Safety Evaluation of Continuous Green T Intersections

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FOREWORD

The research documented in this report was conducted as part of the Federal Highway Administration's (FHWA) Evaluation of Low-Cost Safety Improvements Pooled Fund Study (ELCSI-PFS). FHWA established this PFS in 2005 to conduct research on the effectiveness of the safety improvements identified by the National Cooperative Highway Research Program Report 500 Guides as part of the implementation of the American Association of State Highway and Transportation Officials Strategic Highway Safety Plan. The ELCSI-PFS studies provide a crash modification factor and benefit-cost (B/C) economic analysis for each of the targeted safety strategies identified as priorities by the pooled fund member States.

This study compares the safety performance of the continuous green T (CGT) intersections with conventional signalized T intersections using treatment and comparison sites from Florida and South Carolina. The results show crashes were reduced for expected total, fatal and injury, and target (rear-end, angle, and sideswipe) crashes at the CGT intersection compared with the conventional signalized T intersection. Further, the B/C analysis indicated that the CGT intersection is a cost-effective alternative to the traditional, signalized T intersection. This report is intended for practicing engineers when contemplating application of CGT intersections and for researchers who wish to consider the propensity scores-potential outcomes framework in non-randomized, observational traffic safety evaluations.

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16. Abstract
The continuous green T (CGT) intersection is characterized by a channelized left-turn movement from the minor street approach onto the major street, along with a continuous through movement on the major street. The continuous through movement typically has a green through arrow indicator to inform drivers that they do not have to stop. Past research has consistently shown that there are operational and environmental benefits to implementing this intersection form at three-leg locations when compared with a conventional signalized T intersection. These benefits include reduced delay, fuel consumption, and emissions. The safety effects of the conventional signalized T intersection are less clear. Past research has been limited to a small sample of intersections in a single State and considered only comparisons in reported crashes between adjacent lanes on the major street approach (continuous flow versus the opposing through lanes). The study designs used in past safety research were limited to simple statistical comparisons using reported crash data. The present study overcomes past safety research evaluations by using a propensity scores-potential outcomes framework to compare the safety performance of the CGT with conventional signalized T intersections using 30 treatment and 38 comparison sites from Florida and 16 treatment and 21 comparison sites from South Carolina. The results showed that the expected total, fatal and injury, and target crash (rear-end, angle, and sideswipe) frequencies were lower at the CGT intersection relative to the conventional signalized T intersection (CMFs of 0.958 (95 percent confidence interval (CI) = 0.772–1.189), 0.846 (95 percent CI = 0.651–1.099), and 0.920 (95 percent CI = 0.714–1.185), respectively). Further, the benefit-cost analysis indicated that the CGT intersection is a cost-effective alternative to the traditional, signalized T intersection. The results of the safety evaluation were not statistically significant, likely due to a small sample of treatments. When considered in combination with the operational and environmental benefits, the CGT intersection appears to be a viable alternative intersection form, although anecdotal feedback from South Carolina and Florida indicate that some non-motorized users (pedestrians and bicyclists) find it challenging to cross the continuous flow through lanes on the major street approach when traffic volumes limit the number or size of available gaps.

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SI* (MODERN METRIC) CONVERSION FACTORS				
APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa
APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380.
(Revised March 2003)

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

AADT	average annual daily traffic
AASHTO	American Association of State Highway and Transportation Officials
B/C	benefit-cost
CDF	cumulative distribution function
CGT	continuous green T
CI	confidence interval
CMF	crash modification factor
DCMF	Development of Crash Modification Factors
EB	empirical Bayes
ELCSI-PFS	Evaluation of Low-Cost Safety Improvements Pooled Fund Study
FDOT	Florida Department of Transportation
FHWA	Federal Highway Administration
HSM	*Highway Safety Manual*
K-S	Kolmogorov-Smirnov
NCHRP	National Cooperative Highway Research Program
NN	nearest-neighbor
PDO	property damage only
PFS	pooled fund study
SCDOT	South Carolina Department of Transportation
SUTVA	Stable Unit Treatment Value Assumption

EXECUTIVE SUMMARY

This study used a propensity scores-potential outcomes framework to evaluate the safety performance of the continuous green T (CGT) intersection relative to a conventional signalized T intersection. Data from 30 CGT (treated) and 38 conventional signalized (untreated) intersections from Florida were used in the evaluation, as were 16 treated and 21 untreated sites from South Carolina. In the propensity scores-potential outcomes framework, a propensity scores model was estimated using a binary logistic regression model, where the dependent variable was codified as a binary variable based on the presence of the CGT or the conventional T signalized intersection form. The independent variables in the propensity scores model included safety-influencing features present at the intersections, including the average annual daily traffic on the major and minor street approaches, the posted speed limit, cross-sectional widths, and the type of intersection channelization. The propensity scores were then used to match treated (CGT) to untreated (conventional signalized) intersections, mimicking a randomized experiment. After matching, the potential outcomes were estimated using mixed effects negative binomial or Poisson count regression models (where possible) and weighted using negative binomial regression with robust standard errors otherwise. The expected total, fatal and injury, and target crash frequencies were used as the dependent variables in the count models, while the intersection safety-influencing variables were used as independent variables. In addition, an indicator variable was used in the potential outcomes model to assess the safety performance of the CGT relative to a conventional T signalized intersection.

The results showed that there was a small but statistically insignificant benefit associated with the CGT intersection relative to the conventional signalized T intersection. The crash modification factors (CMFs) associated with total crashes, fatal and injury crashes, and target crashes were 0.958 (*p*-value = 0.699, 95-percent confidence interval (CI) = 0.772–1.189), 0.846 (*p*-value = 0.211, 95-percent CI = 0.651–1.099), and 0.920 (*p*-value = 0.519, 95-percent CI = 0.714–1.185), respectively. Because the propensity scores-potential outcomes framework involves matching, some treated and untreated intersections in the database were not included in the analysis sample. For purposes of comparison, cross-sectional regression models using all available data were estimated, and the results were similar to the propensity scores-potential outcomes results. In these models, the CMFs associated with total, fatal and injury, and target crashes were 0.886 (*p*-value = 0.389), 0.844 (*p*-value = 0.230), and 0.808 (*p*-value = 0.187), respectively. The benefit-cost analysis confirmed that the CGT is a cost-effective intersection design alternative to the conventional T signalized intersection.

CHAPTER 1. INTRODUCTION

BACKGROUND ON CGT INTERSECTION

The Federal Highway Administration's (FHWA) Development of Crash Modification Factors (DCMF) program was established in 2012 to address highway safety research needs for evaluating new and innovative safety strategies (improvements) by developing reliable quantitative estimates of their effectiveness in reducing crashes. The goal of the DCMF program is to provide measures of their safety effectiveness and benefit-cost (B/C) ratios for new safety strategies based on research. Promotion of the effective safety strategies has the potential benefit of decreasing total crashes and, subsequently, reducing fatalities. Furthermore, transportation agencies will be able to use safety effectiveness estimates and B/C ratios to manage safety on the highway and street network by making effective use of limited resources. There are 40 State transportation departments that provide technical feedback on safety improvements to the DCMF program and implement new safety improvements to facilitate evaluations. These States are members of the Evaluation of Low Cost Safety Improvements Pooled Fund Study (ELCSI-PFS) and have selected this study to be conducted under this program.

At-grade intersections are an inherent conflict location on the highway and street network because the turning or crossing paths of motorized and non-motorized users frequently interact at these locations. As a result, crashes involving both user groups often occur at intersections. FHWA estimates that, on average, 26 percent of fatal and 50 percent of injury crashes in the United States occur at intersections. National Cooperative Highway Research Program (NCHRP) Report 500, Volume 12, *A Guide for Reducing Collisions at Signalized Intersections* estimated that approximately 30 percent of fatal intersection crashes occur at locations with signalized control.(1) Intersection safety is a priority among transportation agencies in the United States.

