA Enhanced Models C and C-1:
Shoulder Width Adjusted for Lane Width, ADT, Speed and Horizontal Curvature

Lane Width

The lane width CMF for Washington is slightly different depending on the adjustment method (Figure 52). For lane widths less than twelve feet, the estimates are consistently less for the matching scheme. The greatest difference in crash risk occurs for lane widths of 13.0 feet. Results from the matching scheme indicate that 13.0 foot lanes have a significantly higher crash risk than 12.0 foot lanes; however, the estimated crash risk is insignificant for the covariate scheme. For practical purposes, this difference could have slight impacts on benefit-cost estimates. Overall, the two methods produce relatively similar results, but the matching scheme is recommended because estimates do not fluctuate as greatly for wide lane widths.

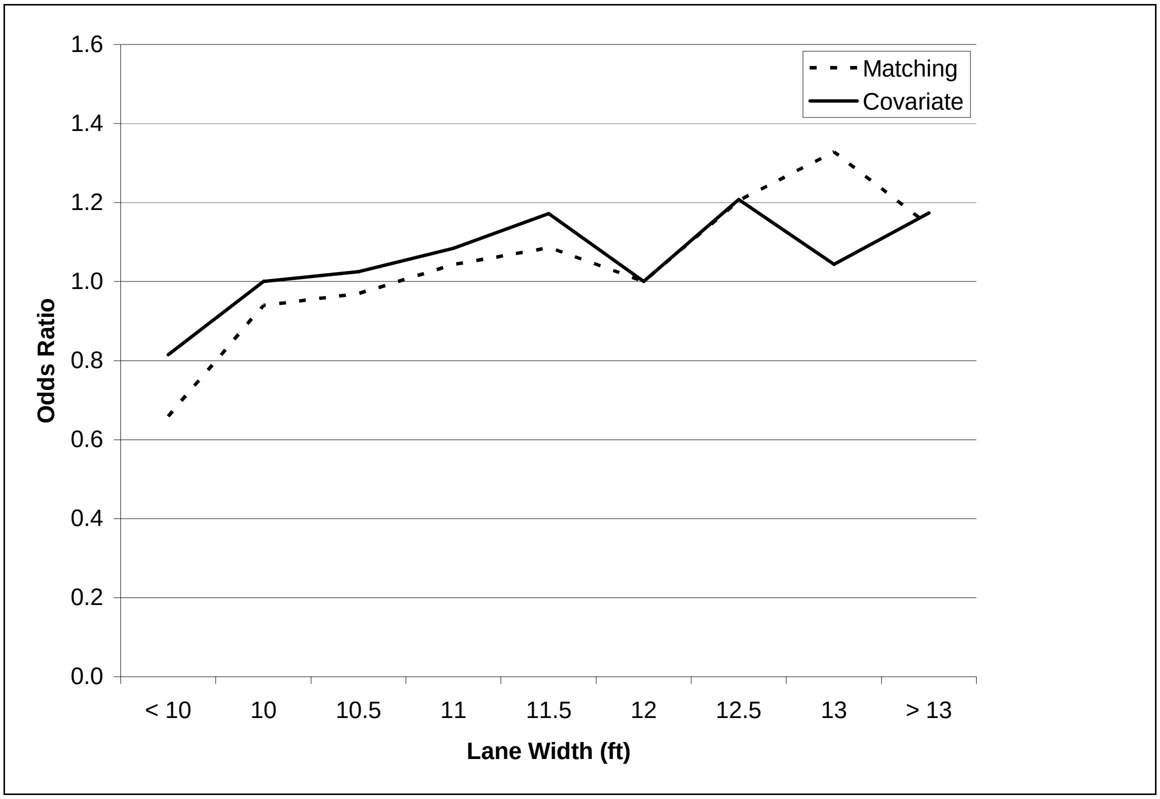

FIGURE 52 CMF comparison of WA Enhanced Models C and C-1:
Lane Width Adjusted for Shoulder Width, ADT, Speed and Horizontal Curvature

6.4.3.4 Vertical Curvature: Matching versus Covariate

Estimated results from matching and covariate schemes for vertical curvature are compared. Both models represent the effect of shoulder width and lane width on crash risk after adjusting for the effects of ADT, speed and vertical curvature. These models adjust for ADT and speed by matching and compare the use of vertical curvature as both a covariate and matching criterion. Estimates from WA Enhanced Model D are taken from Section 6.4.2.4 above and represent adjustment by use of a covariate. Enhanced Model D-1 includes vertical curvature as a matching criterion and represents the effects of adjustment by matching. Detailed model results are shown in Appendix A.8 and CMFs are compared in Figures 53 and 54 for shoulder width and lane width, respectively.

Shoulder Width

The shape of the CMF for shoulder width is very similar regardless of the adjustment method for vertical curvature (Figure 53) and there is no clear pattern to the shift in the magnitude of the estimates. The largest difference between the two methods occurs for one foot shoulders; matching produces a crash risk greater than one while the covariate scheme indicates a crash risk less than one. Although the estimates are contradictory for one foot shoulders, the estimates are not significantly different from 1.0 and the interpretation remains the same. Results, for the most part, are very similar for the two methods of adjustment. In either case, it appears that vertical curvature has a negligible effect on the CMF and adjusting for vertical curvature may not be necessary after adjusting for ADT and speed.

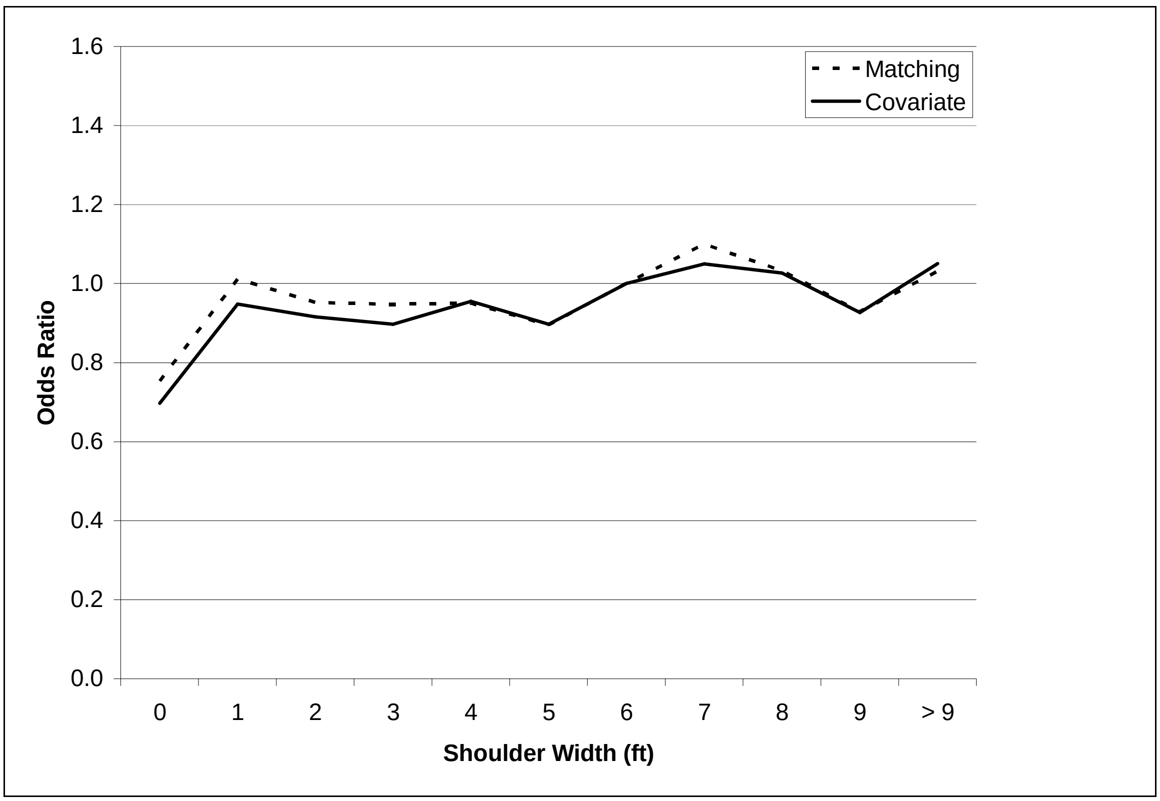

FIGURE 53 CMF comparison of WA Enhanced Models D and D-1:
Shoulder Width Adjusted for Lane Width, ADT, Speed and Vertical Curvature

Lane Width

The lane width CMF for Washington is also very similar when comparing the results from the two adjustment methods (Figure 54). There is one major difference that is similar to the horizontal curvature model, which occurs in the 13.0 foot lane width category. Adjustment by matching indicates a 42 percent increase in risk while the covariate method suggests a 9 percent increase in risk. This difference is concerning because it would have significant impacts on a benefit-cost analysis. Other than the 13.0 lane width, the two methods produce very similar results. Again, the matching scheme produces estimates that are less variable and is therefore recommended over the covariate scheme.

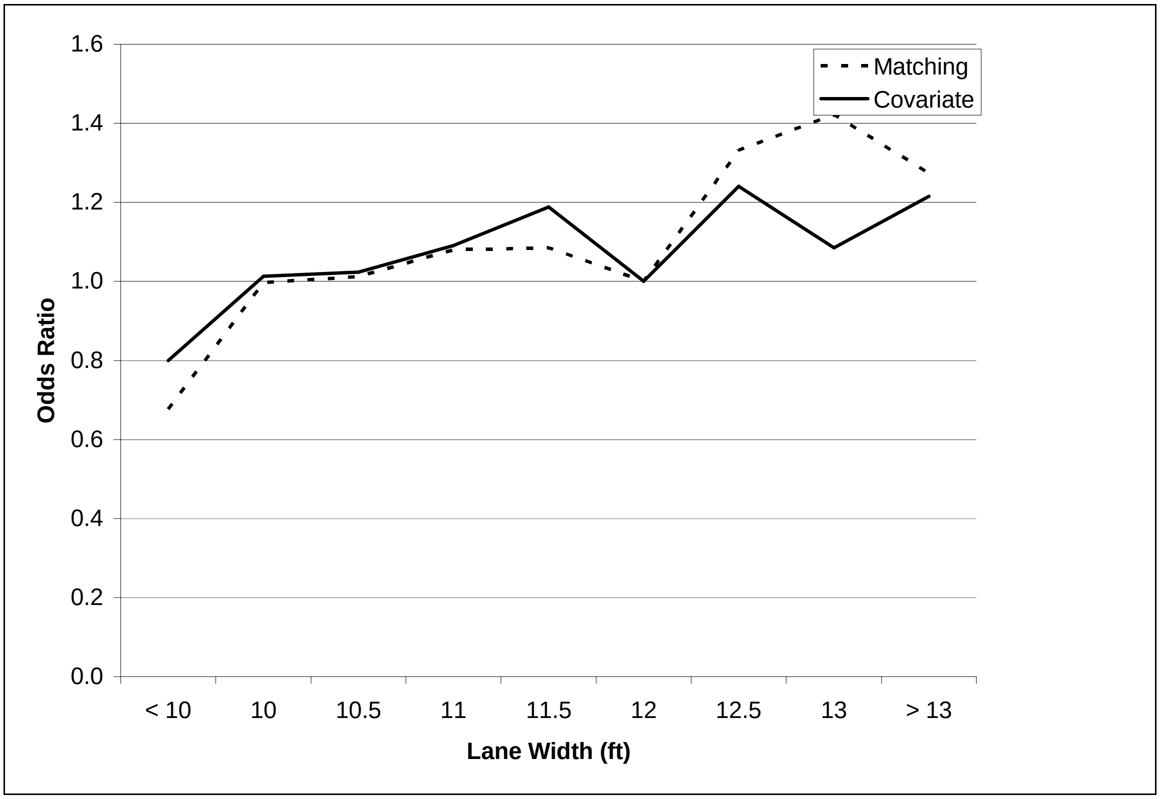

FIGURE 54 CMF comparison of WA Enhanced Models D and D-1:
Lane Width Adjusted for Shoulder Width, ADT, Speed and Vertical Curvature

6.4.4 Alternative Response Models:

6.4.4.1 Related Crashes versus Total Crashes

Previous research has indicated that lane and shoulder width are most likely to effect specific crashes types (i.e. head-on, sideswipe, and run-off-the-road crashes). To this point, case-control models have been estimated including all crash types in the response variable. Data reflecting related crashes are now used to estimate models of the effects of shoulder and lane width on safety to provide a direct comparison with CMFs in the Highway Safety Manual.

Estimated CMFs from PA Related-Crash Model A are presented in comparison to the CMFs from the Highway Safety Manual for both shoulder width (Figure 55) and lane width (Figure 56). Detailed model results are presented in Appendix A.9 in comparison to both PA Enhanced Model B and the Highway Safety Manual. Both models represent the safety effectiveness of lane and shoulder width after adjusting for the effects of ADT and speed (matching) and segment length (covariate). Estimates from PA Enhanced Model B are taken from Section 6.4.2.2 and represent the effect of shoulder width and lane width on *total* crashes. PA Related-Crash Model A represents the effects of lane and shoulder width on a *related* subset of crashes. Both models are estimated using conditional logistic regression.

Shoulder Width

The shape of the CMF is very similar when comparing results from the shoulder width models of total and related crashes. From top to bottom, however, the estimates from the model of related crashes are more pronounced than those from the model of total crashes. For the related-crash model, the estimated safety effectiveness ranges from 1.31 to 0.64 in comparison to 1.21 to 0.68 for the model of total crashes. In effect, several of the crash risks become more significant.

Results from the related-crash model are more consistent with the CMF provided in the Highway Safety Manual. Almost the entire CMF from the Highway Safety Manual falls within the 95 percent confidence limits from the case-control model. This is reassuring because the related-crash model is based on the same crash types used to develop the CMFs in the Highway Safety Manual. The most apparent difference is for shoulder widths less than two feet. Results from the Highway Safety Manual indicate a steady decrease in risk as shoulder width increases, but the case-control models indicate a slight increase in risk from zero to two feet.

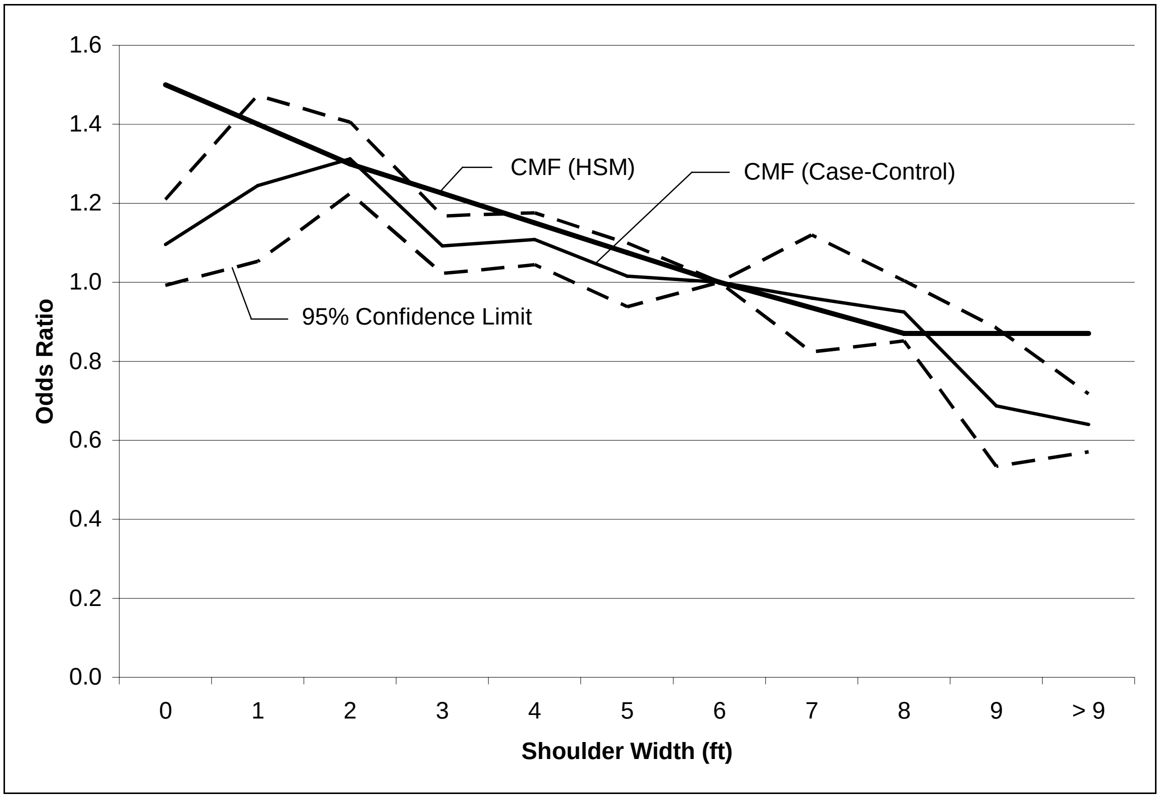

FIGURE 55 CMF comparison of PA Related-Crash Model A and Highway Safety Manual: Shoulder Width Adjusted for Lane Width, ADT, Speed and Segment Length

Lane Width

The CMF for lane width is again very similar when comparing the two models. There is, however, an apparent shift in the estimates for lane widths less than thirteen feet. Estimates from the related-crash model are consistently greater than those from the total-crash model. The only deviation in this trend occurs for lane widths greater than thirteen feet. As a result of the upward shift of the CMF, lane widths 10 to 12 feet are expected to have a greater impact on related crashes compared to the effect on total crashes. Odds ratios for lane widths less than 10 feet and greater than 12 feet are closer to unity for the related-crash model indicating less of an effect compared to the total-crash model.

The lane width CMF from the related-crash model is more consistent with the Highway Safety Manual than the CMF from the total-crash model. Much of the CMF from the Highway Safety Manual again falls within the 95 percent confidence limits of the case-control model. There is a slight difference between the two CMFs for lane widths greater than 12 feet, but this difference is not significant when considering the confidence intervals. The most apparent difference between the case-control results and the Highway Safety Manual appears in lane widths less than 10.5 feet.

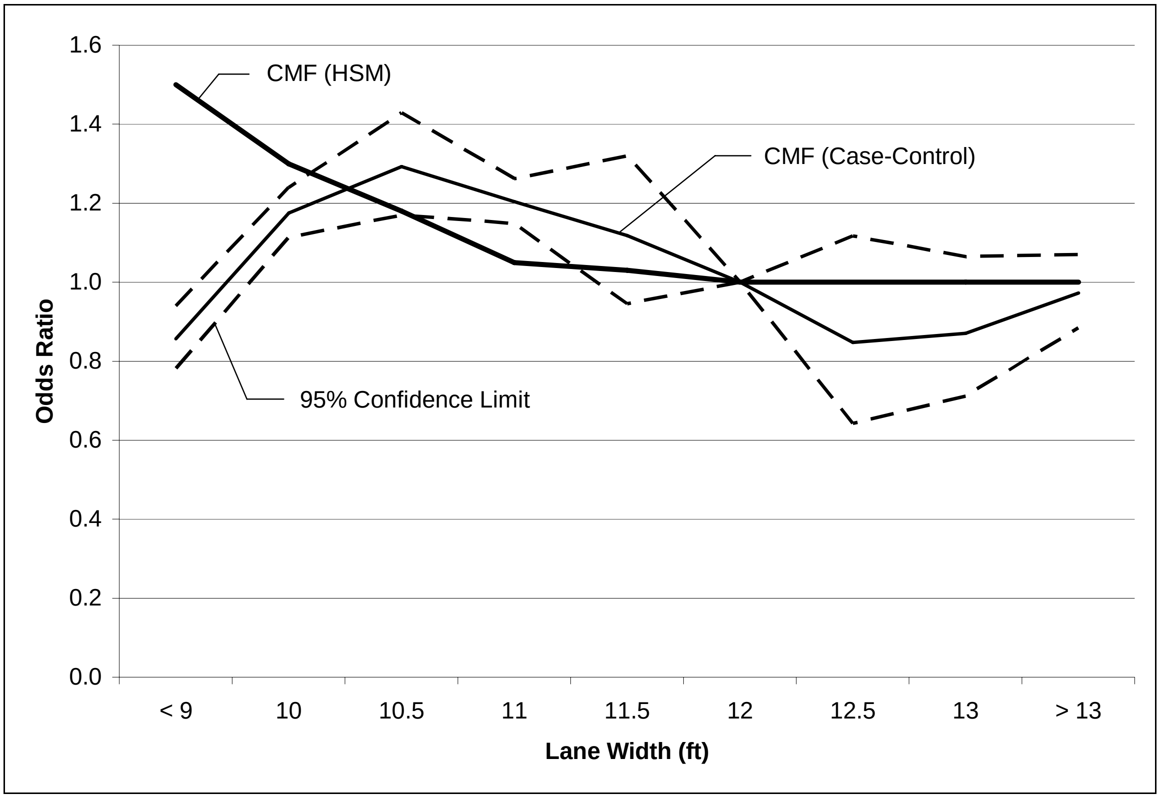

FIGURE 56 CMF comparison of PA Related-Crash Model A and Highway Safety Manual: Lane Width Adjusted for Shoulder Width, ADT, Speed and Segment Length

The estimated safety effectiveness of shoulder width and lane width are different when comparing the models of total crashes and related crashes. The difference in model estimates is not particularly surprising because previous research has shown that shoulder width and lane width have a greater effect on certain crash types. It is important, however, to recognize the difference in effectiveness because not all crash types are associated with similar costs. For example, rear-end crashes may increase as a result of some safety improvement while angle crashes are observed to decrease. If the cost of angle collisions is significantly higher than the cost of rear-end collisions then this may be an acceptable result. For both shoulder width and lane width, the CMF is similar for both models (total and related crashes). While the effect appears to be more pronounced for related crashes, there does not appear to be an adverse effect on other crash types.