Alternative intersection designs have emerged in recent years to improve traffic operations and safety. Implementation of specific alternative intersection forms is dependent on the conditions present at the location of interest. The presence of traffic congestion, high crash frequencies, or severe crash outcomes at existing intersections often necessitates either operational or safety improvements. Rather than seeking traditional traffic measures to mitigate delay or traffic safety problems, practitioners are now seeking opportunities to convert conventional intersections into alternative, innovative forms. Examples of alternative intersections include the displaced left-turn, restricted crossing U-turn, and median U-turn.

Another alternative intersection type that has been employed in several States is the continuous green T (CGT) intersection. CGT intersections are an alternative to conventional signalized T intersections. CGT intersections are characterized by a channelized left-turn movement from the minor street approach onto the mainline (major street), along with a continuous mainline through movement that occurs at the same time.(2) The continuous-moving through lanes are not controlled by a traffic signal phase, while the other intersection movements are controlled by a three-phase signal. The through lanes on the mainline that have continuous flow typically contain a green through arrow signal indicator to inform drivers that they do not have to stop. The continuous through lanes are often separated from the left-turn and merge lanes with delineators, curbed islands, pavement markings, or other separations. Figure 1 shows a major street approach to the continuous through lanes of a CGT intersection. An aerial view of a full CGT intersection is shown in figure 2.

Original image: ©2014 Google®.

Figure 1. Photo. Driver view of approach toward continuous through lanes at CGT intersection (latitude: 32.210420, longitude: -80.695000).[(3)]

Original image: ©2014 Google®.

Figure 2. Photo. Overhead view of approach toward continuous through lanes at CGT intersection (latitude: 32.240866, longitude: -80.816626).[4]

BACKGROUND ON STUDY

In 1997, the American Association of State Highway and Transportation Officials (AASHTO) Standing Committee on Highway Traffic Safety, with the assistance of FHWA, the National Highway Traffic Safety Administration, and the Transportation Research Board Committee on Transportation Safety Management, met with safety experts in the fields of driver, vehicle, and highway issues from various organizations to develop a strategic plan for highway safety. These participants developed 22 key emphasis areas that affect highway safety. NCHRP published a series of guides to advance the implementation of countermeasures targeted to reduce crashes and injuries. Each guide addresses one of the emphasis areas and includes an introduction to the problem, a list of objectives for improving safety, and strategies for each objective. Each strategy is designated as proven, tried, or experimental. Many of the strategies discussed in these guides have not been rigorously evaluated; about 80 percent of the strategies are considered tried or experimental.

In 2005, to support the implementation of the guides, FHWA organized a PFS to evaluate low-cost safety strategies as part of this strategic highway safety effort. Over the years, the ELCSI-PFS has grown in size and now includes 40 States. The purpose of the ELCSI-PFS is to evaluate the safety effectiveness of tried and experimental, low-cost safety strategies through scientifically rigorous crash-based studies. The use of CGT at signalized intersections was selected as a strategy to be evaluated as part of this effort.

CHAPTER 2. LITERATURE REVIEW

SAFETY

CGT intersections have been used for several decades in Florida.[5] It has been reported that Florida citizens do not feel that CGT intersections are safe, especially for unfamiliar drivers.[5] For this reason, Sando et al. completed a safety evaluation of the CGT intersection using only data from Florida.[5] The authors used a paired *t*-test and an ordered probit model to analyze crash type proportions and severity, respectively. The analysis compared crashes that were reported on the continuous through lane on the major CGT roadway with crashes that were reported on the major road turning lane (i.e., the lane that must stop at the signal). Data consisted of crashes at nine Florida intersections from the years 2003 through 2008. There were a total of 398 crashes in the study sample.

The paired *t*-tests compared the proportions of total crashes in each direction that were lane-changing (sideswipe), rear-end, and angle. No differences were found in the proportion of rear-end and angle crashes when comparing the two travel lanes (i.e., continuous flow versus signal-controlled travel lane). The continuous flow lanes had a statistically significant higher proportion of sideswipe crashes than the lanes that had to stop. This was likely due to turning vehicles merging onto the continuous flow lanes. This analysis did not account for the total crash frequency or any potential confounding factors. Because the analysis results were based on a simple comparison of crash proportions between lane groups, rather than rigorous statistical methods, the results of the study have limited practical value.

The ordered probit was used to analyze crash severity outcomes. The severity levels considered in the model included no injury, non-incapacitating injury, incapacitating injury, and fatal. Two ordered probit models were estimated—one model that controlled for crash type and one that controlled for geometric elements, lighting, weather, time of day, speed limit, and driver age. The findings indicated that the continuous flow lanes on the CGT major road had lower severity outcomes when controlling for geometrics, lighting, weather, time of day, speed limit, and driver age when compared with the turning lane on the major road. The opposite finding occurred when only crash type was considered in the model. Neither of these findings, however, were statistically significant.

In a second study using Florida CGT intersection information to evaluate safety, Jarem compiled crash data from five intersections to compare crash rates at each CGT intersection with a critical crash rate.[6] The method to determine the critical crash rate was not provided by the author; however, this method often involves determining the average crash rate for similar roadway types plus an adjustment for the desired level of statistical confidence. The study included reported crashes at the CGT intersections from 2000 through 2003, which included a total of 117 crashes (10 of which were rear-end collisions caused by drivers inadvertently stopping in the continuous flow lanes). The crash rate analysis assumes a linear relationship between crash frequency and traffic volumes, which is rarely found in traffic-safety relationships.[7] The findings from the analysis suggested that the reported crash rates for each of the CGT intersections were lower than the critical crash rates, likely indicating that the CGT intersections did not produce crash rates that exceeded average rates at similar intersections without the continuous green movement. A diagnostic review of the reported crashes at CGT intersections in Florida found that rear-end, sideswipe, and angle crashes were the most common types. The rear-end crashes were often caused by drivers who unexpectedly stopped in the continuous flow lane. Sideswipe and angle crashes occurred when drivers turning left from the minor leg of the intersection were turning or merging with the through traffic on the major road.

TRAFFIC OPERATIONS

Jarem also completed an analysis of the operational effectiveness of CGT intersections.(6) The analysis considered the five CGT intersections used in the safety analysis and subsequently performed traffic simulations using traffic analysis software to estimate the total delay savings (per vehicle) and total fuel savings achieved by the continuous flow lanes (compared with a standard signalized T intersection). The findings indicated that the CGT intersections resulted in savings of 3.7 to 28.4 s of delay per vehicle (1,601 and 4,786 vehicles/h, respectively) and 0.005 to 0.015 gal of fuel saved per vehicle (5,275 and 1,622 vehicles/h, respectively). The traffic volumes for the movements other than for the through lanes were not provided.

Litsas and Rakha provided a more comprehensive operational analysis of CGT intersections.(8) Simulation software was used to run 2,445 unique intersection condition combinations to compare CGT with traditional signalized T intersections.(8) The analysis estimated the reduction in vehicle delay, fuel usage, hydrocarbon emissions, carbon monoxide emissions, nitrogen oxide emissions, and carbon dioxide emissions. The simulation results indicated that CGT intersections resulted in a 10.29 percent reduction in vehicle delay, 2.78 percent fuel savings, 12.47 percent fewer hydrocarbon emissions, 14.44 percent fewer carbon monoxide emissions, 4.38 percent fewer nitrogen oxide emissions, and 2.29 percent fewer carbon dioxide emissions than traditional signalized T intersections.

SUMMARY OF CGT INTERSECTIONS

Safety and operational evaluations of the CGT intersection are relatively limited in the literature. With regards to safety, crash type proportion analyses have indicated that continuous flow movements at CGT intersections do not differ from the through lanes in the opposing direction. There are preliminary findings to suggest that the proportion of sideswipe crashes on the continuous flow lanes on the major road were higher relative to the opposing through lanes, but there were not significant differences in other crash types. No statistically significant differences among severity outcomes have been reported when comparing the CGT continuous flow lanes to the lanes in the opposing direction. With regard to operations, published research indicates that the vehicle delay, emissions, and fuel consumption are lower at CGT intersections relative to traditional signalized T intersections.

CHAPTER 3. OBJECTIVES

The objective of the present study was to examine the safety effectiveness of CGT intersections in terms of crash frequency using a rigorous methodology. The propensity scores-potential outcomes framework described by Sasidharan and Donnell was used.[9] In this analysis, the safety performance of CGT intersections was compared with the safety performance of traditional, signalized T intersections. The following target crashes were included in the evaluation:

- Total crashes within 250 ft of the intersection.
- Fatal and injury crashes within 250 ft of the intersection.
- Rear-end, angle, and sideswipe crashes within 250 ft of the intersection.

The 250-ft measurement was defined by Harwood et al. as the boundary for intersection-related crashes when assessing the safety performance of left- and right-turn lanes at three- and four-legged, stop- and signal-controlled intersections.[10]

CHAPTER 4. METHODOLOGY

This chapter describes the propensity scores-potential outcomes framework that was used to estimate the safety effectiveness of the CGT intersection relative to a traditional signalized T intersection. The propensity scores estimation method, matching methods, and the potential outcomes estimation method are described in this chapter. An observational before-after evaluation (using the empirical Bayes (EB) method) could not be used in the present study, because the CGT intersections were either constructed as such or the conversion from a traditional signalized T intersection to a CGT intersection took place long ago, precluding the availability of electronic crash data from the before period. Recent research has shown that the propensity scores-potential outcomes framework produces safety effect estimates (i.e., CMFs) that are nearly identical to EB observational before-after and cross-sectional statistical models when treatments are deployed at locations that were not selected for countermeasure implementation based on high crash frequencies.(11) Because the CGT is an intersection form that is constructed to improve traffic operations when site conditions permit, and because only after data were available for analysis (i.e., no crash data were available when the intersections may have operated either under a different configuration or with different control), the analysis is therefore not subject to site-selection bias. Thus, it is assumed that the propensity scores-potential outcomes framework will produce results equivalent to the EB method.

The propensity scores-potential outcomes methodology used in the study controlled for the following:

- Comparability of the comparison intersections (traditional signalized T intersection).
- Missing traffic volume data.
- The need to pool data from multiple States to improve the sample size.

PROPENSITY SCORES FRAMEWORK

Randomized experiments are considered the gold standard for determining the causal effects of treatments. Well-conducted randomized experiments yield unbiased estimates of average treatment effects because there is no correlation between the treatment and all other important covariates, other than the outcome of interest (i.e., there is no confounding).(12,13) Thus, methods that remove correlation between the treatment and other important predictor (independent) variables in observational studies lead to estimates of treatment effects that are similar to the results of a randomized experiment.

Propensity score analysis can be used to mimic randomized experiments by using observed covariates to estimate the probability that an observation received a treatment (i.e., the propensity score).(14) Propensity scores can be viewed as a scalar summary of the multivariate covariates, and balancing the true propensity score will lead to balance of all observed covariates.(14) In the context of traffic safety, examples may include the probability that an at-grade intersection contains lighting (or not) based on site-specific features such as traffic volume, type of traffic control, and level of pedestrian demand. Another example may be the probability that a roadway segment contains a horizontal curve as a function of traffic volume, lane width, and roadside geometry. The estimated propensity scores are then used to match treated and untreated observations.[15,16] This process removes correlation between the treatment and observed covariates. When propensity score matching is paired with regression analysis (performed after matching), selection bias is reduced.

Binary logit or probit models are commonly used to estimate propensity scores.[9,15,16] The estimated propensity scores should include all variables that could potentially be relevant to the treatment. As such, the variables included in the propensity score model should not be selected based on statistical significance.[9,17,18] Since the goal of propensity score analysis is to remove correlation between the treatment and other potentially important predictor variables, the functional form of the variables in the propensity score model should be selected based on which functional form yields the best matching results.

Propensity Score Assumptions

The following assumptions are associated with propensity score analysis:[9,15,16]

1. **Stable Unit Treatment Value Assumption (SUTVA):** This assumption states that when a treatment is applied to an entity, it does not affect the outcome for any other entity. Since the CGT intersections and the comparison intersections were separated, it is not likely that the CGT intersections affected the safety outcomes for the comparison intersections. Thus, the SUTVA was met for this study.

2. **Positivity:** This assumption states that the probability of receiving the treatment is non-zero for all observations. The comparison intersections were carefully selected to ensure that it would be possible to install CGT intersections at the reference intersection locations. The comparison intersections all had high enough traffic volumes on the main road to warrant continuous flow lanes (on major highways). In addition, they were all signalized T intersections, were in urban/suburban areas, were located near the CGT intersections (whenever possible), and had existing left-turn lanes from the major road onto the intersecting road. Thus, this assumption was met for the current study.

3. **Unconfoundedness:** The treatment assignment is unconfounded if the treatment status (treated or untreated) is conditionally independent of the potential outcomes for a given set of covariates. It must be assumed that all confounding covariates were measured and available for this analysis.

Binary Logit Estimation

The propensity score for a treatment was estimated in the present study using binary logit regression, which is specified in the equation in figure 3.[19]

$$p(i) = \frac{\exp(\beta x_i)}{1 + \exp(\beta x_i)}$$

Figure 3. Equation. Binary logit model for propensity scores.

Where:

x_i = A set of covariates for entity i (i.e., intersection safety-influencing features such as average annual daily traffic (AADT), the intersection skew angle, and the intersection's location (if any) on a horizontal curve).

β = A vector of parameters to be estimated.

$p(i)$ = The propensity score for entity i.

The standard error for the propensity score can also be calculated. The formula for the standard error of a binary logit is specified as seen in the equation in figure 4. [20]

$$SE\left(p(i)\right) = \sqrt{\frac{p(i)\left(1 - p(i)\right)}{n}}$$

Figure 4. Equation. Binary logit standard error.

Where:

n = The sample size used to estimate the propensity score.
$SE(p_n(i))$ = The standard error of the propensity score for entity i.

In traffic safety evaluations, it is common to assess the quality of model fit using the McFadden Pseudo R-squared (ρ^2), which is analogous to the R-squared value used to express the goodness-of-fit of an ordinary least squares regression model, where higher values indicate a better fit to the data, and can take a value between 0 and 1. It is expressed as seen in the equation in figure 5:[19,21]

$$\rho^2 = 1 - \frac{L(full)}{L(0)}$$

Figure 5. Equation. Psuedo R-squared goodness-of-fit.

Where:

$L(full)$ = Log-likelihood of the model with explanatory variables.
$L(0)$ = Log-likelihood of the intercept-only model.

However, the best model when using matching, within the propensity scores-potential outcomes framework, is the model that yields the best covariate balance, not the model with the best ρ^2 value.

MATCHING ALGORITHMS AND METHODS

Numerous algorithms exist for propensity score matching. Among them are nearest-neighbor (NN) matching, K-nearest neighbor matching, radius matching, kernel matching, and Mahalanobis matching.[9,15,16] The optimal method for matching is dependent on the available data. Typically, either caliper-based NN or Mahalanobis matching is used.[16] Either 1:1 (one treated to one untreated) matching or 1:*n* (1 treated to *n* untreated) matching can be done using either NN or Mahalanobis matching. If the sample sizes of the treated and untreated groups are similar, 1:1 matching is often an appropriate choice. [16]

Other issues related to propensity score matching relate to allowing replacement (permitting a comparison or untreated entity to be matched to more than one treated entity) and eliminating data for use in the potential outcomes estimation.[9,15,16] Discussion of these issues follow descriptions of the NN and Mahalanobis matching algorithms in the following subsections.

NN Matching

The first step in NN matching is to randomly order the data.[9] If the data are not randomly ordered and there are multiple observations with the same propensity scores, the results may be biased.[15] Once this is done, it is possible to use either 1:1 or 1:*n* matching. When closeness of the match is critical (how similar the matched entities are based on the estimated propensity score), or the sample size of the two groups are similar, 1:1 matching is preferred.[16] On the other hand, 1:*n* matching increases the total sample size, leading to lower standard errors in regression estimates of the potential outcomes (with potentially smaller standard errors than in simple cross-sectional analysis of the data). [22] However, this often comes at the expense of making the treated and comparison groups less comparable.[16] Issues related to replacement are described in more detail in the following sections.