6.4.4.2 Ordinal Response versus Binary Response

Estimated CMFs for PA Ordinal Model A are illustrated for shoulder width (Figures 57, 58 and 59) and lane width (Figures 60, 61 and 62). Detailed model results are presented in Appendix A.10. PA Ordinal Model A is similar to PA Enhanced Model B (Section 6.4.2.2); however, a different approach is used to account for segments that experience multiple crashes. Previously, multiple-crash segments were accounted for by creating multiple observations in the dataset and estimates were obtained through conditional binary logistic regression. Now, each multiple-crash segment is represented by a single observation in the dataset and estimates are obtained using multinomial logistic regression. These models represent the effects of shoulder width and lane width on crash risk after adjusting for the effects of ADT, speed and segment length; however, a separate model is estimated for each crash frequency (i.e. 1, 2, and 3+ crashes) in comparison to the baseline (0 crashes).

Shoulder Width

The general shape of the shoulder width CMFs from PA Ordinal Response Model A are similar to PA Enhanced Model B. The models indicate that crash risk decreases as shoulder width increases; however, the effect is not the same for all crash frequencies. The decrease in risk is almost linear when comparing one-crash segments to zero-crash segments (Figure 57), but there is greater fluctuation for multiple crash segments. It also appears that increases in shoulder width are expected to have greater effects on segments with higher crash frequencies. This is evident from the steeper slopes of the CMFs in Figures 58 and 59. In previous models, an upturn in crash risk is shown for shoulders greater than nine feet. This appears to be due to differential effects of shoulder width; the multiple-crash models indicate an upturn in risk for shoulders greater than nine feet, but the single crash model shows a steady decrease in risk.

FIGURE 57 CMF for PA Ordinal Model A (1 Crash compared to 0 Crashes): Shoulder Width Adjusted for Lane Width, ADT, Speed and Segment Length

FIGURE 58 CMF for PA Ordinal Model A (2 Crashes compared to 0 Crashes): Shoulder Width Adjusted for Lane Width, ADT, Speed and Segment Length

FIGURE 59 CMF for PA Ordinal Model A (3+ Crashes compared to 0 Crashes): Shoulder Width Adjusted for Lane Width, ADT, Speed and Segment Length

Lane Width

The CMF for lane width is also comparable between PA Enhanced Model B and PA Ordinal Model A. Again, the three models appear to produce CMFs with the same general trend, but lane width has a more pronounced effect on segments with higher crash frequencies. The confidence intervals are also wider for the multiple-crash models because there are fewer segments with multiple crashes than single crashes. Finally, the multinomial models indicate that segment length has differential effects on segments with different crash frequencies. All else being equal, the crash risk increases much more dramatically for multiple crash segments than for single- or zero-crash segments.

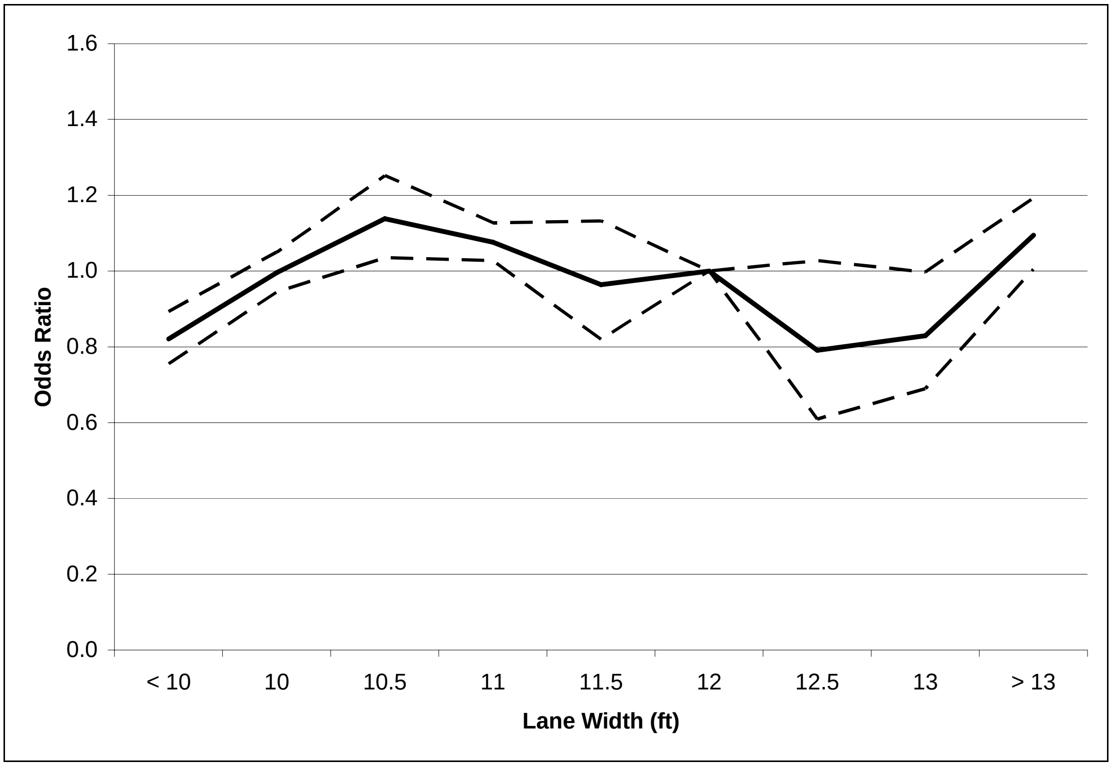

FIGURE 60 CMF for PA Ordinal Model A (1 Crash compared to 0 Crashes): Lane Width Adjusted for Shoulder Width, ADT, Speed and Segment Length

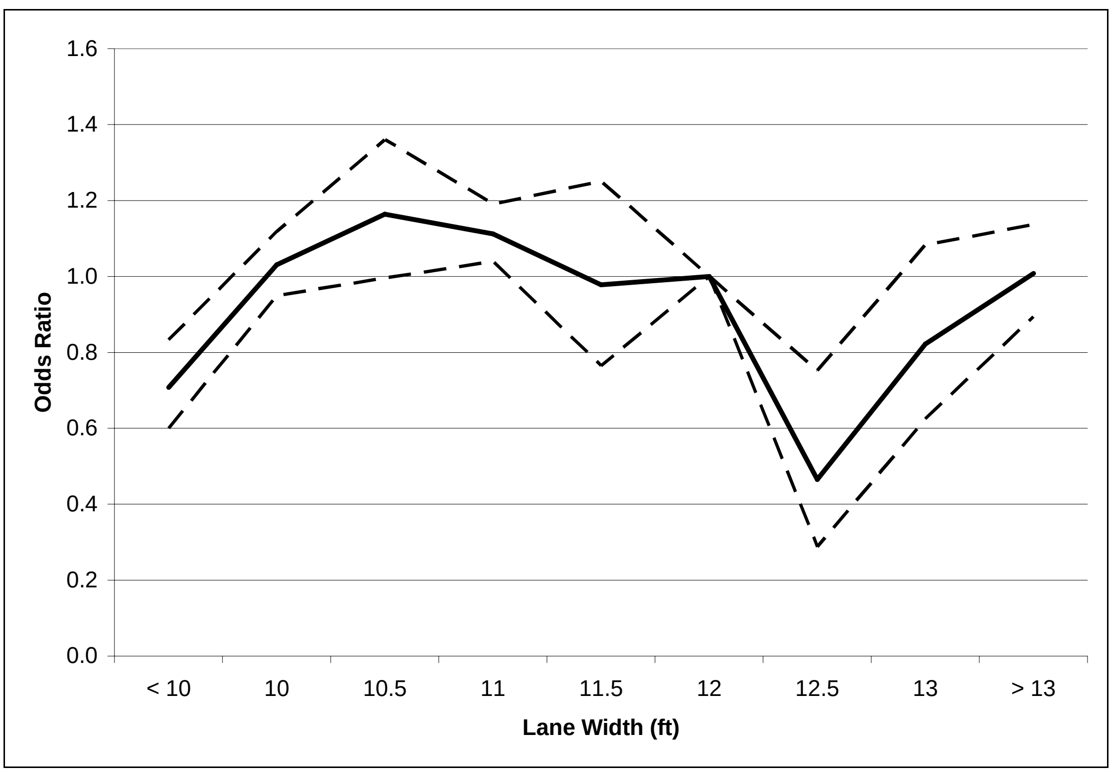

FIGURE 61 CMF for PA Ordinal Model A (2 Crashes compared to 0 Crashes): Lane Width Adjusted for Shoulder Width, ADT, Speed and Segment Length

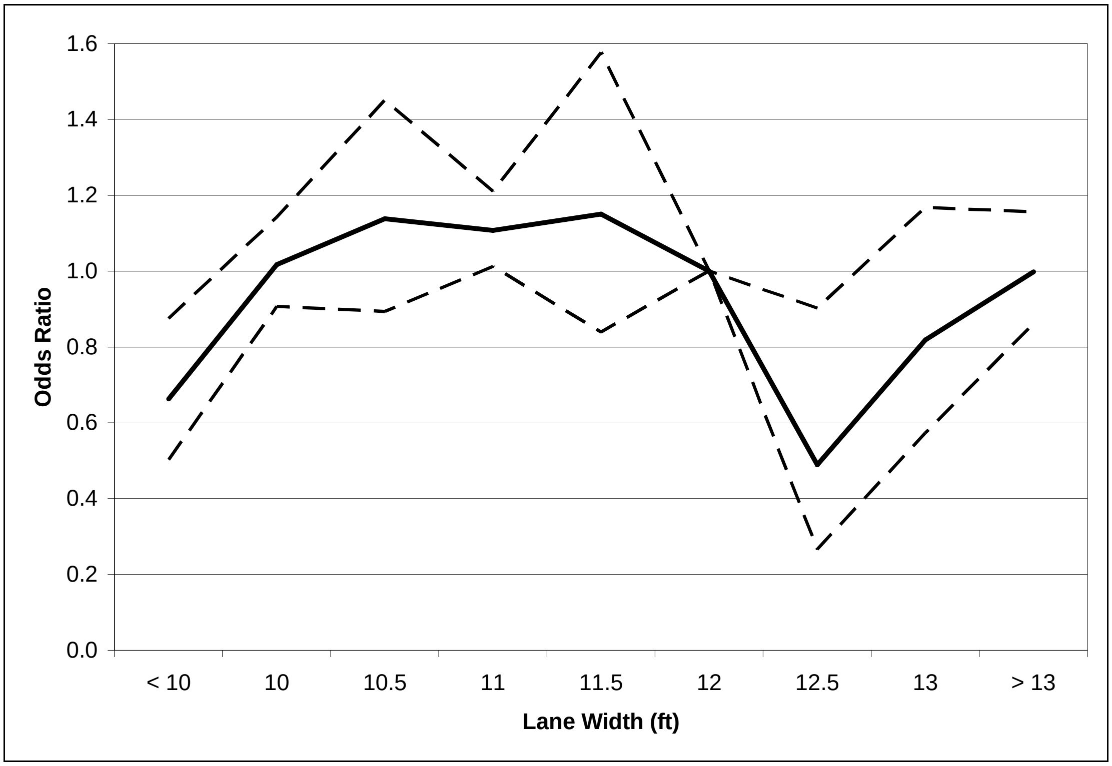

FIGURE 62 CMF for PA Ordinal Model A (3+ Crashes compared to 0 Crashes): Lane Width Adjusted for Shoulder Width, ADT, Speed and Segment Length

The response variable ranged from zero to eleven crashes within the study sample and additional models were developed using alternative ordinal scales. Sample sizes became small when using more than four categories, which produced relatively wide confidence intervals and the greater fluctuation in the estimates. In the previous model, the response variable was reduced to just four categories (0, 1, 2, and > 2) and the models appear to be reasonable.

6.4.5 Case-Control Summary

Case-control methods were applied to roadway and crash data to estimate crash modification factors for lane width and shoulder width. Data from two different states were used to compare the consistency of results. A thorough analysis of several potential confounding variables identified ADT, speed and segment length as the most critical confounders when estimating CMFs for lane and shoulder width. This is not to say that other variables will not significantly affect the estimation of CMFs for lane and shoulder width, but these factors are not readily available in the current databases.

The purpose of this research, however, was not to exhaust the list of potential confounders. Instead, this study evaluated the use of case-control methods to estimate CMFs. Results from the case-control models were relatively consistent with the Highway Safety Manual when comparing the general trends of the CMFs for lane and shoulder width. Results from the PA models were more consistent with the Highway Safety Manual than the WA models and horizontal and vertical curvature did not appear to improve the estimates. The PA models based on "related" crash types were almost identical to those presented in the Highway Safety Manual. Based on the consistency of results from this initial evaluation, the case-control method has proven to be well suited for estimating CMFs for lane and shoulder width.

6.5 CMF Estimation: The Cohort Method

This section presents the results of several cohort designs as illustrated in Figure 63. Results are presented in progression from base models (without covariates) to enhanced models (with adjustment for confounders) as was discussed in the model estimation structure in Figure 29. Both Pennsylvania and Washington datasets are analyzed and results are presented separately for lane and shoulder width. Comparisons are made between the results from Pennsylvania and Washington where applicable. Within each of the modeling stages results are also compared to the case-control estimates and the Highway Safety Manual.

The purpose of the cohort analysis is not to repeat the process undertaken in the case-control design. The question remaining is whether or not there is a causal relationship between lane or shoulder width and crashes. Case-control methods may not be used to show a causal sequence because the data are cross-sectional. Instead, the cohort design is used to show stronger evidence of causal affects by accounting for the time sequence of events. Case-control designs are typically less expensive and relatively quick to complete when compared to cohort studies. Therefore, the case-control design, or another theoretically inferior design, is often used to explore potential risk factors for a given outcome. Once risk factors and confounding variables have been identified, the cohort study may be used to examine the causal relationship between risk factor and outcome. In the case-control study, lane and shoulder width were shown as risk factors of a highway crash and critical confounding variables were identified (i.e. ADT, speed and segment length).

Cohort designs are first set-up without adjustment for confounding variables and then adjustments are made for ADT, speed and segment length. Alternative measures of time at risk are evaluated, segment-days and segment-length-days. Survival models and count models are both applied to estimate the relative risk of a crash and results are compared. Results from the two estimation methods are evaluated and then compared to the results from the case-control study. If results are similar between the two methods, then it may be sufficient to rely on the case-control design for development of CMFs for lane and shoulder width in future research studies.

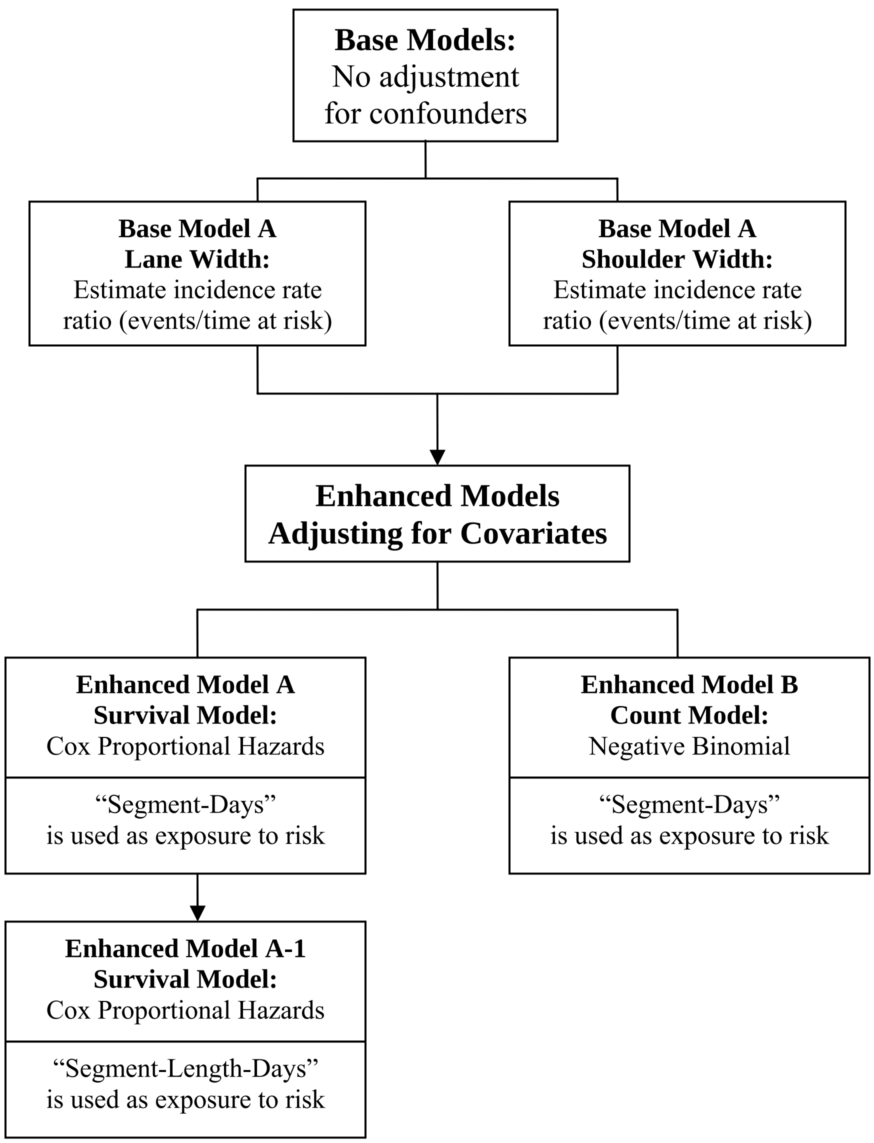

FIGURE 63 Cohort Design Flow Diagram

6.5.1 Base Models without Adjustment for Confounders

Shoulder Width

The estimated shoulder width results for PA Base Model A and WA Base Model A are shown in Tables 35 and 36, respectively. "Segment-days" is used as the measure of exposure to indicate the time at risk. The incidence rate ratio (relative risk) and 95 percent confidence limits are presented for each shoulder width in comparison to a baseline shoulder width of six feet. The base CMF for shoulder width is derived from the relative risk and is shown in Figures 64 and 65 for Pennsylvania and Washington, respectively.

The base CMF indicates a general increase in crash risk as shoulder width increases between two and eight feet. The CMFs are very similar for the two states in this range and show other similarities in the extremes. From zero to two feet, both states show a general decreasing crash risk and the change in risk is almost identical (about 40 percent). Beyond eight feet, the results for Pennsylvania and Washington are slightly different. For Pennsylvania, crash risk drops below one and continues to decrease indicating a reduced risk for shoulder widths greater than eight feet. For Washington, the crash risk decreases slightly for a nine foot shoulder, but continues to increase as widths increase beyond nine feet. The Washington base model seems to indicate a more consistent increase in risk as shoulder width increases.