When using NN matching, the differences between treated and untreated observations may be small or large. In order to account for large differences, two things should be considered. First, the data should be checked for common overlap (the distribution of propensity scores that is shared between the treated and comparison groups). Second, use of calipers or confidence intervals (CIs) should be used to ensure that differences between matched treated and untreated observations are not significantly dissimilar.[9,15,16]

Specifying a caliper width ensures that all matched observations will have a maximum propensity score difference within the range of the caliper width. Common caliper widths used are 0.25 or 0.20 multiplied by the standard deviation of the propensity scores within the treated group.[9,16] Other caliper widths can be used as long as the standardized bias in the matching results is not too large (typically assumed to be greater than 0.25 or 0.20). Larger caliper widths allow increased selection bias to remain in the data due to larger differences between the treated and comparison groups. Smaller caliper widths minimize the differences between the treated and comparison groups but often come at the expense of dropped observations.[16] However, it has been shown that with large datasets, the treatment effects estimates do not change significantly as the caliper width changes.[23]

Once the matching criteria have been established, the treated observations are matched to the untreated observations with the most similar propensity score (within the caliper width or CI).[9,15,16] If replacement is allowed, a single untreated observation can be copied and matched to multiple treated observations if it has the nearest propensity score. If replacement is not permitted, then each untreated observation may only be used once. After matching has occurred, unmatched treated and comparison observations are dropped from the dataset and not used in the potential outcomes.[9] The results should then be checked, and the standardized bias for the unmatched data and the matched data should be compared.[9] The standardized bias indicates whether the matching was effective in achieving covariate balance.

Mahalanobis Matching

Mahalanobis matching uses the same algorithm as NN matching with one difference: the treated observations are matched to the untreated observations with the closest match based on multiple variables, not just the propensity score.[16] The closest match based on multiple variables uses the Mahalanobis distance. This method may specify that the untreated observations available for matching to a treated observation be within a specified caliper or CI based on the propensity score, but this is not required as long as the matching results lead to small values of standardized bias.[9,15,16] As with NN matching, the data should be randomly ordered prior to matching. The Mahalanobis distance is calculated using the equation in figure 6.[16]

$$d(\vec{x},\vec{y}) = \sqrt{(\vec{x}-\vec{y})^T S^{-1} (\vec{x}-\vec{y})}$$

Figure 6. Equation. Mahalanobis distance.

Where:

$d(\vec{x},\vec{y})$ = The Mahalanobis distance matrix between groups *x* and *y* (i.e., treated and untreated groups) using the variables specified for the matching.

$(\vec{x}-\vec{y})$ = The matrix of the differences in values between groups *x* and *y* for the variables included in the matching.

S = The covariance matrix between *x* and *y*.

The propensity scores can be included as one of the variables in the Mahalanobis distance along with other important matching variables.

Genetic Matching

Genetic matching is a sequential process that optimizes covariate balance by finding the best matches for each treated entity.[16] The genetic matching process minimizes imbalance across the covariates; therefore, it optimizes covariate balance.[24] This is accomplished by minimizing a general Mahalanobis distance defined in figure 7.[24]

$$GMD(\vec{x},\vec{y},W) = \sqrt{(\vec{x}-\vec{y})^T \left(S^{-1/2}\right)^T S^{-1/2} W (\vec{x}-\vec{y})}$$

Figure 7. Equation. Genetic matching distance.

Where:

GMD = The genetic matching distance.

$S^{-1/2}$ = The Cholesky decomposition of S (i.e., $S = S^{-1/2}(S^{-1/2})^T$).
W = The weighting matrix.

With genetic matching, both the propensity score and other covariates can be included in the matching scheme. The iterative process uses Kolmogorov-Smirnov (K-S) statistics to measure covariate balance in addition to standardized bias measures.(24) Genetic matching results in optimal matches but often does so at the cost of high computation times.(16)

Replacement

Replacement is defined as allowing a single untreated observation to be replicated and matched to multiple treated observations. Allowing replacement may be beneficial when the amount of common overlap (portion of distribution of propensity scores shared by the treated and comparison groups) is not sufficient to produce good matching or when a significant amount of dropped observations would result if replacement is not permitted. When there is only a moderate amount of common overlap, replacement reduces the amount of dropped observations and is likely to reduce the amount of bias in the data.(16) When there is a significant amount of common overlap, matching without replacement is preferred.(16)

Dropped Observations

Dropped observations can result from poor common overlap and from narrow caliper widths. Dropped untreated observations often occur when matching. However, restricting caliper widths will result in treated observations being dropped from the analysis sample when no untreated observations have propensity scores within the acceptable range for matching. The tradeoffs between caliper width, replacement allowance, and the number of dropped observations must be considered in the propensity scores-potential outcomes framework. When caliper width is increased, the standardized bias (discussed in the next subsection) could increase, which will also increase the sample size used in the analysis (i.e., fewer dropped observations resulting from matching). An increased sample size often leads to greater statistical power (i.e., smaller standard errors of the estimates). It has been shown in previous research that when the standardized bias is kept within a small maximum value (usually 0.20 to 0.25), and the sample size is maximized, the matched estimates of treatment effects can yield unbiased estimates of the treatment effects that have smaller standard errors than an unmatched sample.(22)

Standardized Bias

As noted previously, standardized bias should be checked for propensity scores and other important covariates to assess the quality of covariate balance achieved from matching. The equation in figure 8 is used to compute the standardized bias.(9)

$$SB = \frac{100\left(\bar{x}_T - \bar{x}_C\right)}{\sqrt{\frac{\left(S_T^2 + S_C^2\right)}{2}}}$$

Figure 8. Equation. Standardized bias.

Where:

SB = The standardized bias.
$\overline{x}_T$ = The sample mean of the treated group for variable x.
$\overline{x}_C$ = The sample mean of the comparison group for variable x.
S_T^2 = The sample variance of the treated group for variable x.
S_C^2 = The sample variance of the comparison group for variable x.

Before-after matching comparisons of standardized bias for the propensity score and other covariates provide an indication of the improvement in covariate balance resulting from matching on the propensity score. A standardized bias with an absolute value of 20 or smaller indicates no statistical difference between the treated and comparison groups (i.e., they are equivalent).[16]

It has also been pointed out that even when the mean and standard error two groups are similar, the distributions of the two groups may still be significantly different due to different distributional shapes.[25] Thus, a K-S test is also used to assess covariate balance.[26] The K-S test compares the cumulative frequencies of two samples. Based on this comparison, the statistical fit of the two distributions is estimated.[27] This test uses the maximum difference (D_n) between the two distributions to estimate the statistical fit. The distance is calculated using figure 9.[27]

$$D_n = \max\left|F_n(x_i) - S_n(x_i)\right|$$

Figure 9. Equation. K-S test.

Where:

Max = Maximize function.
$F_n(x_i)$ = The cumulative distribution function (CDF) of the treated group for variable x at value i.
$S_n(x_i)$ = The CDF of the untreated group for variable x at value i.

The p-values for the K-S tests are obtained from a standard mathematical table.[27] This test can be used to test the covariate balance for any covariate of interest.

In summary, the present study estimated the propensity scores using a binary logistic regression model. The propensity scores compare the probability that a signalized intersection in the pool of observations is a CGT form versus a traditional signalized intersection based on the covariates (e.g., traffic volume, intersection skew angle, and presence of horizontal curve). NN matching was first used to match each CGT intersection (treatment site) to a traditional signalized intersection (comparison site). If, based on the reduction of the standardized bias in the covariates among the matched data, acceptable matching was not produced, then Mahalanobis matching was used. Replacement was permitted when matching to minimize the amount of dropped data from the analysis sample.

POTENTIAL OUTCOMES USING COUNT REGRESSION MODELS

After matching treated (CGT) and untreated sites (conventional signalized T intersections), the potential outcomes (crash frequency) were estimated using count regression models. The use of Poisson regression to model crash frequency was introduced in 1986.[28] Negative binomial regression, a general form of Poisson regression that accounts for overdispersion, was later used to estimate crash frequencies in the traffic safety literature.[29,30] Negative binomial regression was used to develop the safety performance functions in the first edition of the *Highway Safety Manual* (HSM).[31] However, the standard Poisson and negative binomial models do not account for serial correlation, which results when crash data are recorded annually at a site over a period of years, and these repeated observations are the analysis unit (i.e., annual expected crash frequency is the dependent variable in a statistical model). Thus, the standard errors for the regression results using these models were likely underestimated.

Regression models that account for the count nature of crash frequency data, serial (spatial or temporal) correlation, and correlation between variables in the model (e.g., major and minor road traffic volumes) and that can estimate parameters for variables that do not vary over time include mixed effects negative binomial and Poisson models.[21,32] Since this study used data with correlation between variables included in the model, the data included yearly data (repeated measurements) for each of the intersections and the variable of interest (if it was a CGT intersection or not), all of these issues were present in this study. A discussion of each of these models follows.

Mixed Effects Negative Binomial

The mixed effects negative binomial allows parameters to be fixed or random when specifying the model.[21] The inclusion of random parameters corrects for serial correlation while allowing estimation of an overdispersion parameter to capture the effects of within-cluster overdispersion (i.e., when the variance of crashes is greater than the mean for each individual intersection). The log-likelihood function for the mixed effects negative binomial is shown in figure 10.[33]

$$\ell(\beta,\Sigma,\alpha) = (2\pi)^{-q/2}|\Sigma|^{-1/2}\int f(y_k \mid u_k,\alpha)\exp\left(-u'_k\,\Sigma^{-1}u_k/2\right)du_k$$

Figure 10. Equation. Mixed effects negative binomial log-likelihood.

Where:

u_k = The random intercept/slope for entity k.
y_k = The outcome for entity k.
q = The number of covariates included in the model.

$$f(y_k \mid u_k,\alpha) = \exp\left[\sum_{i=1}^{n_j}\left\{\begin{array}{l}-\log\Gamma\left(y_{ik}+\frac{1}{\alpha}\right)-\log\Gamma(y_{ik}+1)-\log\Gamma\left(\frac{1}{\alpha}\right)-\frac{1}{\alpha}\log\{1+\exp(x_{ik}\beta+u_k+\log\alpha)\}-\\ y_{ik}\log\{1+\exp(-x_{ik}\beta-u_k-\log\alpha)\}\end{array}\right\}\right]$$

β = The vector of coefficients.
α = The overdispersion parameter.

A mixed effects negative binomial regression model with only the intercept allowed to be random is known as a *random intercept model*.[21] If all parameters are specified to be random, the model is known as a *random parameters model*. The mixed effects model is sometimes referred to as a *random parameter* or *random coefficient model*, even if some of the parameters are specified as fixed parameters.[21] When multiple parameters are allowed to be random, the model adds more adjustment for overdispersion into the model than the mixed-effects Poisson or the random intercept negative binomial. Thus, the model must be checked to ensure that it is not adjusting for more correlation than is warranted in the data.[21] This can be done by assessing the statistical significance of the overdispersion parameter as well as using a chi-square test to assess if the mixed effects model is preferred to a standard negative binomial regression. The null hypothesis for the chi-square test is that the mixed effects model does not fit the data better than the standard negative binomial regression.

When multiple random coefficients are used, the variance function for a mixed effects model is difficult to derive. However, for the case of a random intercept negative binomial, the variance function (for observation *i*) is specified as seen in figure 11.[33]

$$Var(\mu_i) = \mu_i + \{\exp(\sigma^2)(1-\alpha)-1\}(\mu_i)^2$$

Figure 11. Equation. Mixed effects negative binomial variance function.

Var = The variance.
μ = The expected mean.
σ = The standard deviation of the random intercept.
α = The overdispersion parameter.

When the overdispersion parameter is not statistically significant, the mixed effects negative binomial regression model reduces to a mixed effects Poisson model. The expected mean for observation *i*, based on the random intercept negative binomial model, is given as seen in figure 12.[32]

$$\mu_i = \exp(\xi_i)\exp(\beta x_i)$$

Figure 12. Equation. Mixed effects predictions.

Where:

ξ_i = The random intercept for observation *i*.
x_i = The vector of variables for observation *i*.

When a mixed effects model is used for prediction, the mean values of the estimated random parameters are used as the constant for the prediction model.

Mixed Effects Poisson

The mixed effects Poisson model is the same as a mixed effects negative binomial model but without overdispersion within clusters (a *cluster* for this study is defined as multiple repeated measurements at the same intersection over time). The log-likelihood for the mixed effects Poisson is shown in figure 13.[33]

$$\ell(\beta,\Sigma) = (2\pi)^{-q/2}|\Sigma|^{-1/2}\int f(y_k \mid u_k)\exp(-u'_k\,\Sigma^{-1}\,u_k/2)du_k$$

Figure 13. Equation. Mixed Poisson log-likelihood.

Where:

$$f(y_k \mid u_k) = \exp\left[\sum_{i=1}^{n_j}\{y_{ik}(x_{ik}\beta + u_k) - \exp(x_{ik}\beta + u_k) - \log(y_{ik}!)\}\right]$$

In figure 13, the subscript *i* refers to the observation, while all other variables and subscripts are defined in figure 10 and figure 12. In the context of this study, the observation *i* refers to a year associated intersection or entity *k*.

The variance function for a mixed effects Poisson model with the random term limited to the intercept only (random intercept Poisson) is specified using the equation in figure 14.[32]

$$Var(\mu_i) = \mu_i + \{\exp(\sigma^2) - 1\}(\mu_i)^2$$

Figure 14. Equation. Mixed effects Poisson variance function.

The expected mean value for an observation using a random intercept Poisson model is found using the equation in figure 12.

CMF Estimation

CMFs derived from regression models in the propensity scores-potential outcomes framework are estimated using the coefficient for the treatment indicator variable (included in the model) as the exponent of the base number *e*. The formula for this is shown in figure 15.

$$CMF_{Treatment} = \exp(\beta_{Treatment})$$

Figure 15. Equation. Regression CMF estimation.

Where:

$CMF_{Treatment}$ = The CMF for the treatment.
$\beta_{Treatment}$ = The estimated coefficient for the treatment.

It should be noted that figure 15 uses the regression coefficient for the treatment indicator variable, which is included in the mixed effects Poisson or negative binomial regression model.

The 95-percent CIs for CMFs using count models are calculated using the equation in figure 16.

$$CI_{95\%} = \exp\left(\beta_{Treatment} \pm 1.96\sigma_{Treatment}\right)$$

Figure 16. Equation. Regression CMF CI.

Where:

$CI_{95\%}$ = The 95-percent CI.
$\sigma_{Treatment}$ = The standard error of $\beta_{Treatment}$ from the regression model.

Cross-Sectional Modeling Comparison

Because traffic safety evaluations often estimate CMFs using a cross-sectional regression model, the present study also utilized this approach with all of the observations as a means of comparison to the propensity scores-potential outcomes framework. The cross-sectional model did not use any matched data and was estimated using a mixed-effects negative binomial regression model, which was previously described. The cross-sectional statistical model was specified using the form shown in figure 12. In the model, an indicator variable (CGT versus conventional signalized T intersection) was included in the specification to assess the safety performance of the CGT relative to the conventional signalized T intersection.

CHAPTER 5. DATA COLLECTION

Florida and South Carolina are two States with multiple CGT intersections that have existed for several years. Data from both of these States were used in the present study. The data collection procedure and summary of the data are provided in this chapter of the report.