CMFs from both states bear a striking resemblance to the base models from the case-control study. In either design, the base models produce counterintuitive results; however, the results are consistent across methods. The general shape of the CMF is almost identical comparing results from the two designs. The difference is that the case-control design appears to estimate crash risks that are more pronounced than the cohort estimates. For example, crash risks in Pennsylvania range from 0.53 to 1.18 using the case-control study compared to 0.61 and 1.10 from the cohort design. Preliminary results suggest that cohort designs will produce similar estimates to the case-control study and this hypothesis is tested in the following sections. Additional variables (ADT, speed, and segment length) are included in the enhanced models to adjust for confounding effects and results are compared to the case-control estimates.

TABLE 35 PA Base Model A: Shoulder Width Only

Shoulder Width	Incidence (crashes)	Exposure (segment-days)	Incidence Rate	Incidence Rate Ratio	95% Limits	
					Lower	Upper
0	2099	1,500,477	0.001399	0.958	0.910	1.008
1	402	411,510	0.000977	0.669	0.602	0.738
2	5193	5,820,094	0.000892	0.611	0.588	0.636
3	5351	5,283,601	0.001013	0.694	0.667	0.721
4	11828	9,522,143	0.001242	0.851	0.823	0.880
5	3056	2,251,330	0.001357	0.930	0.888	0.973
6	4831	3,308,616	0.001460	1.000	0.961	1.041
7	611	382,238	0.001598	1.095	1.003	1.188
8	3265	2,119,032	0.001541	1.055	1.009	1.103
9	192	152,153	0.001262	0.864	0.740	0.990
> 9	1145	953,804	0.001200	0.822	0.770	0.876

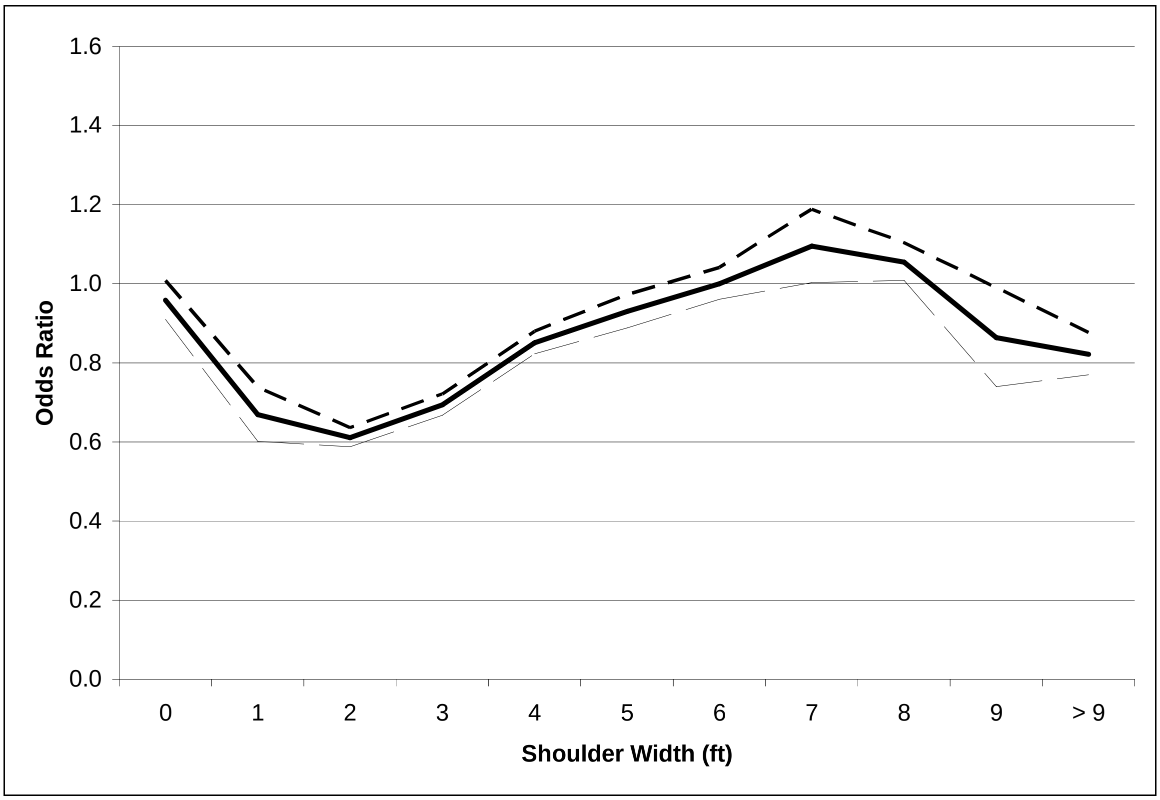

FIGURE 64 CMF for PA Base Model A: Shoulder Width Only

TABLE 36 WA Base Model A: Shoulder Width Only

Shoulder Width	Incidence (crashes)	Exposure (segment-days)	Incidence Rate	Incidence Rate Ratio	95% Limits	
					Lower	Upper
0	1965	6984843	0.000281	0.76	0.72	0.80
1	1056	6441064	0.000164	0.44	0.41	0.47
2	3422	20898166	0.000164	0.44	0.42	0.46
3	5040	21554525	0.000234	0.63	0.60	0.66
4	5807	19395127	0.000299	0.81	0.78	0.84
5	2038	6995639	0.000291	0.79	0.74	0.83
6	3838	10348619	0.000371	1.00	0.96	1.05
7	2939	7341153	0.000400	1.08	1.03	1.13
8	7046	15084833	0.000467	1.26	1.21	1.31
9	405	1006137	0.000403	1.09	0.98	1.20
> 9	2045	4037224	0.000507	1.37	1.29	1.44

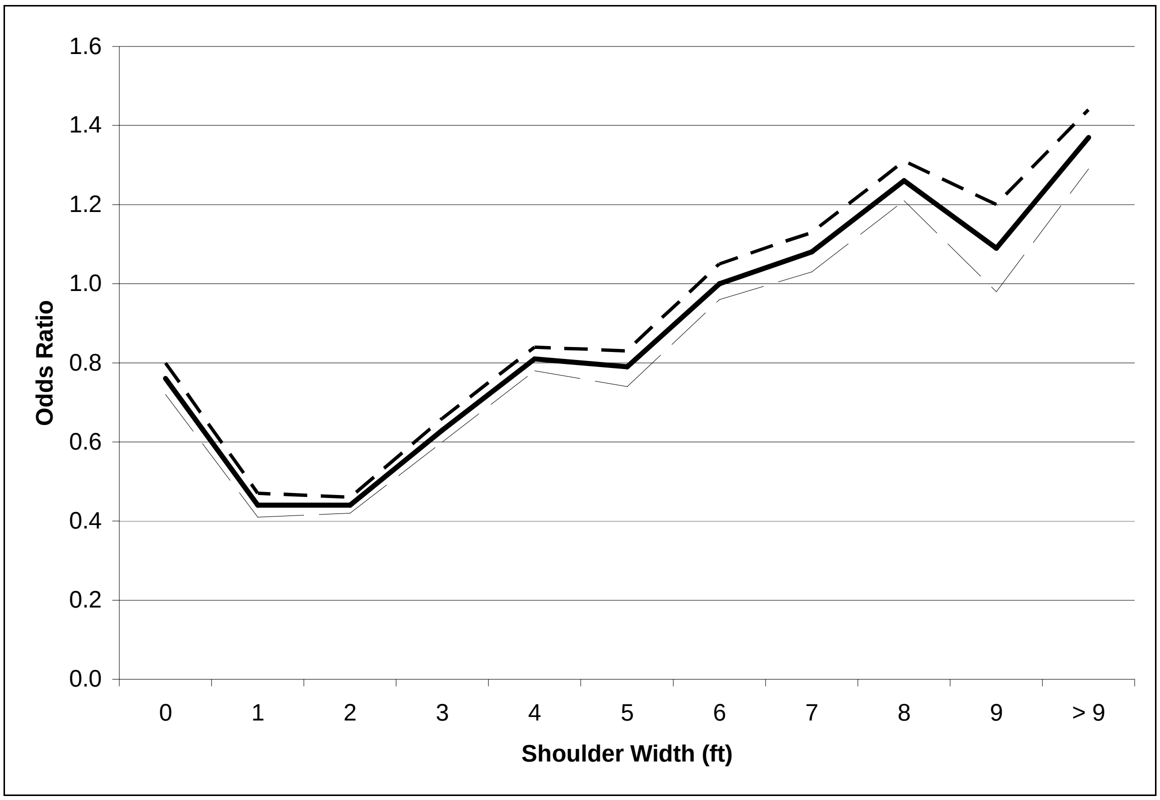

FIGURE 65 CMF for WA Base Model A: Shoulder Width Only

Lane Width

The estimated lane width results for PA Base Model A and WA Base Model A are shown in Tables 37 and 38, respectively. The incidence rate ratio (relative risk) and 95 percent confidence limits are presented for each lane width in comparison to a baseline lane width of twelve feet. The base CMF for lane width is derived from the relative risk and is shown in Figures 66 and 67 for Pennsylvania and Washington, respectively.

The base CMF for lane width indicates a general increasing crash risk as lane width increases. The relative risks are almost identical for the two states ranging from about 0.35 (< 10 feet) to almost 1.20 (> 13 feet). Both states show a relatively steep slope in the CMF up to 11.0 feet where the CMF begins to level-off briefly. There is also a slight decrease in crash risk around 12.5 or 13.0 feet before risk continues to increase for lane widths greater than 13.0 feet. Confidence intervals are similar when comparing the two states with relatively larger intervals for the wider lane widths.

CMFs from both states are again very similar to the base models from the case-control study. The general shape of the CMFs is almost identical when comparing results from the two studies; however, the estimated crash risks are slightly different. The cohort design again produces estimates of relative risk that are closer to unity than the corresponding odds ratios from the case-control study, but results from the base models are still counterintuitive. Additional variables (ADT, speed, and segment length) are included in the enhanced models in following sections to adjust for confounding effects.

TABLE 37 PA Base Model A: Lane Width Only

Lane Width	Incidence (crashes)	Exposure (segment-days)	Incidence Rate	Incidence Rate Ratio	95% Limits	
					Lower	Upper
< 10	1424	2661940	0.000535	0.383	0.362	0.405
10.0	8467	8761585	0.000966	0.692	0.671	0.713
10.5	1225	1207968	0.001014	0.726	0.683	0.770
11.0	15372	11067876	0.001389	0.994	0.968	1.021
11.5	414	340255	0.001217	0.871	0.785	0.957
12.0	8149	5832452	0.001397	1.000	0.970	1.031
12.5	131	131744	0.000994	0.712	0.589	0.835
13.0	319	255633	0.001248	0.893	0.794	0.993
> 13	2472	1445545	0.001710	1.224	1.169	1.280

TABLE 38 WA Base Model A: Lane Width Only

Lane Width	Incidence (crashes)	Exposure (segment-days)	Incidence Rate	Incidence Rate Ratio	95% Limits	
					Lower	Upper
< 10	104	1063227	0.000098	0.29	0.23	0.35
10.0	1254	7426484	0.000169	0.50	0.47	0.53
10.5	881	4980720	0.000177	0.52	0.49	0.56
11.0	14503	51204682	0.000283	0.84	0.82	0.86
11.5	3237	9602878	0.000337	1.00	0.96	1.04
12.0	13216	39166345	0.000337	1.00	0.98	1.02
12.5	361	975213	0.000370	1.10	0.98	1.21
13.0	217	713487	0.000304	0.90	0.78	1.02
> 13	1828	4954294	0.000369	1.09	1.04	1.15

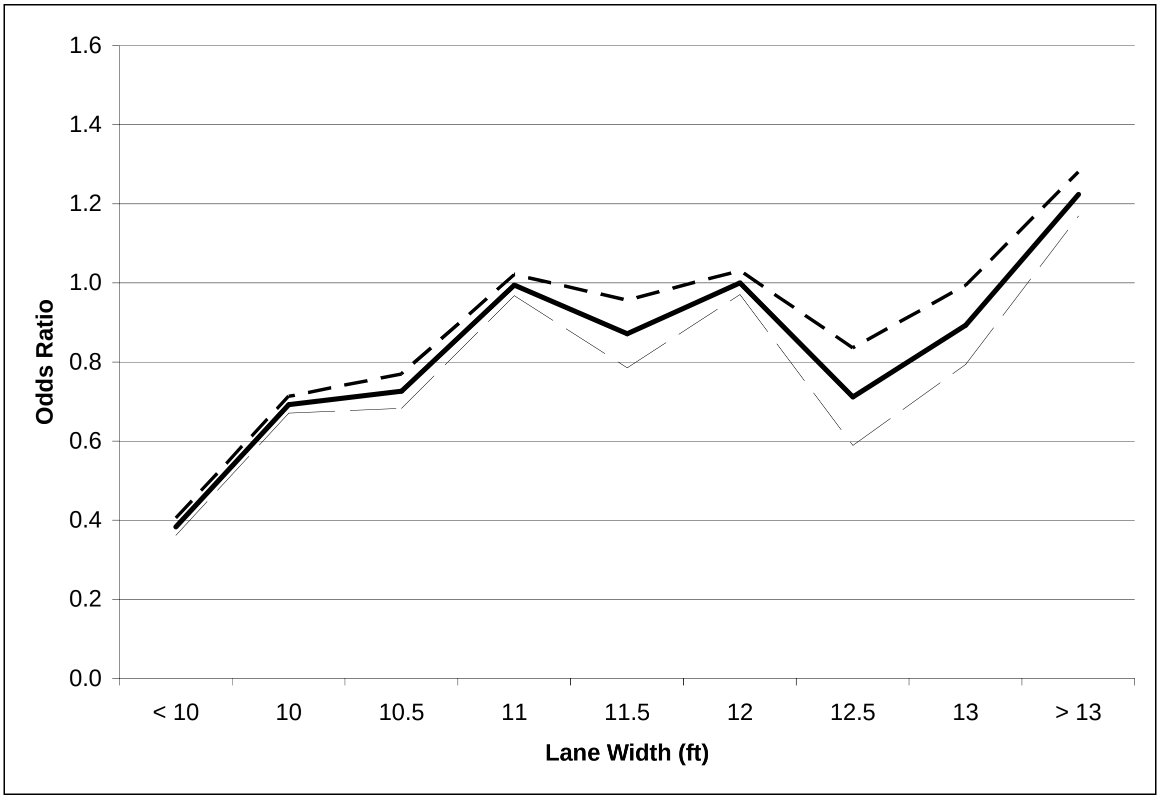

FIGURE 66 CMF for PA Base Model A: Lane Width Only

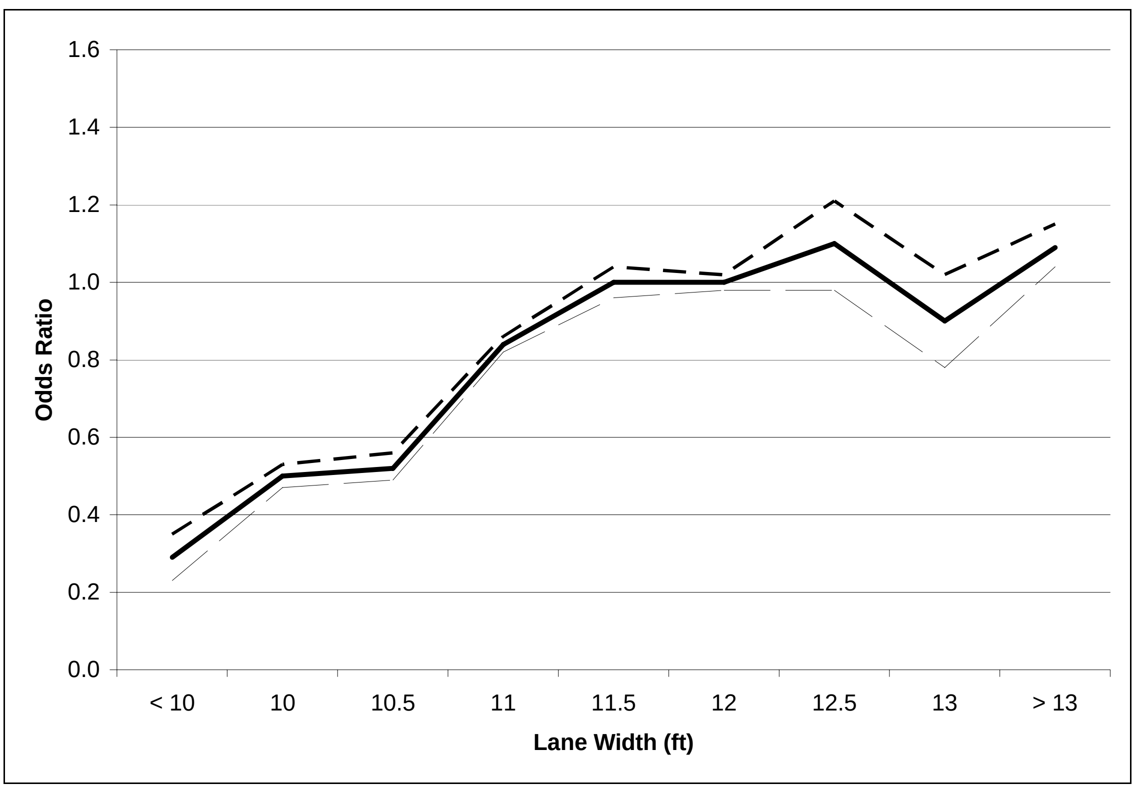

FIGURE 67 CMF for WA Base Model A: Lane Width Only

6.5.2 Enhanced Models with Adjustment for ADT, Speed and Segment Length

6.5.2.1 Cox Proportional Hazard Method

Estimated CMFs are presented for shoulder width (Figures 68 and 69) and lane width (Figures 70 and 71) for Pennsylvania and Washington, respectively. Detailed model results for PA Enhanced Model A and WA Enhanced Model A are shown in Appendix B.1. These cohort models represent the effect of shoulder width and lane width on crash risk after adjusting for the effects of ADT, speed and segment length. As discussed previously, there are no matching schemes in the cohort designs and adjustment for confounding is accomplished through covariates in the model. Hazard ratios (relative risk) and 95 percent confidence limits are presented for each shoulder width and lane width in comparison to a baseline six feet (shoulder width) and twelve feet (lane width).

Shoulder Width

A comparison of the shoulder width CMFs from the two states reveals significant differences. For Pennsylvania, the CMF indicates a general decrease in risk as shoulder width increases. On the other hand, the CMF for Washington is relatively flat, which indicates almost no change in crash risk as shoulder width increases. While the results for the two states are quite different, the estimates are very similar to the results from the corresponding case-control designs. There are slight variations in the estimates of relative risk from the cohort deigns and odds ratios from the case-control studies, but this may be due more to the fact that matching was used in the case-control design and not in the cohort design. The general shape of the CMF is comparable and the same trends are observed in the extremes. Zero foot shoulders are again less likely to experience a crash than one foot shoulders and nine foot shoulders are less likely to experience a crash than shoulders greater than nine feet.

It appears that the cohort study has a slight advantage over the case-control design after comparing results from the two methods. The CMF from the cohort study is much smoother and indicates a fairly steady decrease in risk as shoulder width increases. Confidence intervals are also much narrower from the cohort results. Smaller confidence intervals are an artifact of the design where matching was not used in the cohort study, which allowed for a larger sample size in the analysis. Another difference is that the case-control design produces estimates that are more pronounced.