FLORIDA

Florida began installing CGT intersections as early as 1972. CGT intersections considered in this study were constructed between 1972 and 2004, and the geometry remained unchanged during the safety evaluation period. The Florida Department of Transportation (FDOT) provided locations of CGT and comparable conventional signalized T intersections for analysis.

FDOT provided traffic volume data for the major and minor roads for each intersection where possible. When FDOT did not have traffic volume data, local jurisdictions were contacted to obtain traffic volume data. Traffic volumes for 2013 were available for all of the major roads, which included the high-speed, continuous through movement at the CGT intersections. When FDOT and the local jurisdictions did not have traffic volume data for the intersecting roadway, the *Trip Generation Manual* was used to predict the traffic volume based on the land uses along the properties adjacent to the minor intersecting roadway.[34] After these steps were taken, there were 4 CGT and 11 comparison intersections from Florida with missing traffic volumes on the minor street approach. Because most of the minor street approaches with missing traffic volume data were in residential areas, it was assumed that the volumes on these approach roadways would be approximately equal to 500 vehicles per day. One local jurisdiction (Melbourne, FL) performed a multiday traffic count for one of the missing minor street approaches and confirmed that a 500 vehicle per day volume was accurate.

FDOT also provided crash data in geographic information system files. These files were used to identify all crashes (total crashes), fatal and injury crashes, rear-end crashes, sideswipe crashes, and angle crashes within 250 ft of the intersections for 2008–2012 (inclusive).

Google Earth™ was used to collect other key variables, including variables related to the intersection design and traffic control features. These variables included the following:

- Posted speed limits on the major and minor street approaches.
- Lane and shoulder widths on all approaches.
- The number of through lanes on the major and minor approaches.
- The presence of right- and left-turn lanes on the through and intersecting roadways.
- The presence of a channelized right-turn lane from the major approach to the minor street.
- The presence of a channelized right-turn lane from the minor approach to the major street.

- Whether right-turn-on-red movements were permitted on either the major or minor street approaches.

- Whether the intersection is located on a horizontal curve.

- Whether a rail line crosses the intersecting roadway near the intersection.

- Whether there was a driveway (right-in, right-out only) where a fourth leg of the intersection would be.

- The skew angle for the intersection.

In total, there were 30 CGT intersections and 38 comparison intersections from Florida included in the analysis database. Variable names and the associated definitions are provided in table 1 for the Florida intersections. The variables include traffic volumes and posted speed limits on the through and intersecting roadways, lane-use controls, cross-section dimensions, geometric characteristics, and crash-related information.

Table 1. Variable descriptions for Florida intersections.

Variable	Variable Description
AADTThrough	Through road AADT (2013)
AADTIntersecting	Intersecting road AADT (2013)
LN_AADTThrough	The natural log of the through road AADT (2013)
LN_AADTIntersecting	The natural log of the intersecting road AADT (2013)
AADTMiss	AADT on intersecting road missing
THRU_SPEED	Through road posted speed limit (mi/h)
INT_SPEED	Intersecting road posted speed limit (mi/h)
RTOR Allowed Through	1 = right-turn-on-red allowed from through to intersecting legs, 0 = otherwise
RTOR Intersecting	1 = right-turn-on-red allowed from intersecting to through legs, 0 = otherwise
INT_LW	Intersecting road lane width (ft)
INT_SW	Intersecting road shoulder width (ft)
IntNumLane	Intersecting road number of lanes
THRU_LW	Through road lane width (ft)
THRU_SW	Through road shoulder width (ft)
ThruNumLane	Through road number of lanes
THRU_RLT	1 = right-turn lane from through road to intersecting road, 0 = otherwise
INT_RTL	1 = right-turn lane from intersecting road to through road, 0 = otherwise
THRU_LTL	1 = left-turn lane from through road to intersecting road, 0 = otherwise
INT_LTL	1 = left-turn lane from intersecting road to through road, 0 = otherwise
RAILCROSS	1 = railroad crossing intersecting road near the intersection, 0 = otherwise
FRTH_LEG	1 = driveway where fourth leg would be (right-in, right-out only), 0 = otherwise
CURVE	1 = intersection located on horizontal curve, 0 = otherwise
SKEW	Intersection skew angle (degrees)
CHAN_RTL_THRU	1 = channelized right-turn lane from through road to intersecting road, 0 = otherwise
CHAN_RTL_INT	1 = channelized right-turn lane from intersecting road to through road, 0 = otherwise
TOT_2008	Total crashes in 2008
TOT_2009	Total crashes in 2009
TOT_2010	Total crashes in 2010
TOT_2011	Total crashes in 2011
TOT_2012	Total crashes in 2012
TOT_2013	Total crashes in 2013
FI_2008	Fatal and injury crashes in 2008
FI_2009	Fatal and injury crashes in 2009

FI_2010	Fatal and injury crashes in 2010
FI_2011	Fatal and injury crashes in 2011
FI_2012	Fatal and injury crashes in 2012
FI_2013	Fatal and injury crashes in 2013
RREND_2008	Rear-end crashes in 2008
RREND_2009	Rear-end crashes in 2009
RREND_2010	Rear-end crashes in 2010
RREND_2011	Rear-end crashes in 2011
RREND_2012	Rear-end crashes in 2012
RREND_2013	Rear-end crashes in 2013
ANGLE_2008	Angle crashes in 2008
ANGLE_2009	Angle crashes in 2009
ANGLE_2010	Angle crashes in 2010
ANGLE_2011	Angle crashes in 2011
ANGLE_2012	Angle crashes in 2012
ANGLE_2013	Angle crashes in 2013
SDSWPE_2008	Sideswipe crashes in 2008
SDSWPE_2009	Sideswipe crashes in 2009
SDSWPE_2010	Sideswipe crashes in 2010
SDSWPE_2011	Sideswipe crashes in 2011
SDSWPE_2012	Sideswipe crashes in 2012
SDSWPE_2013	Sideswipe crashes in 2013
Florida	1 = intersection located in Florida, 0 = otherwise
Treated	1 = CGT intersection, 0 = comparison intersection
Thru_Spd_35	1 = through road posted speed is 35 mi/h, 0 = otherwise
Thru_Spd_40	1 = through road posted speed is 40 mi/h, 0 = otherwise
Thru_Spd_45	1 = through road posted speed is 45 mi/h, 0 = otherwise
Thru_Spd_50	1 = through road posted speed is 50 mi/h, 0 = otherwise
Thru_Spd_60	1 = through road posted speed is 60 mi/h, 0 = otherwise

Descriptive statistics for CGT intersection variables included in the Florida analysis data files are provided in table 2 and table 3.

Table 2. Descriptive statistics of continuous variables for Florida CGT intersections.

Variable	Mean	Standard Deviation	Minimum	Maximum
AADTThrough	28,822	10,189	14,400	47,000
AADTIntersecting	11,269	9,997	500	40,000
THRU_SPEED	45.63	5.51	35	55
INT_SPEED	35.07	10.17	15	55
SKEW	7.42	12.71	0	54.37
INT_LW	11.42	0.84	10	14
THRU_LW	11.30	0.67	10	12
INT_SW	1.61	2.21	0	9
IntNumLane	3.36	1.10	2	6
THRU_SW	3.30	2.59	0	9
ThruNumLane	5.51	0.88	4	8
TOT_2008	3.36	2.64	0	13
TOT_2009	4.00	4.42	0	24
TOT_2010	3.93	4.82	0	25
TOT_2011	3.33	3.70	0	18
TOT_2012	4.96	4.38	1	23
RREND_2008	1.14	1.86	0	9
RREND_2009	1.37	2.27	0	11
RREND_2010	1.33	2.54	0	13
RREND_2011	1.37	1.94	0	9
RREND_2012	2.19	2.10	0	10
ANGLE_2008	0.36	0.68	0	2
ANGLE_2009	0.26	0.53	0	2
ANGLE_2010	0.37	0.63	0	2
ANGLE_2011	0.37	0.69	0	3
ANGLE_2012	0.42	0.64	0	2
FI_2008	1.36	1.28	0	5
FI_2009	1.78	1.40	0	5
FI_2010	1.56	1.25	0	4
FI_2011	1.67	1.57	0	6
FI_2012	2.27	1.95	0	9
SDSWPE_2008	0.32	0.61	0	2
SDSWPE_2009	0.33	0.55	0	2
SDSWPE_2010	0.19	0.40	0	1
SDSWPE_2011	0	0.00	0	0
SDSWPE_2012	0	0.00	0	0

Table 3. Descriptive statistics of categorical variables for Florida CGT intersections.