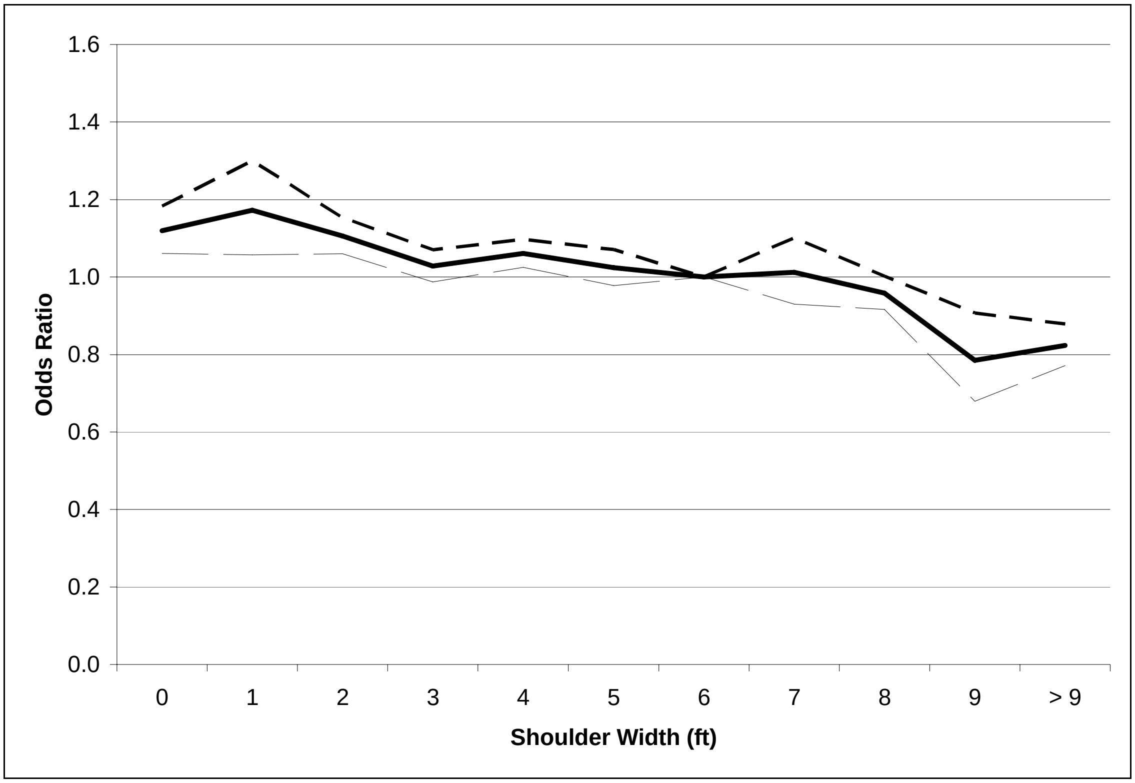

FIGURE 68 CMF for PA Enhanced Model A: Shoulder Width Adjusted for Lane Width, ADT, Speed and Segment Length

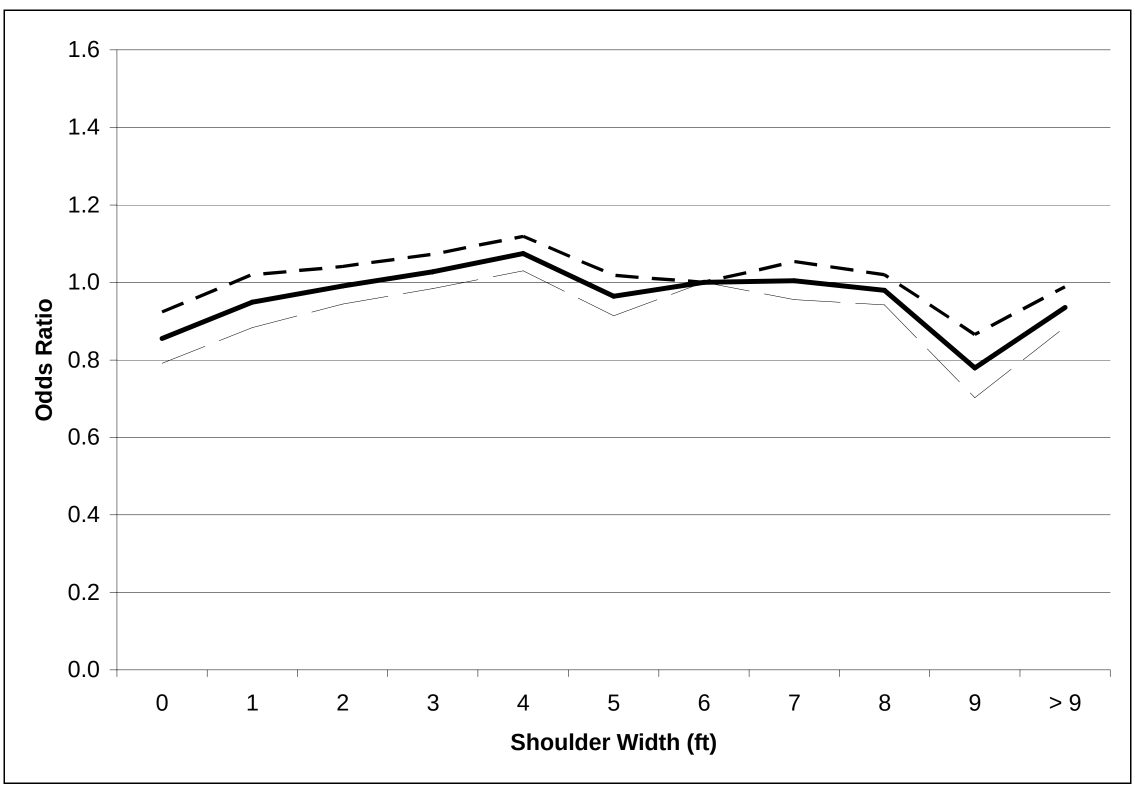

FIGURE 69 CMF for WA Enhanced Model A: Shoulder Width Adjusted for Lane Width, ADT, Speed and Segment Length

Lane Width

The enhanced models indicate a general decreasing crash risk as lane width increases. CMFs for the two states, however, are slightly different. Both states show a reduction in crash risk as lane width increases from 10.5 to 12.0 feet and both models show an increased risk for lanes greater than 12.5 feet. The crash risk for narrow lane widths is the major difference. For Pennsylvania, crash risk is less than one for narrow lane widths (< 10 feet) while the Washington model indicates elevated crash risks up to twelve feet. Confidence intervals are also different for the two states. The Washington model indicates greater variability for narrow (< 10.0 feet) and wide (> 12.0 feet) lane widths.

The CMF from Pennsylvania is again similar to the enhanced model from the case-control study, but the Washington models are slightly different. The general shape of the Pennsylvania CMF is almost identical, but the cohort design produces estimates that are closer to unity than the corresponding odds ratios from the case-control study. For Washington, the case-control model indicates a general increasing trend in crash risk as lane width increases; crash risk is less than one for narrow lane widths and increases above one for wider lanes. The Washington cohort model indicates a general decrease in risk; crash risk is greater than one for narrow lane widths and decreases as lane width increases from ten to twelve feet. Results for wider lanes are more similar between the cohort and case-control models; both indicate an increased risk for lane widths greater than twelve feet. While results for Pennsylvania are consistent when comparing the case-control and cohort methods, results are more intuitive for the Washington cohort model when compared to the case-control model.

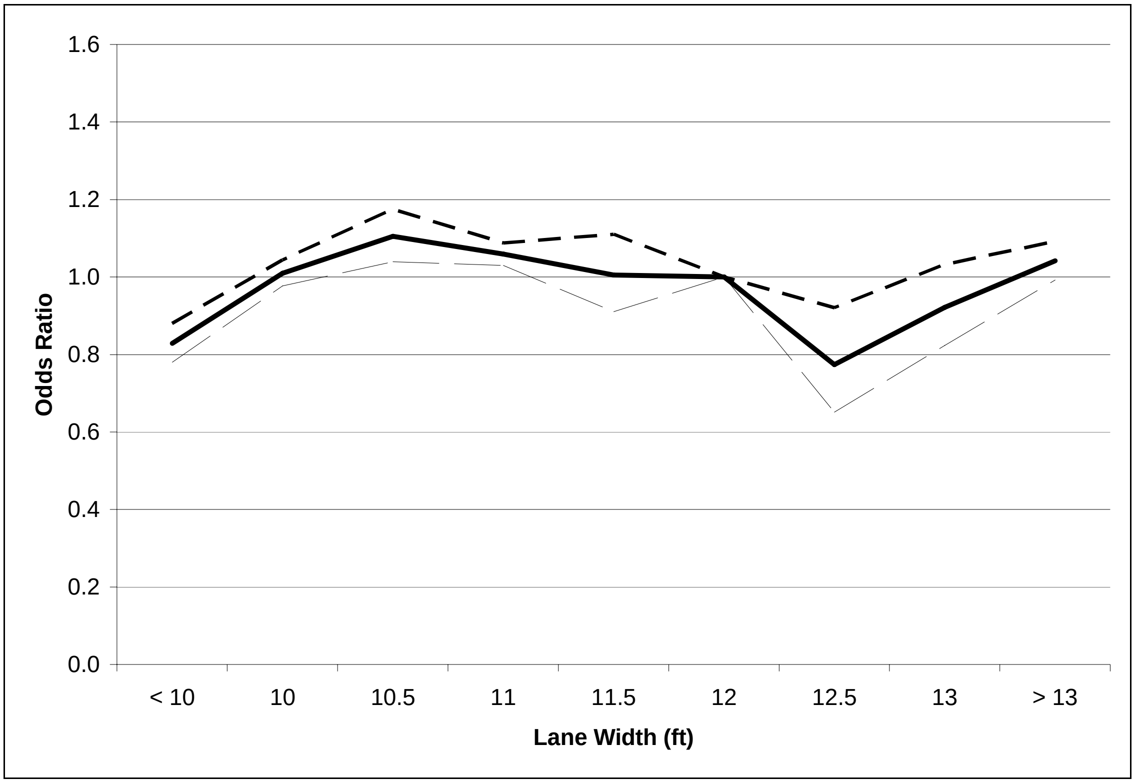

FIGURE 70 CMF for PA Enhanced Model A: Lane Width Adjusted for Shoulder Width, ADT, Speed and Segment Length

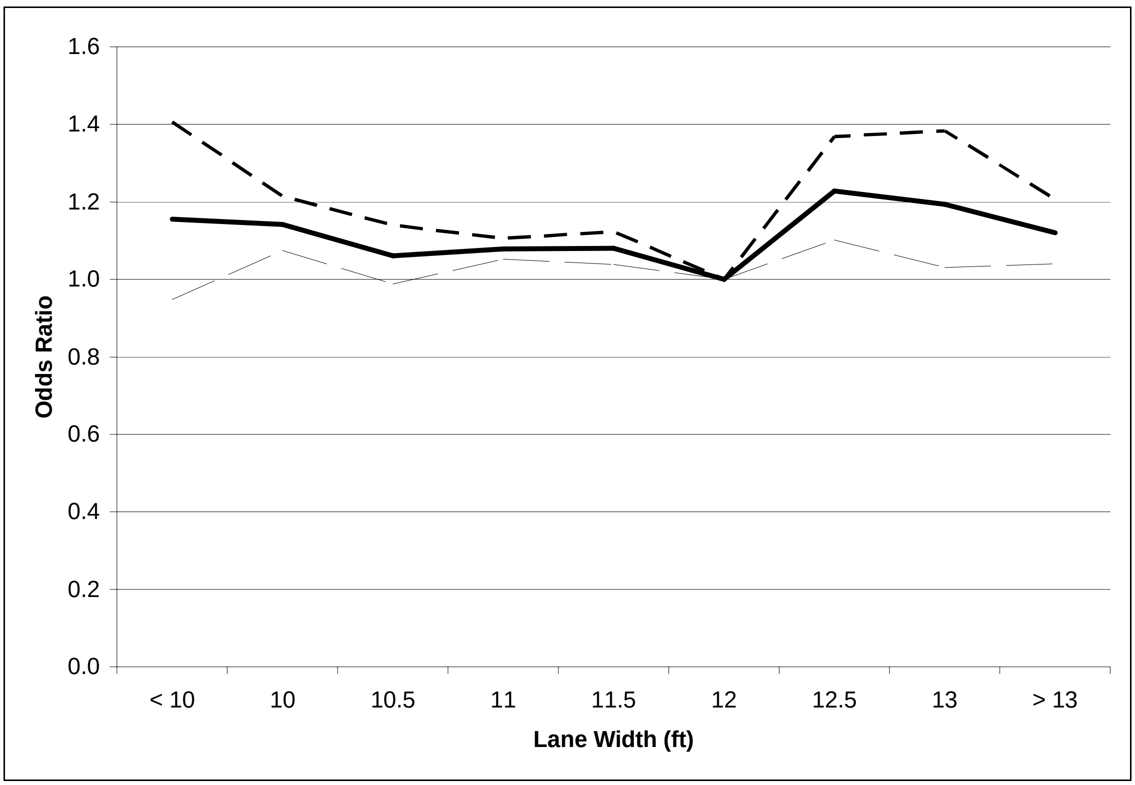

FIGURE 71 CMF for WA Enhanced Model A: Lane Width Adjusted for Shoulder Width, ADT, Speed and Segment Length

6.5.2.2 Negative Binomial Method

Count models were developed as an alternative to survival modeling and results are compared. Both Poisson and Negative Binomial regression models were developed to estimate the incident rate ratio (relative risk) for lane and shoulder width. The data, however, exhibit over-dispersion (alpha is highly significant with a p-value of 0.000) indicating the appropriateness of the Negative Binomial model rather than the Poisson.

Results from the Negative Binomial model (Enhanced Model B) are almost identical to those from the survival modeling. Estimated CMFs for shoulder width (Figures 72 and 73) and lane width (Figures 74 and 75) are presented for Pennsylvania and Washington. The CMFs from the survival analysis were discussed in the previous section and it suffices to say that interpretation remains the same. Detailed estimates from the lane and shoulder width models are presented in Appendix B.2.

FIGURE 72 CMF for PA Negative Binomial Model: Shoulder Width Adjusted for Lane Width, ADT, Speed and Segment Length

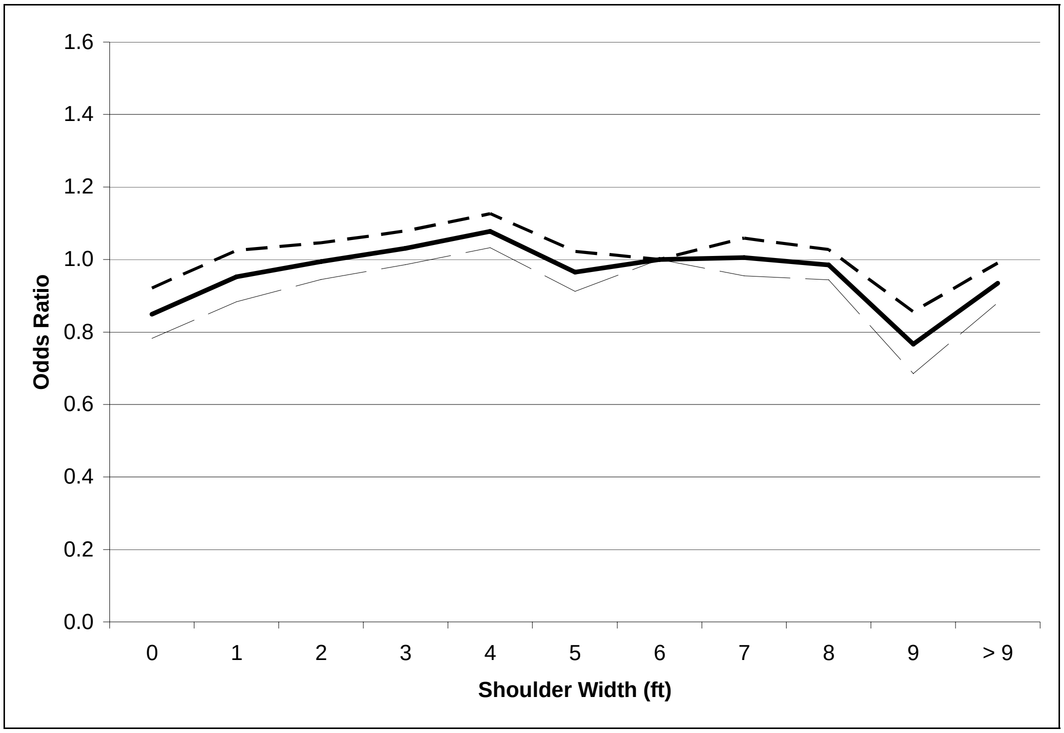

FIGURE 73 CMF for WA Negative Binomial Model: Shoulder Width Adjusted for Lane Width, ADT, Speed and Segment Length

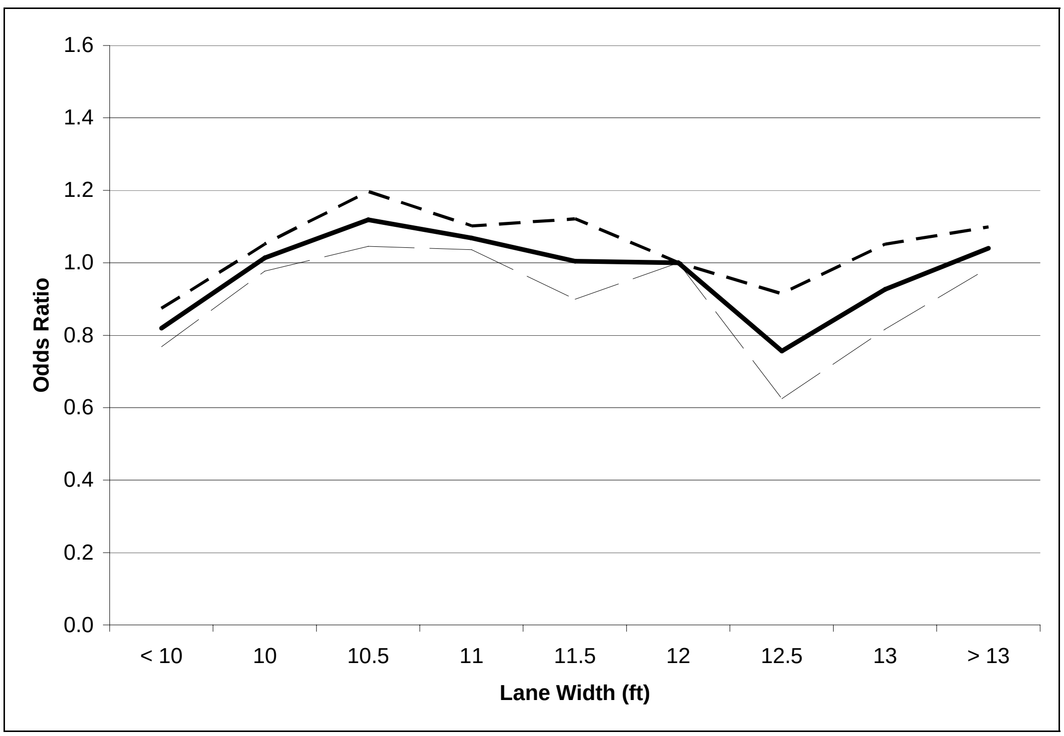

FIGURE 74 CMF for PA Negative Binomial Model: Lane Width Adjusted for Shoulder Width, ADT, Speed and Segment Length

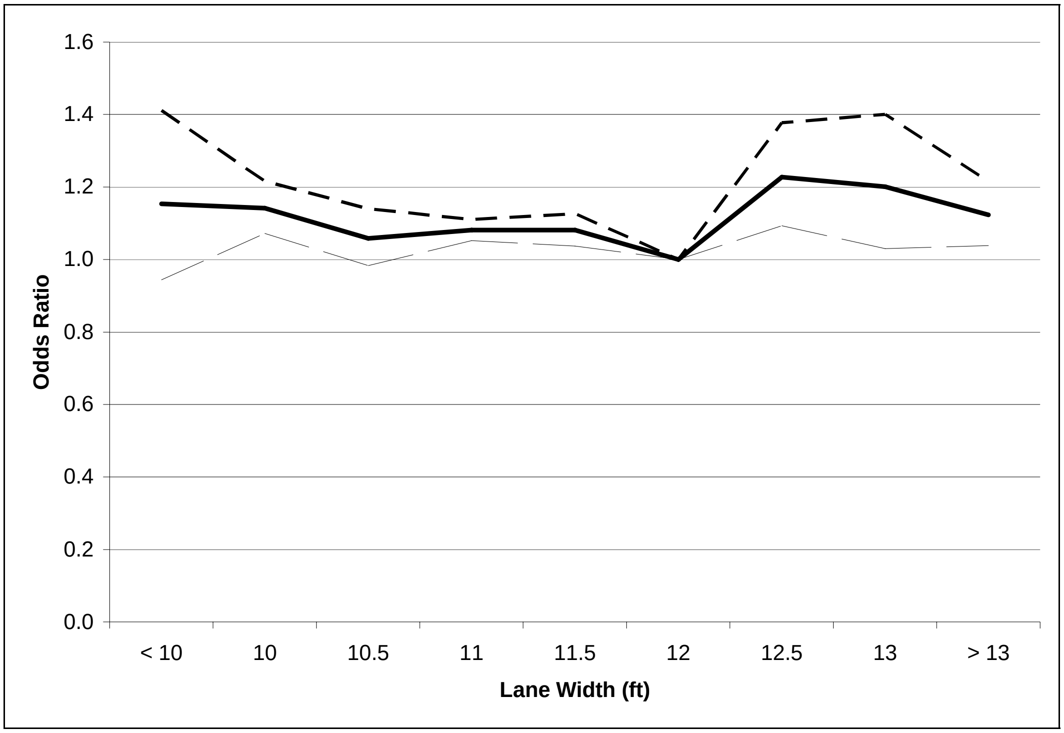

FIGURE 75 CMF for WA Negative Binomial Model: Lane Width Adjusted for Shoulder Width, ADT, Speed and Segment Length

6.5.3 Enhanced Models using Segment-Length-Days as Exposure

In this section, segment length is included as part of the measure of exposure. Models were re-estimated using segment-length-days as the response variable. Estimated CMFs and 95 percent confidence limits are presented for shoulder width (Figures 76 and 77) and lane width (Figures 78 and 79). Estimates were developed using Cox Proportional Hazard models and represent the effect of shoulder width and lane width on crash risk after adjusting for the effects of ADT, speed and segment length. Detailed model results for PA Enhanced Model A-1 and WA Enhanced Model A-1 are shown in Appendix B.3.