Variable	Proportion with a Value of 1
AADTMiss	0.15
RTOR Allowed Through	1.00
RTOR Intersecting	0.96
THRU_RLT	0.60
INT_RTL	0.85
THRU_LTL	1.00
INT_LTL	0.85
RAILCROSS	0.03
FRTH_LEG	0.11
CURVE	0.26
CHAN_RTL_THRU	0.38
CHAN_RTL_INT	0.22

Descriptive statistics for the comparison intersection variables included in the Florida analysis data files are provided in table 4 and table 5.

Table 4. Descriptive statistics of continuous variables for Florida comparison intersections.

Variable	Mean	Standard Deviation	Minimum	Maximum
AADTThrough	22,332	10,206	5,600	42,500
AADTIntersecting	8,372	9,134	500	43,000
THRU_SPEED	38.07	7.04	25	60
INT_SPEED	32.44	7.15	15	55
SKEW	5.21	8.13	0	29.40
INT_LW	11.09	0.83	9	12
THRU_LW	11.25	0.64	10	12
INT_SW	1.50	1.77	0	6
IntNumLane	3.53	1.01	2	6
THRU_SW	2.63	2.39	0	8
ThruNumLane	4.59	0.92	3	7
TOT_2008	2.79	2.05	0	9
TOT_2009	2.51	2.14	0	8
TOT_2010	2.87	2.87	0	15
TOT_2011	2.23	2.14	0	10
TOT_2012	2.53	2.33	0	9
RREND_2008	1.10	1.17	0	4
RREND_2009	0.95	1.43	0	5
RREND_2010	0.79	1.10	0	4
RREND_2011	0.85	1.17	0	5
RREND_2012	0.90	1.32	0	5
ANGLE_2008	0.23	0.43	0	1
ANGLE_2009	0.21	0.41	0	1
ANGLE_2010	0.36	0.74	0	4
ANGLE_2011	0.30	0.61	0	2
ANGLE_2012	0.30	0.61	0	3
FI_2008	1.28	1.38	0	7
FI_2009	1.33	1.42	0	6
FI_2010	1.41	1.80	0	9
FI_2011	0.98	1.00	0	4
FI_2012	1.13	1.45	0	6
SDSWPE_2008	0.23	0.43	0	1
SDSWPE_2009	0.05	0.22	0	1
SDSWPE_2010	0.13	0.34	0	1
SDSWPE_2011	0.00	0.00	0	0
SDSWPE_2012	0.00	0.00	0	0

Table 5. Descriptive statistics of categorical variables for Florida comparison intersections.

Variable	**Proportion with a Value of 1**
AADTMiss	0.279
RTOR Allowed Through	1.00
RTOR Intersecting	0.98
THRU_RLT	0.47
INT_RTL	0.82
THRU_LTL	0.92
INT_LTL	0.90
RAILCROSS	0.03
FRTH_LEG	0.18
CURVE	0.20
CHAN_RTL_THRU	0.19
CHAN_RTL_INT	0.13

SOUTH CAROLINA

CGT intersections in South Carolina included in the database for this evaluation were installed between the period prior to 1990 through 2010. The South Carolina Department of Transportation (SCDOT) worked with the research team to identify the CGT and comparison intersections for use in the analysis.

Traffic volume data for the major and minor approach roads for each intersection were obtained from SCDOT where possible. Traffic volumes for 2013 were available for all of the major roads. When SCDOT did not have traffic volume data for the intersecting roadway, the *Trip Generation Manual* was used to predict the traffic volumes based on the land use of land adjacent to the minor street approach.[(34)] After these steps were taken, there were no intersections from South Carolina with missing traffic volumes.

SCDOT also provided crash data for 2009 through 2013. These files were used to identify all crashes (total crashes), fatal and injury crashes, rear-end crashes, sideswipe crashes, and angle crashes within 260 ft of the intersections for each of the years. The distance of 260 ft was selected due to the measurement values associated with the crash data. (It was not possible to use 250 ft.)

Google Earth™ was used to collect other geometric and traffic control data. The variables were the same as those collected for the Florida data.

In total, there were 16 CGT intersections and 21 comparison intersections from South Carolina included in the analysis database. One CGT intersection was constructed in 2009, and one was constructed in 2010. Thus, data for the years of construction and the year before (in the case of the CGT intersection constructed in 2010) were excluded from the analysis period. The descriptive statistics for CGT intersections from South Carolina are provided in table 6 and table 7.

Table 6. Descriptive statistics of continuous variables for South Carolina CGT intersections.

Variable	Mean	Standard Deviation	Minimum	Maximum
AADTThrough	34,944	12,170	8,300	59,000
AADTIntersecting	5,957	4,667	1,075	15,000
THRU_SPEED	45.63	3.02	40	55
INT_SPEED	31.56	4.94	25	45
SKEW	6.84	12.74	0	35.34
INT_LW	11.94	0.24	11	12
THRU_LW	12.00	0.00	12	12
INT_SW	0.00	0.00	0	0
IntNumLane	3.19	0.53	2	4
THRU_SW	0.19	0.73	0	3
ThruNumLane	6.69	1.05	5	8
TOT_2009	8.13	7.56	0	27
TOT_2010	8.88	7.82	0	29
TOT_2011	4.69	3.63	0	14
TOT_2012	6.06	4.75	0	20
TOT_2013	7.56	4.16	1	17
FI_2009	2.31	2.09	0	7
FI_2010	2.13	1.75	0	7
FI_2011	1.19	1.05	0	4
FI_2012	2.13	1.86	0	6
FI_2013	1.50	1.55	0	4
RREND_2009	3.88	4.49	0	16
RREND_2010	5.38	6.26	0	24
RREND_2011	3.06	2.82	0	11
RREND_2012	3.69	3.55	0	14
RREND_2013	3.25	2.41	0	7
ANGLE_2009	2.25	2.96	0	9
ANGLE_2010	1.44	1.31	0	4
ANGLE_2011	0.88	0.96	0	3
ANGLE_2012	1.06	1.06	0	3
ANGLE_2013	2.13	1.89	0	6
SDSWPE_2009	0.06	0.25	0	1
SDSWPE_2010	0	0.00	0	0
SDSWPE_2011	0.06	0.25	0	1
SDSWPE_2012	0	0.00	0	0
SDSWPE_2013	0	0.00	0	0

Table 7. Descriptive statistics of categorical variables for South Carolina CGT intersections.

Variable	Proportion with a Value of 1
RTOR Allowed Through	1.00
RTOR Intersecting	1.00
THRU_RTL	0.44
INT_RTL	0.94
THRU_LTL	1.00
INT_LTL	0.94
RAILCROSS	0.06
FRTH_LEG	0.81
CURVE	0.06
CHAN_RTL_THRU	0.13
CHAN_RTL_INT	0.13

The descriptive statistics for comparison intersections from South Carolina are provided in table 8 and table 9.

Table 8. Descriptive statistics of continuous variables for South Carolina comparison intersections.