Coefficients and p-values are almost identical when comparing results from the alternative exposure models. The results are not discussed further as a detailed interpretation was presented in Section 6.5.2.1 for Enhanced Model A. It is sufficient to state that the measure of exposure (segment-days or segment-length-days) does not have a dramatic impact on the estimation of safety effectiveness for lane and shoulder width.

FIGURE 76 CMF for PA Cox Proportional Hazard Model: Shoulder Width Adjusted for Lane Width, ADT, Speed and Segment Length

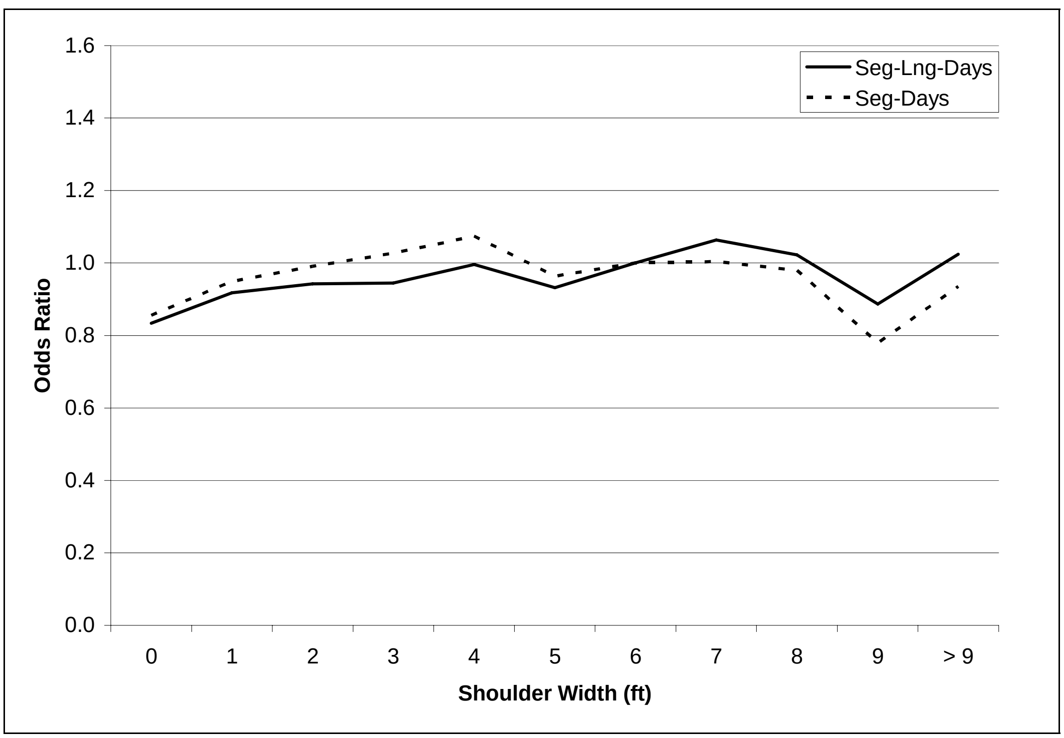

FIGURE 77 CMF for WA Cox Proportional Hazard Model: Shoulder Width Adjusted for Lane Width, ADT, Speed and Segment Length

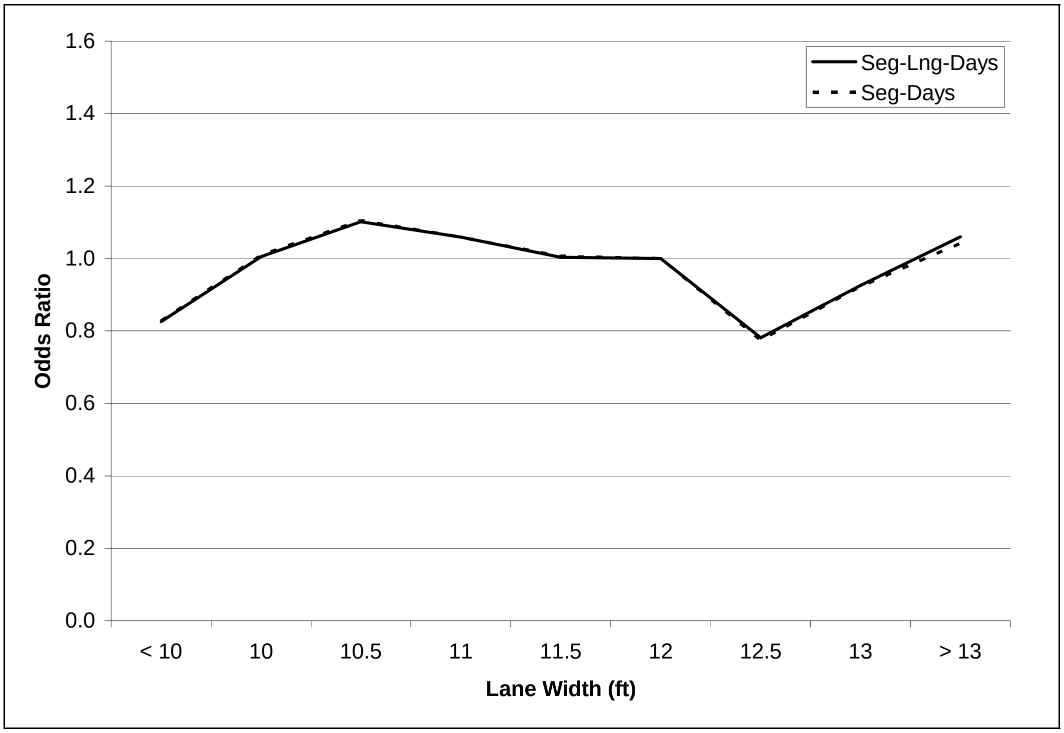

FIGURE 78 CMF for PA Cox Proportional Hazard Model: Lane Width Adjusted for Shoulder Width, ADT, Speed and Segment Length

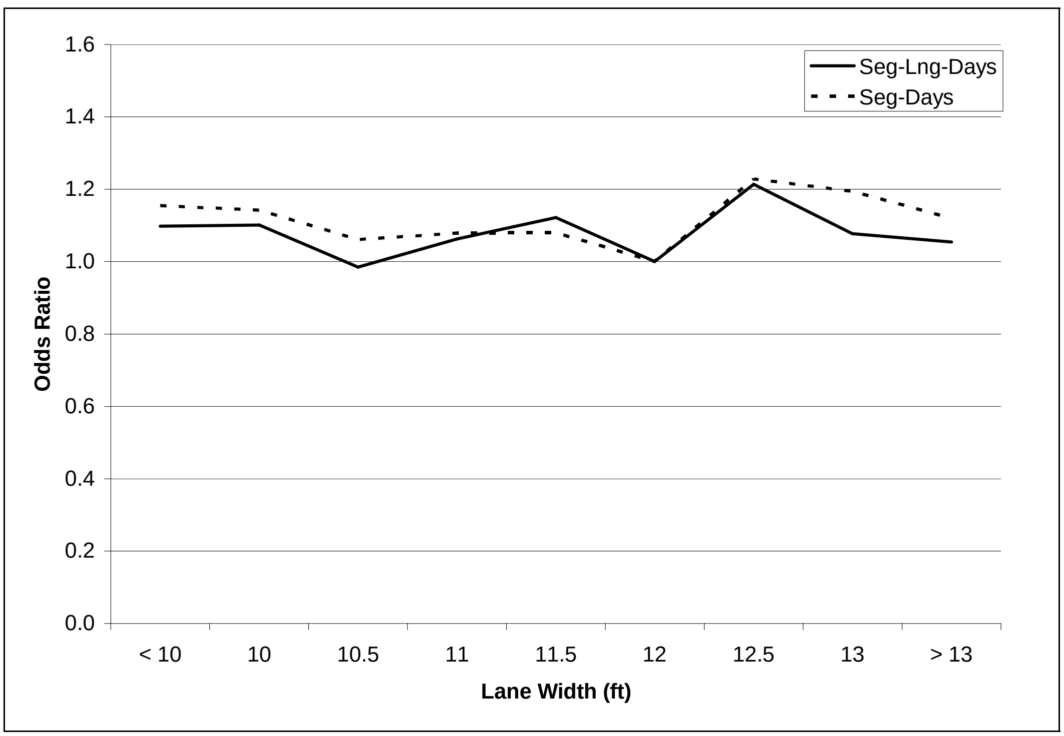

FIGURE 79 CMF for PA Cox Proportional Hazard Model: Lane Width Adjusted for Shoulder Width, ADT, Speed and Segment Length

6.5.4 Cohort Summary

Cohort methods were applied to roadway and crash data to estimate crash modification factors for lane and shoulder width while making adjustments for ADT, speed and segment length. Data from two different states were used to compare the consistency of results. The cohort analyses included an additional measure of exposure (time at risk) and results were compared to those obtained from the case-control analyses.

Results from the cohort models were consistent with those from the case-control models for both states. Based on the consistency of results, the cohort method also appears to be well suited for estimating the safety effectiveness of geometric design elements. This also indicates that the odds ratio from the case-control design may be a good approximation of relative risk for rural, two-lane roads. In general, cohort designs are more powerful than similar case-control designs because of the additional measure of exposure. Cohort studies are, however, often more expensive and time consuming, which limits the use of cohorts for practical purposes. For this application, geometric and crash data were as easy to obtain for the cohort as the case-control studies. Database set-up and data analysis were also faster for cohort than for case-control design because there was no matching involved. This resulted in a larger available sample for cohort analyses leading to smaller confidence intervals and smoother CMFs. While matching has potential advantages to control for confounding, results were consistent when covariates were used to make adjustments for confounding variables.

The relative risk of lane and shoulder width was estimated using survival models and count models. A comparison of the results indicated that survival and count models are appropriate for analyzing cohort data and produce consistent estimates of relative risk. The Cox Proportional Hazards model was evaluated and the proportionality assumption appears to hold. Negative Binomial models were identified as the appropriate type of count model because over-dispersion was present in the data.

Two different measures of exposure were finally evaluated (segment-days and segment-length-days). In the former model, segment length is included as a right-hand variable and time at risk is measured in days. The second measure of exposure combined segment length as part of the response variable and segment length was not included as a covariate. Results from the two models were nearly identical and either measure of exposure will produce similar estimates of relative risk. Segment-days, however, is the recommended measure of exposure because the effects of segment length may be estimated in the model.

6.6 Model Transferability and Validation

In the previous sections, several models were developed to estimate the safety effectiveness of lane and shoulder width. Data were obtained from Pennsylvania and Washington and the models were developed separately for each state. Results were compared in the previous sections and it was concluded that the safety effectiveness of lane and shoulder width may be different in Pennsylvania and Washington. It is appropriate, however, to conduct a formal test to determine if results are spatially transferable between states. Spatial transferability between states is desirable because it means that separate models are not necessary for each state, saving time and money.

Likelihood ratio tests are applied to test the spatial transferability of safety effectiveness models between Pennsylvania and Washington. Tests were conducted separately for the case-control and cohort models even though it was hypothesized that neither of the models would be transferable. The test statistic is given in Equation (32). The test statistic is chi-square distributed with degrees of freedom equal to the summation of the number of estimated parameters in all regional models minus the number of estimated parameters in the full model (Washington et al., 2003).

$$X^2 = -2[LL(\beta_F) - LL(\beta_P) - LL(\beta_W)] \; \ldots \; (32)$$

Where,

$LL(\beta_F)$ = Log-Likelihood from Full Model

$LL(\beta_P)$ = Log-Likelihood from Pennsylvania Model

$LL(\beta_W)$ = Log-Likelihood from Washington Model

The Pennsylvania and Washington datasets were combined and the full model was estimated. The effects of lane and shoulder width were estimated in the full model while adjusting for ADT, speed and segment length. Log-likelihoods are compared in Table 39 for the full model and similar models from the individual state databases. All three models included the same covariates.

TABLE 39 Test of Model Transferability

	Case-Control		Cohort	
	Log-Likelihood	Degrees of Freedom	Log-Likelihood	Degrees of Freedom
Full Model	-52,760.76	29	-912,601.94	29
PA Model	-30,046.93	29	-426,225.23	29
WA Model	-22,313.23	29	-434,906.95	29
Test Statistic	801.20		102,939.52	
χ^2 (29, 0.05)	42.6		42.6	
Conclusion	Reject H_o		Reject H_o	

The null hypothesis (H_o) is that the parameters are transferable between states. In both the case-control and cohort models, the test statistic is much higher than the critical chi-square value with 29 degrees of freedom. Therefore, the null hypothesis is rejected at a 0.05 level of significance and it is concluded that the models are not transferable between Pennsylvania and Washington.

There may be several explanations why the estimates of safety effectiveness from the two states are not transferable. First, the test of transferability assumes that the models are specified correctly. Lack of control for additional confounding variables would violate this assumption. Potential confounding variables such as roadside hazard rating should be evaluated before the models are deemed non-transferable. In addition, the databases were created differently for Pennsylvania and Washington. Roadway segments in Pennsylvania were divided into homogeneous sections without accounting for horizontal and vertical curvature. The Washington database was also divided into homogeneous segments, but segments were further divided for each change in curvature and grade. The difference in the definition of homogeneous segments resulted in very different distributions of segment length; Pennsylvania segments are relatively longer than Washington segments. The mean segment length in Pennsylvania is about 0.5 miles while the mean segment length in Washington is closer to 0.1 miles. Finally, the crash reporting threshold is different between the two states, which could lead to different estimates of safety effectiveness. In Pennsylvania, crashes are reported when a vehicle has to be towed from the scene. In Washington, the reporting threshold is \$500 or personal injury. While the initial results indicate that the models are not transferable, several issues should be considered before making any definitive conclusions.

The final step in the model building process is model validation. Model validation involves checking the model against independent data to determine is the estimates are stable. Typical methods to validate a model include collection of new data, comparison with theoretical expectations, and use of a split sample (Neter et al., 1996). The preferred method for validation is the collection of new data; however, it is not usually practical or feasible to collect another sample. Comparison with theoretical expectations is also difficult because there is often little theory that can be used to validate models. A split sample is an alternative to collecting new data, but may only be used when the sample size is large enough to split the data into two sets. The datasets for Pennsylvania and Washington are relatively large and allow for the use of the split sample method. The Pennsylvania dataset is used to validate the PA Enhanced Model B from Section 6.4.2.2.

The concept of the split sample is similar to that of model transferability, but now the models are being compared within the same dataset. The dataset is split randomly in half and separate models are estimated for each of the subsets. Estimates from the subset models are then compared to the full model using the test for model transferability in Equation (32). If the models are transferable then it can be concluded that the estimates are stable and the model is validated.

Log-likelihoods are compared in Table 40 for the full model and subset models for PA Enhanced Model B. All three models included the same covariates. The null hypothesis (H_o) is that the parameters are transferable between the two subset models. The test statistic is less than the critical chi-square value with 29 degrees of freedom. Therefore, the null hypothesis is not rejected at a 0.05 level of significance and it is concluded that the model estimates are transferable. Transferability of the model estimates indicates that the models are stable and valid.

TABLE 40 Model Validation

	PA Enhanced Model B	
	Log-Likelihood	Degrees of Freedom
Full Model	-30046.928	29
Subset Model 1	-15030.654	29
Subset Model 2	-15002.722	29
Test Statistic	27.1	
χ^2 (29, 0.05)	42.6	
Conclusion	Fail to Reject H_o	

6.7 Discussion

In general, the results from the case-control and cohort studies are similar to the CMFs presented in the Highway Safety Manual. There were, however, variations in the extremes for the lane width models. In some instances, narrow lane widths (less than 10 feet) were shown to provide improved safety benefits. In addition, there was an apparent U-shaped trend in crash risk for wider lanes; crash risk decreased up to a certain point and then began to increase as lane width continued to increase. Several factors may help to explain the contradictory results observed for narrow lane widths (less than 10 feet) and wide lane widths (greater than 12 feet).

Extremely narrow and wide lanes are uncommon on two-lane, rural roads and data records were spot-checked using Penn DOT video logs to verify the proper coding of lane widths. Three different types of wide segments were observed in the video logs. In the first case, lane widths were measured accurately and there was simply a wide cross-section with no center or edge lines and zero foot shoulders. In the second case, segments were miscoded as "undivided" where the video logs show a painted median that was included as part of the lane width measurement. Finally, some segments were miscoded as "two-lane" where there was a two-way left-turn lane that was included as part of the lane width measurement. Narrow lane widths were observed less often than wide lane widths and appeared to be coded correctly for almost all of the observed cases. In rare instances, the width of one lane was recorded as the total surface width; however, the majority of narrow segments were observed in extremely rural areas where there was a paved cross-section with no center or edge lines. All segments were included in the analysis, but additional analyses should systematically identify outliers and remove them from the dataset.

The observed decrease in crash risk for narrow lanes may reflect reporting issues associated with their location. Narrow lanes were observed mostly in rural areas where crashes that do occur may be less likely to be reported. Under-reporting of crashes would result in a perceived safety benefit. Human factor issues could also affect the safety effectiveness of lane and shoulder width. On narrow cross-sections, drivers may adapt their driving style to the more demanding environment (e.g. heightened alertness or lower speeds). In the other extreme, drivers may feel more secure and increase speeds or become more careless when traveling on relatively wide cross-sections. While miscoding, under-reporting, and human factor issues may help to explain the odd results in the extremes, it is likely that additional confounding variables are also responsible in part.

Another possible explanation for the differences in the results is related to the fact that several studies were aggregated by an expert panel to develop CMFs for the Highway Safety Manual. The reviewed studies were based on data from Kentucky and Texas, and may not be appropriate for estimating safety effectiveness in Pennsylvania and Washington. A discussion of model transferability was provided in Section 6.6, suggesting that models of safety effectiveness are not transferable between Pennsylvania and Washington. Limitations of the previous studies were also discussed and addressed as part of this research. Estimates from the enhanced case-control and cohort models may therefore be more accurate representations of the safety effectiveness for lane and shoulder width in Pennsylvania and Washington. The comparison of results to the Highway Safety Manual should only be used to determine if the models are reasonable.

Results in the extremes should not, however, be automatically dismissed as anomalies. There were several studies identified in the literature review that also showed a U-shaped trend in crash risk for wide lane widths. Four studies indicated that lane widths of 11 feet are associated with the lowest crash risk on rural, two-lane highways (Belmont, 1954; Dart and Mann, 1970; Roy Jorgensen Associates, 1978; Zegeer et al., 1981). Head (1960), indicated that narrow lane widths are expected to improve safety. While many of these studies have been criticized for lack of control for confounding variables, it is important to consider the realm of possibilities.

CHAPTER VII CONCLUSIONS

Case-control and cohort methods were applied to roadway and crash data to estimate crash modification factors for lane width and shoulder width. In an empirical example, data from Pennsylvania and Washington were used to test the adequacy of the methods and evaluate appropriate analytic procedures. A thorough analysis of several potential confounding variables identified ADT, speed and segment length as critical confounders when estimating CMFs for lane and shoulder width. Horizontal curvature and vertical curvature were relatively insignificant and did not improve the estimates. This is not to say that other variables will not significantly affect the estimation of CMFs, but the purpose of this research was not to exhaust the list of potential confounders.

Results from the base case-control and cohort models were counterintuitive. The base models were not adjusted for confounding variables, and the estimated CMFs for lane and shoulder width were inconsistent with those presented in the Highway Safety Manual. These models illustrate the danger of not controlling for potential confounders.

Enhanced models were developed to adjust for ADT, speed, and segment length. Results from the enhanced models were more intuitive and better matched the crash modification factors provided in the Highway Safety Manual. These findings were consistent for both the case-control and cohort designs. The enhanced Pennsylvania and Washington models both indicated a general decrease in crash risk as lane and shoulder width increase. Results from the Pennsylvania models, however, were more consistent with the Highway Safety Manual, showing a more pronounced effect for lane and shoulder width than the Washington models.

The cohort models were compared to the corresponding case-control models for both states. Results were consistent for both methods indicating that the odds ratio from the case-control design may be a good approximation of relative risk for rural, two-lane roads. Typically, the case-control method is less expensive and time consuming than the cohort method although not as powerful. The cohort design, however, proved to be less time consuming for this highway safety application because there was no matching of cases and controls. The cohort design was, therefore, able to utilize more data, which resulted in narrower confidence intervals.

Several additional models were developed using the case-control and cohort approaches. Case-control models were estimated using a subset of the Pennsylvania crashes. These models were based on “related” crash types and results were nearly identical to those presented in the

Highway Safety Manual. This lends support to the credibility of the case-control methods for estimating CMFs for lane and shoulder width. Models were also developed using multinomial logistic regression and results indicated that lane and shoulder width have differential effects on segments with various crash frequencies. In general, lane and shoulder width were shown to have more pronounced effects as crash frequency increased. Two different modeling approaches were used to estimate relative risk from the cohort studies; survival models and count models. A comparison of the results indicated that survival models and count models produced consistent estimates. While both survival and count models may be used, the Negative Binomial model was identified as the appropriate type of count model because over-dispersion was present in the data. Finally, two different measures of exposure were evaluated in the cohort designs (i.e. segment-days and segment-length-days). Results from the two models were nearly identical. Segment-days, however, is the recommended measure of exposure because the effects of segment length may be estimated in the model.

Based on the consistency of results from this investigation, the case-control and cohort methods appear to be well suited for estimating CMFs for lane and shoulder width. An advantage of the case-control design is the efficient use of matching to account for potential confounding variables. The cohort method provides the option to include some measure of time at risk, thus strengthening the evidence of a causal relationship between risk factor and outcome. Both approaches also provide an estimation of confidence intervals around the model estimates. The variability in safety effectiveness is thus conveyed to the analyst and is useful to show a range of potential values when estimating benefit-cost ratios. Confidence intervals are currently not available for the CMFs in the Highway Safety Manual.

CHAPTER VIII DIRECTIONS FOR FURTURE RESEARCH

Results from the case-control and cohort analyses appear to be reasonable when compared to the CMFs presented in the Highway Safety Manual. The models, however, were not transferable between Pennsylvania and Washington. This indicates that a single CMF may not be appropriate across states or that additional confounding variables need to be included in the analysis. These issues will require further exploration with additional data. The Highway Safety Information System (HSIS) contains various roadway and crash data for several states. HSIS data provide an opportunity to validate results and consider additional variables in the matching scheme. It may also be beneficial to repeat this experiment for different segments with different roadway classification in which the CMFs are "known" or at least accepted. These additional tests will help support or refute the utility of the methods.

The matched case-control design presents a uniquely powerful method to control for confounders. It would be interesting to include county or district as variables in the matching scheme to account for regional differences that are otherwise unobserved. Some have argued that regional differences such as winter maintenance practices and driver populations may have a significant impact on crash prediction models. Intensive data collection would be required to evaluate the effects of winter maintenance and driver populations because current databases are lacking this information. Matching by county or district may be an alternative method to account for regional differences without the additional data collection.

There is a need to create similar datasets for Pennsylvania and Washington. In this case, Pennsylvania segments are divided into homogeneous sections without accounting for horizontal and vertical curvature. The Washington database also includes homogeneous segments, but segments are further divided for each change in curvature and grade. The difference in definitions of homogeneous segments results in very different distributions of segment length; Pennsylvania segments are relatively longer than Washington segments. The mean segment length in Pennsylvania is about 0.5 miles while the mean segment length in Washington is closer to 0.1 miles. This may be one reason for the difference in results between the two states; however, further investigation is needed to make any definitive statements.

Horizontal curvature and vertical curvature were shown to have minimal impact on the estimated CMFs for lane and shoulder width. These data are not available in the Pennsylvania roadway inventory file and do not exist for several states in the HSIS database. Results, however, may be adequate without adjusting for curvature and grade. This hypothesis should be tested further in other states where curvature and grade information are readily available.

Direction of travel could not be established within either of the accident databases. This would be critical information to obtain when lane or shoulder width are not consistent in both directions of travel. This issue was addressed briefly in this research by removing any segments with inconsistent lane and shoulder width. The reduced models were compared to the full models and results were consistent. In future studies, this issue should be addressed more thoroughly by obtaining the direction of travel for crash-involved drivers and associating each crash with the appropriate geometric characteristics.

Roadside hazard data are also currently lacking from state databases. Roadside hazards do not necessarily cause a vehicle to run-off the road, but increase the likelihood of a crash given a roadway departure. Several studies have included a roadside hazard rating and show that it is a significant predictor of crash frequency. Roadside hazard rating may also be associated with lane and shoulder width because higher-type facilities often provide more forgiving roadsides. Therefore, roadside hazards may confound the effects of lane and shoulder width. This information is not currently available and requires intensive data collection efforts to code the relative hazard of each roadway segment. Future research could focus on a small sample to evaluate roadside hazard as a confounder using the case-control and cohort methods. If the initial analysis indicates that the variable substantially influences the estimated safety effects of lane and shoulder width, a larger sample of roadside hazard data may need to be obtained.

A review of the Penn DOT video logs indicated several instances where data were miscoded for narrow and wide lane widths. Manual collection of lane and shoulder width is one possible solution to ensure accurate data; however, this is extremely time consuming and often not practical. Future research should focus on database reliability and work towards a standard method for data collection and coding. In the meantime, outliers should be checked to reduce the amount of miscoded data.

An economic evaluation is often the end result of a safety analysis comparing alternative roadway designs. This requires knowledge of both the cost to implement treatments and the expected benefits. The cost to implement countermeasures or treatments is often known or readily available. The case-control and cohort models provide estimates of the expected reduction in total crashes, however, it is necessary to estimate the effects of lane and shoulder width on individual crash types and severities. A treatment may not have the same effect across crash types and severities. This is important to estimate because there are also different costs associated with each crash type and severity. It is obvious that a reduction in fatal crashes is more beneficial than the same reduction in property-damage crashes. The question remains whether a reduction in one crash type or severity is justifiable given an increase in others. Multinomial models also indicated that lane and shoulder width have differential effects on segments with different crash frequencies. This issue deserves further exploration to determine if separate CMFs are necessary for segments with higher expected crash frequencies.

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APPENDIX A Model Estimates for Case-Control Analyses

A.1 Enhanced Models Adjusted for ADT and Speed (Matching)

PA Enhanced Model A

Width (ft)	Odds Ratio	SE	z	P-value	Lower	Upper
Shoulder Width						
0	1.029	0.039	0.770	0.443	0.956	1.108
1	1.256	0.089	3.230	0.001	1.094	1.443
2	1.204	0.034	6.640	0.000	1.140	1.272
3	1.019	0.027	0.700	0.481	0.967	1.074
4	1.082	0.025	3.390	0.001	1.034	1.133
5	0.998	0.031	-0.080	0.940	0.938	1.061
6	1.000	*	*	*	1.000	1.000
7	0.972	0.058	-0.480	0.631	0.865	1.092
8	0.915	0.029	-2.850	0.004	0.860	0.973
9	0.651	0.064	-4.360	0.000	0.537	0.790
> 9	0.712	0.031	-7.870	0.000	0.654	0.775
Lane Width						
< 10	0.836	0.032	-4.630	0.000	0.775	0.902
10.0	1.109	0.024	4.770	0.000	1.063	1.157
10.5	1.251	0.052	5.420	0.000	1.154	1.357
11.0	1.163	0.022	8.120	0.000	1.121	1.206
11.5	1.086	0.073	1.220	0.221	0.951	1.240
12.0	1.000	*	*	*	1.000	1.000
12.5	0.720	0.080	-2.950	0.003	0.578	0.896
13.0	0.859	0.066	-1.990	0.047	0.739	0.998
>13	0.925	0.032	-2.250	0.025	0.865	0.990

WA Enhanced Model A

Width (ft)	Odds Ratio	SE	z	P-value	Lower	Upper
Shoulder Width						
0	0.745	0.035	-6.360	0.000	0.680	0.815
1	0.989	0.047	-0.240	0.808	0.901	1.085
2	0.952	0.030	-1.540	0.122	0.894	1.013
3	0.922	0.025	-2.960	0.003	0.874	0.973
4	0.942	0.024	-2.300	0.021	0.895	0.991
5	0.880	0.030	-3.780	0.000	0.823	0.940
6	1.000	*	*	*	1.000	1.000
7	1.016	0.031	0.530	0.599	0.957	1.079
8	1.011	0.025	0.450	0.655	0.963	1.061
9	0.832	0.051	-3.020	0.002	0.739	0.937
> 9	1.037	0.035	1.070	0.283	0.970	1.108
Lane Width						
< 10	0.757	0.120	-1.760	0.078	0.556	1.032
10.0	1.001	0.041	0.020	0.986	0.923	1.085
10.5	0.975	0.045	-0.550	0.582	0.890	1.067
11.0	1.070	0.017	4.260	0.000	1.037	1.104
11.5	1.101	0.028	3.830	0.000	1.048	1.156
12.0	1.000	*	*	*	1.000	1.000
12.5	1.408	0.104	4.640	0.000	1.219	1.627
13.0	1.355	0.120	3.440	0.001	1.140	1.612
>13	1.151	0.051	3.170	0.002	1.055	1.256

A.2 Enhanced Models Adjusted for ADT and Speed (Matching) and Segment Length (Covariate)

PA Enhanced Model B

Width (ft)	Odds Ratio	SE	z	P-value	Lower	Upper
Shoulder Width						
0	1.210	0.048	4.820	0.000	1.120	1.308
1	1.193	0.088	2.400	0.017	1.033	1.377
2	1.194	0.035	6.120	0.000	1.128	1.264
3	1.027	0.029	0.950	0.344	0.972	1.084
4	1.061	0.026	2.460	0.014	1.012	1.113
5	1.003	0.033	0.100	0.923	0.941	1.069
6	1.000	*	*	*	1.000	1.000
7	0.941	0.058	-0.980	0.325	0.834	1.062
8	0.947	0.031	-1.670	0.096	0.889	1.010
9	0.679	0.069	-3.810	0.000	0.556	0.828
> 9	0.723	0.032	-7.220	0.000	0.662	0.790
Lane Width						
< 10	0.798	0.032	-5.640	0.000	0.737	0.863
10.0	1.060	0.024	2.610	0.009	1.015	1.108
10.5	1.201	0.051	4.290	0.000	1.105	1.306
11.0	1.139	0.022	6.730	0.000	1.097	1.183
11.5	1.044	0.073	0.610	0.540	0.910	1.198
12.0	1.000	*	*	*	1.000	1.000
12.5	0.700	0.082	-3.040	0.002	0.556	0.881
13.0	0.848	0.068	-2.050	0.041	0.724	0.993
>13	1.094	0.040	2.450	0.014	1.018	1.175
Segment Length						
< 1320’	*	*	*	*	*	*
1320’~1980’	2.249	0.097	18.760	0.000	2.066	2.447
1980’~2640’	3.233	0.131	28.990	0.000	2.986	3.500
2640’~3300’	4.532	0.186	36.760	0.000	4.181	4.913
3300’~3960’	6.360	0.278	42.330	0.000	5.838	6.929
≥ 3960’	7.564	0.856	17.880	0.000	6.059	9.443

WA Enhanced Model B

Width (ft)	Odds Ratio	SE	z	P-value	Lower	Upper
Shoulder Width						
0	0.795	0.038	-4.790	0.000	0.724	0.873
1	0.974	0.049	-0.530	0.598	0.883	1.075
2	0.970	0.033	-0.900	0.368	0.908	1.036
3	1.014	0.029	0.480	0.634	0.958	1.073
4	1.032	0.028	1.140	0.254	0.978	1.088
5	0.918	0.033	-2.420	0.015	0.856	0.984
6	1.000	*	*	*	1.000	1.000
7	0.950	0.031	-1.570	0.116	0.891	1.013
8	0.977	0.025	-0.900	0.366	0.928	1.028
9	0.740	0.048	-4.620	0.000	0.651	0.841
> 9	0.949	0.034	-1.460	0.144	0.885	1.018
Lane Width						
< 10	0.742	0.124	-1.780	0.074	0.535	1.030
10.0	1.006	0.044	0.130	0.898	0.923	1.095
10.5	0.973	0.048	-0.570	0.570	0.884	1.071
11.0	1.073	0.018	4.210	0.000	1.038	1.109
11.5	1.063	0.028	2.310	0.021	1.009	1.120
12.0	1.000	*	*	*	1.000	1.000
12.5	1.339	0.104	3.750	0.000	1.150	1.560
13.0	1.399	0.127	3.690	0.000	1.170	1.672
>13	1.204	0.055	4.080	0.000	1.101	1.316
Segment Length						
< 1320’	*	*	*	*	*	*
1320’~1980’	3.823	0.126	40.650	0.000	3.584	4.078
1980’~2640’	5.444	0.315	29.320	0.000	4.861	6.097
2640’~3300’	8.149	0.771	22.180	0.000	6.770	9.808
3300’~3960’	10.461	1.421	17.290	0.000	8.016	13.651
≥ 3960’	15.152	1.911	21.560	0.000	11.834	19.400

A.3 Enhanced Models Adjusted for ADT, Speed, and Horizontal Curvature (Matching)

WA Enhanced Model C

Width (ft)	Odds Ratio	SE	z	P-value	Lower	Upper
Shoulder Width						
0	0.745	0.034	-6.520	0.000	0.682	0.814
1	1.091	0.051	1.850	0.065	0.995	1.196
2	0.978	0.031	-0.710	0.477	0.920	1.040
3	0.992	0.027	-0.310	0.754	0.940	1.046
4	0.970	0.025	-1.180	0.236	0.922	1.020
5	0.906	0.030	-2.960	0.003	0.849	0.967
6	1.000	*	*	*	1.000	1.000
7	1.084	0.033	2.630	0.008	1.021	1.151
8	1.044	0.025	1.750	0.080	0.995	1.095
9	0.891	0.053	-1.920	0.055	0.793	1.002
> 9	1.050	0.035	1.450	0.148	0.983	1.120
Lane Width						
< 10	0.659	0.098	-2.810	0.005	0.492	0.881
10.0	0.940	0.038	-1.540	0.124	0.868	1.017
10.5	0.970	0.045	-0.670	0.504	0.886	1.062
11.0	1.043	0.016	2.680	0.007	1.011	1.076
11.5	1.085	0.027	3.280	0.001	1.034	1.140
12.0	1.000	*	*	*	1.000	1.000
12.5	1.204	0.086	2.610	0.009	1.047	1.385
13.0	1.328	0.112	3.360	0.001	1.125	1.568
>13	1.143	0.049	3.080	0.002	1.050	1.244

A.4 Enhanced Models Adjusted for ADT, Speed, and Vertical Curvature (Matching)

WA Enhanced Model D

Width (ft)	Odds Ratio	SE	z	P-value	Lower	Upper
Shoulder Width						
0	0.753	0.034	-6.260	0.000	0.690	0.823
1	1.012	0.047	0.250	0.804	0.923	1.109
2	0.953	0.030	-1.540	0.123	0.896	1.013
3	0.948	0.026	-1.980	0.047	0.898	0.999
4	0.951	0.024	-1.960	0.050	0.904	1.000
5	0.895	0.030	-3.320	0.001	0.839	0.956
6	1.000	*	*	*	1.000	1.000
7	1.099	0.034	3.090	0.002	1.035	1.167
8	1.032	0.025	1.280	0.202	0.984	1.082
9	0.929	0.056	-1.230	0.218	0.826	1.045
> 9	1.031	0.034	0.920	0.357	0.966	1.100
Lane Width						
< 10	0.677	0.101	-2.610	0.009	0.505	0.907
10.0	0.997	0.040	-0.070	0.942	0.921	1.080
10.5	1.012	0.047	0.260	0.793	0.925	1.108
11.0	1.080	0.017	4.900	0.000	1.047	1.113
11.5	1.085	0.027	3.290	0.001	1.034	1.139
12.0	1.000	*	*	*	1.000	1.000
12.5	1.331	0.097	3.930	0.000	1.154	1.536
13.0	1.422	0.120	4.170	0.000	1.205	1.677
>13	1.274	0.055	5.600	0.000	1.170	1.386

A.5 Case-Control Matching versus Covariate Schemes for ADT and Speed

PA Enhanced Model A versus Enhanced Model A-1

Width (ft)	PA Enhanced Model A ADT and Speed (Matching)			PA Enhanced Model A-1 ADT and Speed (Covariate)		
	Odds Ratio	SE	P-value	Odds Ratio	SE	P-value
Shoulder Width						
0	1.029	0.039	0.443	1.069	0.041	0.079
1	1.256	0.089	0.001	1.305	0.088	0.000
2	1.204	0.034	0.000	1.209	0.034	0.000
3	1.019	0.027	0.481	1.050	0.029	0.077
4	1.082	0.025	0.001	1.117	0.027	0.000
5	0.998	0.031	0.940	1.026	0.033	0.419
6	1.000	*	*	1.000	*	*
7	0.972	0.058	0.631	1.047	0.064	0.452
8	0.915	0.029	0.004	0.910	0.029	0.003
9	0.651	0.064	0.000	0.608	0.063	0.000
> 9	0.712	0.031	0.000	0.721	0.032	0.000
Lane Width						
< 10	0.836	0.032	0.000	0.814	0.030	0.000
10.0	1.109	0.024	0.000	1.072	0.024	0.002
10.5	1.251	0.052	0.000	1.179	0.048	0.000
11.0	1.163	0.022	0.000	1.116	0.021	0.000
11.5	1.086	0.073	0.221	1.076	0.073	0.281
12.0	1.000	*	*	1.000	*	*
12.5	0.720	0.080	0.003	0.688	0.079	0.001
13.0	0.859	0.066	0.047	0.836	0.063	0.017
>13	0.925	0.032	0.025	0.907	0.032	0.005
Cube Root of Average Daily Traffic ($ADT^{1/3}$)						
< 5.6	NA	NA	NA	*	*	*
5.6 ~10.0	NA	NA	NA	2.502	0.307	0.000
10.0~14.4	NA	NA	NA	7.038	0.861	0.000
14.4~18.8	NA	NA	NA	14.577	1.793	0.000
18.8~23.2	NA	NA	NA	31.203	3.885	0.000
≥ 23.2	NA	NA	NA	78.410	10.423	0.000
Speed	NA	NA	NA	0.843	0.012	0.000

A.6 Case-Control Matching versus Covariate Schemes for Segment Length

PA Enhanced Model B versus Enhanced Model B-1

Width (ft)	PA Enhanced Model B Segment Length (Covariate)			PA Enhanced Model B-1 Segment Length (Matching)		
	Odds Ratio	SE	P-value	Odds Ratio	SE	P-value
Shoulder Width						
0	1.261	0.050	0.000	1.257	0.050	0.000
1	1.272	0.089	0.001	1.283	0.095	0.001
2	1.198	0.035	0.000	1.197	0.035	0.000
3	1.041	0.030	0.156	1.023	0.028	0.415
4	1.100	0.027	0.000	1.077	0.026	0.002
5	1.034	0.034	0.313	1.040	0.033	0.222
6	1.000	*	*	1.000	*	*
7	0.990	0.063	0.874	0.999	0.063	0.983
8	0.935	0.031	0.042	0.960	0.031	0.203
9	0.675	0.071	0.000	0.657	0.067	0.000
> 9	0.733	0.033	0.000	0.726	0.032	0.000
Lane Width						
< 10	0.776	0.030	0.000	0.809	0.032	0.000
10.0	1.027	0.023	0.237	1.027	0.023	0.239
10.5	1.118	0.047	0.008	1.144	0.048	0.001
11.0	1.095	0.022	0.000	1.106	0.021	0.000
11.5	1.073	0.075	0.314	1.027	0.069	0.698
12.0	1.000	*	*	1.000	*	*
12.5	0.667	0.079	0.001	0.725	0.084	0.005
13.0	0.841	0.066	0.028	0.852	0.068	0.044
>13	1.066	0.039	0.081	1.107	0.040	0.005
Segment Length (ft)						
< 1320’	*	*	*	NA	NA	NA
1320’~1980’	2.195	0.092	0.000	NA	NA	NA
1980’~2640’	3.126	0.123	0.000	NA	NA	NA
2640’~3300’	4.369	0.174	0.000	NA	NA	NA
3300’~3960’	5.969	0.253	0.000	NA	NA	NA
≥ 3960’	7.408	0.815	0.000	NA	NA	NA

A.7 Case-Control Matching versus Covariate Schemes for Horizontal Curvature

WA Enhanced Model C versus Model C-1

Width (ft)	WA Enhanced Model C Horizontal Curvature (Covariate)			WA Enhanced Model C-1 Horizontal Curvature (Matching)		
	Odds Ratio	SE	P-value	Odds Ratio	SE	P-value
Shoulder Width						
0	0.679	0.040	0.000	0.745	0.034	0.000
1	0.939	0.046	0.196	1.091	0.051	0.065
2	0.909	0.032	0.007	0.978	0.031	0.477
3	0.896	0.029	0.001	0.992	0.027	0.754
4	0.954	0.030	0.142	0.970	0.025	0.236
5	0.882	0.036	0.002	0.906	0.030	0.003
6	1.000	*	*	1.000	*	*
7	1.030	0.040	0.448	1.084	0.033	0.008
8	1.009	0.032	0.769	1.044	0.025	0.080
9	0.920	0.077	0.319	0.891	0.053	0.055
> 9	1.029	0.047	0.524	1.050	0.035	0.148
Lane Width						
< 10	0.815	0.113	0.141	0.659	0.098	0.005
10.0	1.000	0.044	0.993	0.940	0.038	0.124
10.5	1.025	0.052	0.624	0.970	0.045	0.504
11.0	1.084	0.021	0.000	1.043	0.016	0.007
11.5	1.172	0.036	0.000	1.085	0.027	0.001
12.0	1.000	*	*	1.000	*	*
12.5	1.208	0.108	0.034	1.204	0.086	0.009
13.0	1.044	0.110	0.686	1.328	0.112	0.001
>13	1.174	0.070	0.007	1.143	0.049	0.002
Horizontal Curvature						
Present	0.732	0.013	0.000	NA	NA	NA

A.8 Case-Control Matching versus Covariate Schemes for Vertical Curvature

WA Enhanced Model D versus Model D-1

	WA Enhanced Model D Vertical Curvature (Covariate)			WA Enhanced Model D-1 Vertical Curvature (Matching)		
Width (ft)	Odds Ratio	SE	P-value	Odds Ratio	SE	P-value
Shoulder Width						
0	0.697	0.041	0.000	0.753	0.034	0.000
1	0.948	0.046	0.277	1.012	0.047	0.804
2	0.916	0.033	0.014	0.953	0.030	0.123
3	0.897	0.029	0.001	0.948	0.026	0.047
4	0.955	0.03	0.145	0.951	0.024	0.050
5	0.897	0.037	0.008	0.895	0.030	0.001
6	1.000	*	*	1.000	*	*
7	1.05	0.04	0.204	1.099	0.034	0.002
8	1.027	0.033	0.407	1.032	0.025	0.202
9	0.927	0.077	0.359	0.929	0.056	0.218
> 9	1.051	0.048	0.273	1.031	0.034	0.357
Lane Width						
< 10	0.8	0.111	0.107	0.677	0.101	0.009
10.0	1.013	0.044	0.762	0.997	0.040	0.942
10.5	1.023	0.052	0.649	1.012	0.047	0.793
11.0	1.091	0.021	0	1.080	0.017	0.000
11.5	1.188	0.036	0	1.085	0.027	0.001
12.0	1.000	*	*	1.000	*	*
12.5	1.24	0.11	0.015	1.331	0.097	0.000
13.0	1.085	0.114	0.437	1.422	0.120	0.000
>13	1.216	0.072	0.001	1.274	0.055	0.000
Vertical Curvature						
Present	0.992	0.018	0.643	NA	NA	NA

A.9 Related Crash Model compared to Total Crash Model Adjusting for ADT, Speed and Segment Length

PA Related-Crashes Model A versus PA Enhanced Model B

Width (ft)	PA Enhanced Model B All Crash Types			PA Related-Crash Model A Related Crash Types			CMF from Highway Safety Manual
	Odds Ratio	SE	P-value	Odds Ratio	SE	P-value	
Shoulder Width							
0	1.095	0.055	0.070	1.210	0.048	0.000	1.50
1	1.245	0.107	0.010	1.193	0.088	0.017	1.40
2	1.312	0.046	0.000	1.194	0.035	0.000	1.30
3	1.093	0.037	0.009	1.027	0.029	0.344	1.23
4	1.108	0.033	0.001	1.061	0.026	0.014	1.15
5	1.015	0.041	0.711	1.003	0.033	0.923	1.08
6	1.000	*	*	1.000	*	*	1.00
7	0.960	0.075	0.602	0.941	0.058	0.325	0.94
8	0.925	0.039	0.061	0.947	0.031	0.096	0.87
9	0.687	0.088	0.003	0.679	0.069	0.000	0.87
> 9	0.640	0.038	0.000	0.723	0.032	0.000	0.87
Lane Width							
< 10	0.857	0.040	0.001	0.798	0.032	0.000	1.50
10.0	1.175	0.032	0.000	1.060	0.024	0.009	1.30
10.5	1.293	0.066	0.000	1.201	0.051	0.000	1.18
11.0	1.204	0.029	0.000	1.139	0.022	0.000	1.05
11.5	1.118	0.095	0.191	1.044	0.073	0.540	1.03
12.0	1.000	*	*	1.000	*	*	1.00
12.5	0.847	0.120	0.240	0.700	0.082	0.002	1.00
13.0	0.871	0.089	0.178	0.848	0.068	0.041	1.00
>13	0.973	0.047	0.571	1.094	0.040	0.014	1.00
Segment Length							
< 1320’	*	*	*	*	*	*	*
1320’~1980’	2.222	0.123	0.000	2.249	0.097	0.000	*
1980’~2640’	3.426	0.178	0.000	3.233	0.131	0.000	*
2640’~3300’	4.641	0.245	0.000	4.532	0.186	0.000	*
3300’~3960’	6.642	0.370	0.000	6.360	0.278	0.000	*
≥ 3960’	8.516	1.201	0.000	7.564	0.856	0.000	*

Note: CMFs from the HSM are based on segments with ADT greater than 2000 vehicles per day

A.10 Multinomial Logit Models Adjusted for ADT, Speed and Segment Length

PA Ordinal Model A (1 Crash compared to 0 Crashes)

Width (ft)	Odds Ratio	SE	Z	P-value	95% Limits	
					Lower	Upper
Shoulder Width						
0	1.132	0.054	2.600	0.009	1.031	1.242
1	1.156	0.093	1.810	0.071	0.988	1.352
2	1.053	0.036	1.510	0.131	0.985	1.127
3	1.016	0.034	0.470	0.640	0.951	1.085
4	1.080	0.032	2.630	0.009	1.020	1.145
5	1.047	0.041	1.180	0.236	0.970	1.131
6	1.000	*	*	*	1.000	1.000
7	0.980	0.075	-0.270	0.790	0.843	1.139
8	0.949	0.038	-1.310	0.191	0.878	1.026
9	0.827	0.096	-1.640	0.102	0.659	1.038
> 9	0.798	0.043	-4.150	0.000	0.718	0.888
Lane Width						
< 10	0.821	0.035	-4.600	0.000	0.755	0.893
10.0	0.996	0.027	-0.150	0.877	0.945	1.050
10.5	1.138	0.055	2.670	0.007	1.035	1.252
11.0	1.076	0.025	3.110	0.002	1.028	1.127
11.5	0.964	0.079	-0.450	0.656	0.820	1.133
12.0	1.000	*	*	*	1.000	1.000
12.5	0.791	0.105	-1.760	0.079	0.610	1.027
13.0	0.829	0.078	-1.980	0.047	0.689	0.998
>13	1.095	0.048	2.050	0.040	1.004	1.193
Segment Length (ft)						
< 1320	*	*	*	*	*	*
1320 ~ 1980	1.680	0.079	11.080	0.000	1.533	1.842
1980 ~ 2640	2.177	0.094	17.950	0.000	2.000	2.370
2640 ~ 3300	2.653	0.117	22.070	0.000	2.433	2.893
3300 ~ 3960	3.165	0.150	24.270	0.000	2.884	3.474
≥ 3960	3.230	0.438	8.640	0.000	2.476	4.214

PA Ordinal Model A (2 Crashes compared to 0 Crashes)

Width (ft)	Odds Ratio	SE	Z	P-value	95% Limits	
					Lower	Upper
Shoulder Width						
0	1.212	0.083	2.820	0.005	1.060	1.385
1	1.176	0.158	1.210	0.227	0.904	1.530
2	1.105	0.059	1.880	0.060	0.996	1.226
3	1.040	0.052	0.780	0.436	0.942	1.148
4	1.022	0.044	0.500	0.614	0.939	1.112
5	0.979	0.056	-0.360	0.717	0.875	1.096
6	1.000	*	*	*	1.000	1.000
7	1.013	0.108	0.120	0.904	0.822	1.248
8	0.884	0.050	-2.180	0.029	0.791	0.987
9	0.570	0.107	-3.000	0.003	0.395	0.823
> 9	0.698	0.057	-4.430	0.000	0.595	0.818
Lane Width						
< 10	0.707	0.059	-4.140	0.000	0.600	0.833
10.0	1.031	0.043	0.730	0.468	0.950	1.118
10.5	1.164	0.093	1.910	0.057	0.996	1.360
11.0	1.112	0.038	3.080	0.002	1.040	1.190
11.5	0.978	0.123	-0.180	0.857	0.764	1.251
12.0	1.000	*	*	*	1.000	1.000
12.5	0.465	0.114	-3.120	0.002	0.287	0.752
13.0	0.822	0.116	-1.390	0.164	0.624	1.083
>13	1.008	0.062	0.130	0.899	0.893	1.137
Segment Length (ft)						
< 1320	*	*	*	*	*	*
1320 ~ 1980	2.378	0.211	9.760	0.000	1.998	2.830
1980 ~ 2640	3.549	0.297	15.160	0.000	3.013	4.181
2640 ~ 3300	5.093	0.429	19.340	0.000	4.319	6.007
3300 ~ 3960	6.976	0.609	22.260	0.000	5.880	8.278
≥ 3960	7.187	1.344	10.550	0.000	4.982	10.367

PA Ordinal Model A (3+ Crashes compared to 0 Crashes)

Width (ft)	Odds Ratio	SE	Z	P-value	95% Limits	
					Lower	Upper
Shoulder Width						
0	1.419	0.129	3.850	0.000	1.187	1.696
1	1.351	0.278	1.460	0.143	0.903	2.020
2	1.820	0.132	8.260	0.000	1.579	2.097
3	1.136	0.083	1.750	0.081	0.984	1.311
4	1.254	0.074	3.810	0.000	1.116	1.408
5	1.091	0.085	1.110	0.267	0.936	1.272
6	1.000	*	*	*	1.000	1.000
7	1.175	0.155	1.230	0.220	0.908	1.521
8	0.999	0.073	-0.020	0.987	0.866	1.152
9	0.330	0.103	-3.550	0.000	0.179	0.608
> 9	0.752	0.083	-2.590	0.009	0.606	0.933
Lane Width						
< 10	0.663	0.094	-2.910	0.004	0.503	0.874
10.0	1.018	0.060	0.300	0.767	0.907	1.142
10.5	1.138	0.141	1.050	0.295	0.893	1.451
11.0	1.107	0.051	2.230	0.026	1.012	1.211
11.5	1.150	0.185	0.870	0.385	0.839	1.577
12.0	1.000	*	*	*	1.000	1.000
12.5	0.489	0.153	-2.290	0.022	0.265	0.902
13.0	0.818	0.149	-1.110	0.269	0.573	1.168
>13	0.998	0.075	-0.020	0.981	0.862	1.156
Segment Length (ft)						
< 1320	*	*	*	*	*	*
1320 ~ 1980	5.697	1.102	9.000	0.000	3.900	8.323
1980 ~ 2640	10.527	1.972	12.570	0.000	7.292	15.195
2640 ~ 3300	20.661	3.868	16.180	0.000	14.316	29.818
3300 ~ 3960	34.689	6.562	18.750	0.000	23.943	50.258
≥ 3960	42.868	11.036	14.600	0.000	25.882	71.002

A.11 Base Models Adjusted for ADT, Speed and Segment Length (Covariates)

PA Base Model A

Width (ft)	Odds Ratio	SE	z	P-value	Lower	Upper
Shoulder Width						
0	1.261	0.050	5.830	0.000	1.167	1.364
1	1.272	0.089	3.440	0.001	1.109	1.459
2	1.198	0.035	6.220	0.000	1.132	1.269
3	1.041	0.030	1.420	0.156	0.985	1.101
4	1.100	0.027	3.850	0.000	1.048	1.154
5	1.034	0.034	1.010	0.313	0.969	1.103
6	1.000	*	*	*	1.000	1.000
7	0.990	0.063	-0.160	0.874	0.875	1.121
8	0.935	0.031	-2.040	0.042	0.876	0.998
9	0.675	0.071	-3.740	0.000	0.550	0.829
> 9	0.733	0.033	-6.840	0.000	0.671	0.801
Lane Width						
< 10	0.776	0.030	-6.660	0.000	0.720	0.836
10.0	1.027	0.023	1.180	0.237	0.982	1.074
10.5	1.118	0.047	2.670	0.008	1.030	1.214
11.0	1.095	0.022	4.580	0.000	1.053	1.138
11.5	1.073	0.075	1.010	0.314	0.936	1.229
12.0	1.000	*	*	*	1.000	1.000
12.5	0.667	0.079	-3.420	0.001	0.528	0.841
13.0	0.841	0.066	-2.200	0.028	0.721	0.982
>13	1.066	0.039	1.740	0.081	0.992	1.145
Cube Root of Average Daily Traffic ($ADT^{1/3}$)						
< 5.6	*	*	*	*	*	*
5.6 ~10.0	2.624	0.326	7.760	0.000	2.056	3.348
10.0~14.4	7.250	0.899	15.970	0.000	5.685	9.246
14.4~18.8	15.191	1.895	21.810	0.000	11.896	19.399
18.8~23.2	32.696	4.131	27.600	0.000	25.524	41.884
≥ 23.2	76.105	10.273	32.090	0.000	58.413	99.154
Speed (mph)						
< 50	*	*	*	*	*	*
≥ 50	0.815	0.012	-13.720	0.000	0.792	0.839
Segment Length (ft)						
< 1320	*	*	*	*	*	*
1320~1980	2.195	0.092	18.730	0.000	2.022	2.383
1980~2640	3.126	0.123	29.020	0.000	2.894	3.376
2640~3300	4.369	0.174	36.970	0.000	4.040	4.724
3300~3960	5.969	0.253	42.150	0.000	5.493	6.486
≥ 3960	7.408	0.815	18.200	0.000	5.971	9.191

WA Base Model A

Width (ft)	Odds Ratio	SE	z	P-value	Lower	Upper
Shoulder Width						
0	0.766	0.047	-4.360	0.000	0.679	0.860
1	0.961	0.050	-0.780	0.438	0.868	1.060
2	0.956	0.036	-1.210	0.227	0.889	1.030
3	1.003	0.034	0.080	0.933	0.938	1.070
4	1.048	0.035	1.420	0.155	0.982	1.120
5	0.958	0.041	-0.990	0.320	0.881	1.040
6	1.000	*	*	*	1.000	1.000
7	0.967	0.039	-0.840	0.398	0.893	1.050
8	0.994	0.033	-0.190	0.846	0.931	1.060
9	0.750	0.065	-3.300	0.001	0.632	0.890
> 9	0.945	0.045	-1.200	0.232	0.861	1.040
Lane Width						
< 10	0.837	0.121	-1.230	0.220	0.630	1.110
10.0	1.002	0.046	0.050	0.957	0.916	1.100
10.5	1.027	0.055	0.500	0.619	0.924	1.140
11.0	1.097	0.022	4.570	0.000	1.055	1.140
11.5	1.133	0.036	3.960	0.000	1.065	1.210
12.0	1.000	*	*	*	1.000	1.000
12.5	1.202	0.113	1.960	0.050	1.000	1.450
13.0	1.127	0.123	1.100	0.273	0.910	1.400
>13	1.255	0.077	3.700	0.000	1.113	1.410
Cube Root of Average Daily Traffic ($ADT^{1/3}$)						
< 5.6	*	*	*	*	*	*
5.6 ~10.0	4.791	3.553	2.110	0.035	1.120	20.500
10.0~14.4	15.899	11.780	3.730	0.000	3.721	67.930
14.4~18.8	46.365	34.359	5.180	0.000	10.850	198.140
18.8~23.2	92.440	68.522	6.110	0.000	21.622	395.200
≥ 23.2	250.413	185.733	7.450	0.000	58.522	1071.510
Speed (mph)						
< 50	*	*	*	*	*	*
≥ 50	1.152	0.026	6.240	0.000	1.102	1.200
Segment Length (ft)						
< 1320	*	*	*	*	*	*
1320~1980	3.564	0.133	34.030	0.000	3.313	3.840
1980~2640	4.733	0.288	25.550	0.000	4.201	5.330
2640~3300	9.271	0.902	22.880	0.000	7.661	11.220
3300~3960	9.335	1.308	15.940	0.000	7.092	12.290
≥ 3960	17.349	1.939	25.530	0.000	13.936	21.600

APPENDIX B Model Estimates for Cohort Analyses

B.1 Survival Models Adjusted for ADT, Speed, and Segment Length (Covariates)

PA Enhanced Model A

Width (ft)	Hazard Ratio	SE	Z	P-value	95% Limits	
					Lower	Upper
Shoulder Width						
0	1.120	0.031	4.080	0.000	1.061	1.182
1	1.172	0.062	3.010	0.003	1.057	1.300
2	1.106	0.024	4.700	0.000	1.060	1.153
3	1.028	0.021	1.360	0.174	0.988	1.071
4	1.060	0.019	3.350	0.001	1.025	1.097
5	1.024	0.024	1.010	0.312	0.978	1.071
6	1.000	*	*	*	1.000	1.000
7	1.012	0.044	0.270	0.786	0.930	1.101
8	0.958	0.022	-1.870	0.062	0.916	1.002
9	0.785	0.058	-3.290	0.001	0.679	0.907
> 9	0.823	0.027	-5.850	0.000	0.772	0.879
Lane Width						
< 10	0.828	0.026	-6.080	0.000	0.780	0.880
10.0	1.010	0.017	0.570	0.571	0.977	1.043
10.5	1.105	0.035	3.190	0.001	1.039	1.175
11.0	1.059	0.015	4.090	0.000	1.030	1.088
11.5	1.006	0.051	0.110	0.913	0.911	1.110
12.0	1.000	*	*	*	1.000	1.000
12.5	0.774	0.068	-2.900	0.004	0.651	0.921
13.0	0.922	0.053	-1.400	0.160	0.823	1.033
>13	1.042	0.025	1.660	0.096	0.993	1.093
Cube Root of Average Daily Traffic ($ADT^{1/3}$)						
< 5.6	*	*	*	*	*	*
5.6 ~10.0	2.321	0.272	7.180	0.000	1.844	2.920
10.0~14.4	5.058	0.590	13.890	0.000	4.024	6.359
14.4~18.8	8.180	0.957	17.970	0.000	6.504	10.288
18.8~23.2	12.629	1.485	21.570	0.000	10.030	15.902
≥ 23.2	18.183	2.182	24.170	0.000	14.372	23.004
Speed (mph)						
< 50	*	*	*	*	*	*
≥ 50	0.878	0.009	-12.100	0.000	0.860	0.897
Segment Length (ft)						
< 1320	*	*	*	*	*	*
1320 ~ 1980	1.750	0.060	16.320	0.000	1.636	1.871
1980 ~ 2640	2.258	0.072	25.430	0.000	2.121	2.405
2640 ~ 3300	2.808	0.091	31.970	0.000	2.635	2.991
3300 ~ 3960	3.384	0.114	36.340	0.000	3.169	3.614
≥ 3960	3.879	0.279	18.870	0.000	3.370	4.466

WA Enhanced Model A

Width (ft)	Hazard Ratio	SE	Z	P-value	95% Limits Lower	95% Limits Upper
Shoulder Width						
0	0.855	0.034	-3.980	0.000	0.791	0.923
1	0.949	0.035	-1.430	0.152	0.883	1.020
2	0.991	0.025	-0.350	0.725	0.944	1.041
3	1.027	0.023	1.230	0.219	0.984	1.073
4	1.074	0.023	3.380	0.001	1.030	1.119
5	0.964	0.027	-1.310	0.190	0.914	1.018
6	1.000	*	*	*	1.000	1.000
7	1.004	0.025	0.160	0.875	0.956	1.054
8	0.980	0.020	-0.980	0.325	0.942	1.020
9	0.779	0.042	-4.690	0.000	0.702	0.865
> 9	0.935	0.026	-2.390	0.017	0.885	0.988
Lane Width						
< 10	1.155	0.116	1.430	0.153	0.948	1.406
10.0	1.142	0.036	4.260	0.000	1.074	1.214
10.5	1.061	0.039	1.630	0.102	0.988	1.140
11.0	1.079	0.014	5.900	0.000	1.052	1.106
11.5	1.080	0.022	3.850	0.000	1.038	1.123
12.0	1.000	*	*	*	1.000	1.000
12.5	1.228	0.068	3.710	0.000	1.102	1.369
13.0	1.194	0.089	2.370	0.018	1.031	1.383
>13	1.120	0.042	3.000	0.003	1.040	1.206
Cube Root of Average Daily Traffic ($ADT^{1/3}$)						
< 5.6	*	*	*	*	*	*
5.6 ~10.0	6.612	4.681	2.670	0.008	1.651	26.485
10.0~14.4	18.706	13.234	4.140	0.000	4.675	74.848
14.4~18.8	44.553	31.521	5.370	0.000	11.134	178.276
18.8~23.2	71.572	50.641	6.040	0.000	17.885	286.423
≥ 23.2	129.458	91.606	6.870	0.000	32.345	518.144
Speed (mph)						
< 50	*	*	*	*	*	*
≥ 50	1.031	0.015	2.130	0.033	1.003	1.061
Segment Length (ft)						
< 1320	*	*	*	*	*	*
1320 ~ 1980	3.048	0.056	60.280	0.000	2.940	3.161
1980 ~ 2640	3.921	0.111	48.450	0.000	3.710	4.144
2640 ~ 3300	5.791	0.223	45.640	0.000	5.370	6.244
3300 ~ 3960	6.104	0.312	35.430	0.000	5.523	6.746
≥ 3960	9.646	0.353	61.990	0.000	8.979	10.363

B.2 Negative Binomial Models Adjusted for ADT, Speed, and Segment Length (Covariates)

PA Enhanced Model B

Width (ft)	Incidence Rate Ratio	SE	Z	P-value	95% Limits Lower	95% Limits Upper
Shoulder Width						
0	1.133	0.035	4.000	0.000	1.066	1.205
1	1.180	0.069	2.850	0.004	1.053	1.322
2	1.111	0.026	4.460	0.000	1.061	1.164
3	1.032	0.024	1.380	0.167	0.987	1.079
4	1.066	0.021	3.240	0.001	1.025	1.107
5	1.019	0.027	0.710	0.480	0.968	1.072
6	1.000	*	*	*	1.000	1.000
7	1.024	0.050	0.480	0.631	0.930	1.127
8	0.954	0.025	-1.840	0.066	0.906	1.003
9	0.762	0.062	-3.320	0.001	0.649	0.895
> 9	0.802	0.030	-5.980	0.000	0.746	0.862
Lane Width						
< 10	0.819	0.027	-6.030	0.000	0.768	0.874
10.0	1.014	0.019	0.730	0.467	0.977	1.051
10.5	1.119	0.039	3.250	0.001	1.046	1.197
11.0	1.068	0.017	4.220	0.000	1.036	1.102
11.5	1.004	0.056	0.070	0.942	0.899	1.121
12.0	1.000	*	*	*	1.000	1.000
12.5	0.756	0.073	-2.880	0.004	0.625	0.915
13.0	0.927	0.060	-1.180	0.237	0.816	1.052
>13	1.041	0.029	1.430	0.153	0.985	1.099
Cube Root of Average Daily Traffic ($ADT^{1/3}$)						
< 5.6	*	*	*	*	*	*
5.6 ~10.0	2.376	0.283	7.260	0.000	1.881	3.002
10.0~14.4	5.434	0.646	14.240	0.000	4.305	6.859
14.4~18.8	9.242	1.103	18.640	0.000	7.315	11.677
18.8~23.2	15.147	1.822	22.590	0.000	11.965	19.175
≥ 23.2	23.155	2.872	25.330	0.000	18.158	29.527
Speed (mph)						
< 50	*	*	*	*	*	*
≥ 50	0.867	0.010	-11.890	0.000	0.847	0.888
Segment Length (ft)						
< 1320	*	*	*	*	*	*
1320 ~ 1980	1.828	0.067	16.480	0.000	1.701	1.963
1980 ~ 2640	2.420	0.083	25.790	0.000	2.263	2.588
2640 ~ 3300	3.089	0.108	32.410	0.000	2.885	3.307
3300 ~ 3960	3.829	0.140	36.690	0.000	3.564	4.114
≥ 3960	4.655	0.391	18.300	0.000	3.948	5.488
Alpha	0.44	0.030	Likelihood-ratio test of alpha=0: $\chi^2(1)$ = 225.89; P-value = 0.000			

WA Enhanced Model B

Width (ft)	Incidence Rate Ratio	SE	Z	P-value	95% Limits Lower	95% Limits Upper
Shoulder Width						
0	0.849	0.035	-3.960	0.000	0.783	0.921
1	0.952	0.036	-1.310	0.192	0.883	1.025
2	0.994	0.026	-0.230	0.815	0.945	1.046
3	1.031	0.024	1.320	0.185	0.985	1.079
4	1.078	0.024	3.400	0.001	1.033	1.126
5	0.965	0.028	-1.220	0.221	0.912	1.022
6	1.000	*	*	*	1.000	1.000
7	1.005	0.027	0.210	0.837	0.955	1.059
8	0.985	0.021	-0.710	0.477	0.944	1.027
9	0.766	0.043	-4.720	0.000	0.685	0.856
> 9	0.934	0.028	-2.280	0.022	0.881	0.990
Lane Width						
< 10	1.154	0.118	1.400	0.162	0.944	1.411
10.0	1.142	0.037	4.100	0.000	1.072	1.216
10.5	1.058	0.040	1.500	0.134	0.983	1.140
11.0	1.081	0.015	5.740	0.000	1.053	1.110
11.5	1.081	0.023	3.680	0.000	1.037	1.126
12.0	1.000	*	*	*	1.000	1.000
12.5	1.227	0.072	3.480	0.001	1.094	1.377
13.0	1.201	0.094	2.330	0.020	1.030	1.400
>13	1.123	0.045	2.900	0.004	1.038	1.215
Cube Root of Average Daily Traffic ($ADT^{1/3}$)						
< 5.6	*	*	*	*	*	*
5.6 ~10.0	6.741	4.786	2.690	0.007	1.677	27.101
10.0~14.4	19.494	13.828	4.190	0.000	4.854	78.284
14.4~18.8	47.952	34.016	5.460	0.000	11.940	192.588
18.8~23.2	79.212	56.199	6.160	0.000	19.719	318.197
≥ 23.2	150.037	106.474	7.060	0.000	37.337	602.912
Speed (mph)						
< 50	*	*	*	*	*	*
≥ 50	1.038	0.016	2.470	0.014	1.008	1.069
Segment Length (ft)						
< 1320	*	*	*	*	*	*
1320 ~ 1980	3.232	0.068	55.990	0.000	3.102	3.368
1980 ~ 2640	4.256	0.138	44.750	0.000	3.995	4.535
2640 ~ 3300	6.560	0.298	41.350	0.000	6.000	7.172
3300 ~ 3960	7.002	0.423	32.220	0.000	6.220	7.882
≥ 3960	11.967	0.579	51.280	0.000	10.884	13.158
Alpha	0.53	0.063	Likelihood-ratio test of alpha=0: $\chi^2(1)$ = 79.98; P-value = 0.000			

B.3 Enhanced Model A-1 Adjusted for ADT and Speed using Segment-Length-Days as the Exposure Variable

PA Enhanced Model A-1 compared to Enhanced Model A

	PA Cohort Model A-1 Segment-Length-Days			PA Cohort Model A Segment-Days		
Width (ft)	Hazard Ratio	SE	P-value	Hazard Ratio	SE	P-value
Shoulder Width						
0	1.138	0.031	0.000	1.120	0.031	0.000
1	1.173	0.062	0.002	1.172	0.062	0.003
2	1.103	0.024	0.000	1.106	0.024	0.000
3	1.028	0.021	0.186	1.028	0.021	0.174
4	1.059	0.019	0.001	1.060	0.019	0.001
5	1.022	0.024	0.342	1.024	0.024	0.312
6	1.000	*	*	1.000	*	*
7	1.006	0.043	0.900	1.012	0.044	0.786
8	0.959	0.022	0.069	0.958	0.022	0.062
9	0.794	0.059	0.002	0.785	0.058	0.001
> 9	0.825	0.027	0.000	0.823	0.027	0.000
Lane Width						
< 10	0.826	0.026	0.000	0.828	0.026	0.000
10.0	1.005	0.017	0.777	1.010	0.017	0.571
10.5	1.102	0.035	0.002	1.105	0.035	0.001
11.0	1.059	0.015	0.000	1.059	0.015	0.000
11.5	1.003	0.051	0.952	1.006	0.051	0.913
12.0	1.000	*	*	1.000	*	*
12.5	0.781	0.069	0.005	0.774	0.068	0.004
13.0	0.925	0.053	0.180	0.922	0.053	0.160
>13	1.059	0.026	0.018	1.042	0.025	0.096
Cube Root of Average Daily Traffic ($ADT^{1/3}$)						
< 5.6	*	*	*	*	*	*
5.6 ~10.0	2.335	0.274	0.000	2.321	0.272	0.000
10.0~14.4	5.092	0.594	0.000	5.058	0.590	0.000
14.4~18.8	8.227	0.962	0.000	8.180	0.957	0.000
18.8~23.2	12.669	1.489	0.000	12.629	1.485	0.000
≥ 23.2	18.347	2.201	0.000	18.183	2.182	0.000
Speed (mph)						
< 50	*	*	*	*	*	*
≥ 50	0.872	0.009	0.000	0.878	0.009	0.000
Segment Length (ft)						
< 1320	*	*	*	*	*	*
1320 ~ 1980	*	*	*	1.750	0.060	0.000
1980 ~ 2640	*	*	*	2.258	0.072	0.000
2640 ~ 3300	*	*	*	2.808	0.091	0.000
3300 ~ 3960	*	*	*	3.384	0.114	0.000
≥ 3960	*	*	*	3.879	0.279	0.000

WA Enhanced Model A-1 compared to Enhanced Model A

	PA Cohort Model A-1 Segment-Length-Days			PA Cohort Model A Segment-Days		
Width (ft)	Hazard Ratio	SE	P-value	Hazard Ratio	SE	P-value
Shoulder Width						
0	0.833	0.032	0.000	0.855	0.034	0.000
1	0.918	0.034	0.019	0.949	0.035	0.152
2	0.942	0.023	0.016	0.991	0.025	0.725
3	0.945	0.021	0.010	1.027	0.023	0.219
4	0.996	0.021	0.848	1.074	0.023	0.001
5	0.932	0.026	0.011	0.964	0.027	0.190
6	1.000	*	*	1.000	*	*
7	1.063	0.026	0.014	1.004	0.025	0.875
8	1.022	0.021	0.276	0.980	0.020	0.325
9	0.886	0.047	0.023	0.779	0.042	0.000
> 9	1.024	0.029	0.395	0.935	0.026	0.017
Lane Width						
< 10	1.098	0.110	0.354	1.155	0.116	0.153
10.0	1.101	0.034	0.002	1.142	0.036	0.000
10.5	0.985	0.036	0.685	1.061	0.039	0.102
11.0	1.062	0.014	0.000	1.079	0.014	0.000
11.5	1.121	0.022	0.000	1.080	0.022	0.000
12.0	1.000	*	*	1.000	*	*
12.5	1.214	0.067	0.000	1.228	0.068	0.000
13.0	1.078	0.080	0.317	1.194	0.089	0.018
>13	1.054	0.039	0.156	1.120	0.042	0.003
Cube Root of Average Daily Traffic ($ADT^{1/3}$)						
< 5.6	*	*	*	*	*	*
5.6 ~10.0	4.020	2.847	0.049	6.612	4.681	0.008
10.0~14.4	11.004	7.786	0.001	18.706	13.234	0.000
14.4~18.8	23.631	16.720	0.000	44.553	31.521	0.000
18.8~23.2	39.652	28.058	0.000	71.572	50.641	0.000
≥ 23.2	67.074	47.467	0.000	129.458	91.606	0.000
Speed (mph)						
< 50	*	*	*	*	*	*
≥ 50	1.149	0.016	0.000	1.031	0.015	0.033
Segment Length (ft)						
< 1320	*	*	*	*	*	*
1320 ~ 1980	*	*	*	3.048	0.056	0.000
1980 ~ 2640	*	*	*	3.921	0.111	0.000
2640 ~ 3300	*	*	*	5.791	0.223	0.000
3300 ~ 3960	*	*	*	6.104	0.312	0.000
≥ 3960	*	*	*	9.646	0.353	0.000

Francis Gross Jr.

EDUCATION

2002-present **The Pennsylvania State University**, State College, PA
Master of Science in Civil Engineering: December, 2003
GPA: 4.00

1998-2002 **Clarkson University**, Potsdam, NY
Bachelor of Science in Civil Engineering
GPA: 3.88

PROESSIONAL EXPERIENCE

The Pennsylvania State University: State College, PA 16802
Research/Teaching Assistant: Fall 2002 – present

Research Assistant – Assisted with research on several transportation-safety-related projects. Primary tasks included data collection, database management, statistical analysis, and report writing.

Teaching Assistant – Instructed laboratories for two courses: (1) Highway Engineering, which involved extensive work with Land Desktop to design two alternatives for a rural two-lane collector and (2) Traffic Operations, which involved a series of field studies to develop a model of existing and optimized conditions for signalized intersections.

Transportation Research Board Joint Subcommittee on Safety Workforce Development: March 2004 – present

Active member of safety workforce subcommittee: Helped to develop core competencies for highway safety professionals and assessed university-based highway safety course availability in the United States.

TRANS Associates: State College, PA 16802
Engineering Technician: Summer Internship 2004

Traffic Impact Studies – Analyzed existing and projected traffic operations for a Wal-Mart Expansion, Graystone Courts Development, Mountainview Estates Development, and Kerstetter Subdivision.

Signal Optimization – Assisted in data collection and coding, developed a layout of existing conditions using SYNCRO, and assisted in the signal optimization plan using SYNCRO.

Fisher Associates: Rochester, NY 14623
Engineering Technician: Summer Internships 1999 – 2002

Signal Optimization – Assisted in data collection and developed models of existing and optimized conditions (SYNCRO).

Construction Inspector – Provided inspection of earthwork, utilities and asphalt paving for the Western Gateway Subdivision industrial development. Provided inspection of a resurfacing project on the New York State Thruway between exit 41 and exit 42, which involved the mill and fills of both lanes, left shoulder, and ramps.

Land Surveying – Assisted Fisher Associates survey crew performing topographic survey and control for the preliminary design of converting NYS Route 17 to Interstate Route 86 through and around the City of Horseheads, NY.

Field Work – Aided in air and noise studies. Conducted field and sign edits.

Drafting – Assisted in M&PT planning, detour route design, signal planning and base mapping.

ACADEMIC EXPERIENCE

<u>Refereed Journal Articles:</u>

1. Gross, F. and P.P. Jovanis, (2006). Direct Estimation of Crash Modification Factors: The Case-Control Approach. American Society of Civil Engineers, Journal of Transportation Engineering, *in review*.
2. Gross, F. and P.P. Jovanis, (2006). Traffic Safety Course Offerings in U.S. Engineering and Public Health Programs, American Society of Civil Engineers, Journal of Education and Practice, *in review*.
3. Park, S.W., A. Mukherjee, F. Gross, P.P. Jovanis, (2005). Safety Implications of Multi-Day Driving Schedules for Truck Drivers: Comparison of Field Experiments and Crash Data Analysis. Transportation Research Record, 1195, 167-174.
4. Chen, I, F. Gross, K. Pecheux and P.P. Jovanis, (2005). Modal Preference for ITS-Enhanced Ridesharing and Paratransit Services for Disabled and Elderly Travelers, Journal of Advances in Transportation Studies: An International Journal, April, p. 53-68.

<u>Presentations:</u>

1. Gross, F. and P.P. Jovanis, Prevalence of Traffic Safety Courses in U.S. Engineering and Public Health Programs, Transportation Research Board 86th Annual Meeting, Washington, DC, January 2006.
2. Gross, F. and P.P. Jovanis, Case-Control Methods: An Alternative Method for Estimating Crash Modification Factors, 11th Annual Transportation Engineering and Safety Conference, Pennsylvania Transportation Institute, The Pennsylvania State University, December 2005.
3. Fayish, A.C., F. Gross and P.P. Jovanis, User Perceptions of Web-Based Roadway Weather Information Systems (RWIS): Navigability, Transportation Research Board 85th Annual Meeting, Washington, DC, January 2005.
4. Chen, I, F. Gross, K. Pecheux, P.P. Jovanis, Estimating Demand for Enhanced Paratransit Services by Elderly and Disabled Travelers, Transportation Research Board 84th Annual Meeting, Washington, DC, January 2004.
5. Gross, F., I. Chen, P.P. Jovanis, Advanced Transportation Services to Enhance the Mobility of Elderly and Disabled Travelers, 9th Annual Transportation Engineering and Safety Conference, Pennsylvania Transportation Institute, The Pennsylvania State University, December 2003.
6. Gross, F., I. Chen, P.P. Jovanis, Advanced Transportation Services to Enhance Mobility of Elderly and Disabled Travelers, Pennsylvania Transportation Institute Research Showcase, Transportation Research Board 83rd Annual Meeting, Washington, DC, January 2003.

AWARDS

- Mid-Atlantic University Transportation Centers (MAUTC) Student of the Year 2004
- Mid-Atlantic University Transportation Center Graduate Fellowship
- ENO Leadership Conference
- Clarkson Leadership Award
- Eagle Scout, Boy Scouts of America
- Deans List (16 Semesters)
- Presidential Scholar (15 Semesters)
- Earl E. Towlson Endowed Scholarship

SOCIETIES

Institute of Transportation Engineers, Chi Epsilon, Tau Beta Pi, Phi Kappa Phi, Boy Scouts of America