Variable	Mean	Standard Deviation	Minimum	Maximum
AADTThrough	22,452	10,499	8,500	45,450
AADTIntersecting	8,462	7,419	1,950	30,100
THRU_SPEED	42.62	3.68	35	45
INT_SPEED	34.52	6.56	25	55
SKEW	12.10	13.20	0	45.86
INT_LW	11.81	0.36	11	12
THRU_LW	11.79	0.37	11	12
INT_SW	0.76	2.01	0	8
IntNumLane	3.43	1.05	2	6
THRU_SW	2.00	4.05	0	15
ThruNumLane	5.57	1.18	4	9
TOT_2009	7.67	9.18	0	37
TOT_2010	6.71	8.14	0	31
TOT_2011	5.33	5.24	0	24
TOT_2012	6.57	5.30	0	22
TOT_2013	6.81	5.60	0	22
FI_2009	2.38	2.97	0	11
FI_2010	1.76	2.23	0	8
FI_2011	1.81	1.81	0	7
FI_2012	2.10	1.95	0	6
FI_2013	1.86	1.28	0	4
RREND_2009	3.38	4.64	0	19
RREND_2010	3.57	6.14	0	25
RREND_2011	3.10	3.92	0	18
RREND_2012	3.67	4.48	0	19
RREND_2013	3.38	3.79	0	15
ANGLE_2009	2.19	2.68	0	9
ANGLE_2010	1.71	1.49	0	4
ANGLE_2011	1.52	2.06	0	8
ANGLE_2012	2.00	1.61	0	6
ANGLE_2013	2.19	2.23	0	9
SDSWPE_2009	0.33	1.11	0	5
SDSWPE_2010	0.19	0.51	0	2
SDSWPE_2011	0.00	0.00	0	0
SDSWPE_2012	0.05	0.22	0	1
SDSWPE_2013	0.10	0.30	0	1

Table 9. Descriptive statistics of categorical variables for South Carolina comparison intersections.

Variable	Proportion with a Value of 1
RTOR Allowed Through	1.00
RTOR Intersecting	0.95
THRU_RLT	0.57
INT_RTL	0.86
THRU_LTL	0.95
INT_LTL	0.91
RAILCROSS	0.09
FRTH_LEG	0.29
CURVE	0.33
CHAN_RTL_THRU	0.33
CHAN_RTL_INT	0.19

CHAPTER 6. MATCHING

Since the intersections in Florida and South Carolina likely differ with regard to unobservable variables (e.g., reporting thresholds and driver demographics), matching was done separately for each State. As described in the methodology, binary logistic regression was used to estimate the propensity scores for both States. Since the goal of the binary logit model was to yield matches with good covariate balance, the functional form of the variables in the propensity score models differed between Florida and South Carolina.

The binary logit models estimated the probability that the intersections were CGT intersections (i.e., the propensity score). The models were estimated at the intersection level (all years of data for each intersection). The propensity score model for Florida is shown in table 10, and the model for South Carolina is shown in table 11. For Florida, there were 68 observations, the pseudo R^2 was 0.1850, and the log-likelihood was -37.546. For South Carolina, there were 37 observations, the pseudo R^2 was 0.3318, and the log-likelihood was -16.911.

Table 10. Florida propensity score model.

Variable	Coefficient	Standard Error	*p*-Value
AADTThrough	0.00009	0.00003	0.010
AADTIntersecting	0.00001	0.00003	0.743
AADTmiss	-1.09534	0.99280	0.270
THRU_RLT	0.13667	0.67546	0.840
INT_RTL	-0.29956	0.83036	0.718
RAILCROSS	2.53527	1.60811	0.115
FRTH_LEG	-0.03758	0.95639	0.969
CURVE	0.99022	0.70849	0.162
SKEW	0.02244	0.02772	0.418
THRU_SW	0.99344	0.79216	0.210
INT_SW	-0.48141	0.66091	0.466
Intercept	-3.33964	1.56424	0.033

Table 11. South Carolina propensity score model.

Variable	Coefficient	Standard Error	*p*-Value
LN_AADTThrough	1.49003	1.37409	0.278
LN_AADTIntersecting	-0.70140	0.41815	0.093
THRU_RLT	-0.19744	0.92572	0.831
INT_RTL	0.53584	1.55880	0.731
FRTH_LEG	1.73509	1.14918	0.131
CURVE	-0.93645	1.36229	0.492
Through_Shoulder	-0.24410	1.50289	0.871
Intercept	-10.5416	13.05849	0.420

The distributions of the estimated propensity scores for Florida and South Carolina (by intersection type) are shown in figure 17. The box plot of distributions of propensity scores for the unmatched groups show that the ranges of values were similar for Florida and dissimilar for South Carolina. Since the sample size for both States was small, the amount of overlap in the propensity score distributions between CGT and comparison intersections was not large enough to obtain covariate balance using NN matching. When NN matching was used, there were fewer than 10 total intersections from both States combined that matched well based strictly on the estimated propensity scores.

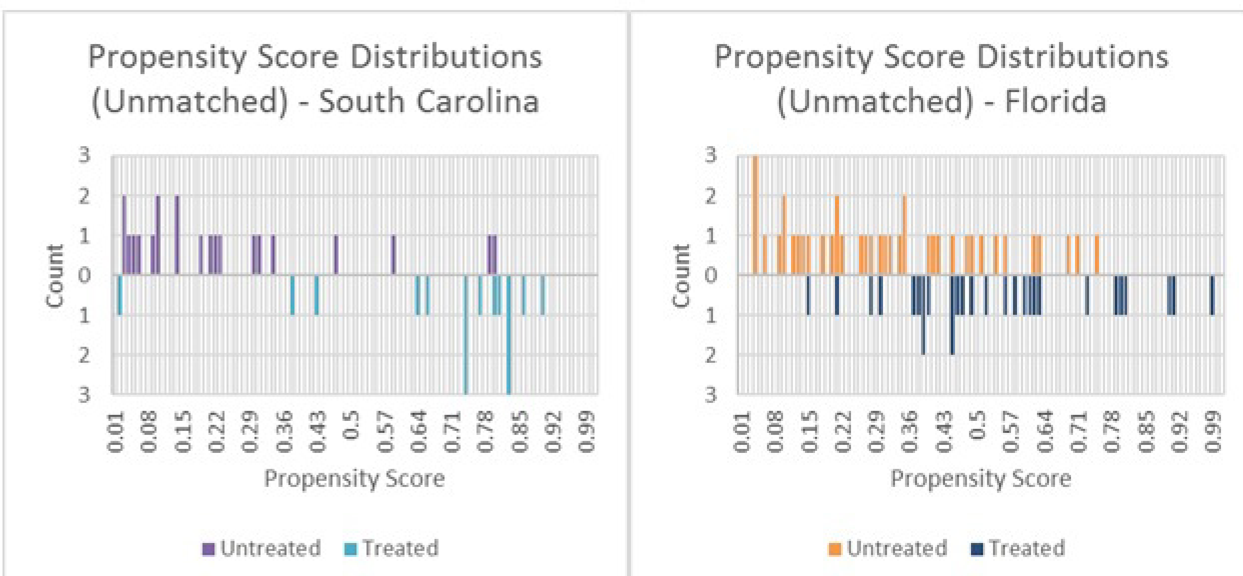


Figure 17. Graphs. Plots of estimated propensity scores by State and treatment status (South Carolina left and Florida right).

Since NN matching did not yield the desired covariate balance without a significant reduction in sample size, Mahalanobis matching was implemented. For the Mahalanobis matching using the Florida data, the propensity score, through and intersecting road traffic volumes, through and intersecting road posted speed limits, and intersecting road shoulder width were included as covariates. For Mahalanobis matching using the South Carolina data, the natural log of through and intersecting road traffic volumes, through and intersecting road posted speed limits, and through and intersecting road lane and shoulder widths were included as covariates. Replacement was allowed. No CGT intersection was dropped from the dataset. The majority of comparison intersections were not duplicated for replacement. (Eight intersections were used more than once: seven in Florida and one in South Carolina.)

The matching results for both States indicated no significant differences for the majority of the covariates based on the standardized bias. Plots of the absolute standardized bias for each of the covariates are shown for Florida and South Carolina in figure 18 and figure 19, respectively. For Florida, the variables with significant bias (greater than 25 percent) remaining after matching included the through road traffic volumes and posted speeds. For South Carolina, the variables with significant bias remaining after matching included the natural log of through and intersecting road traffic volumes, as well as the through road posted speeds. The Mahalanobis matching was effective at removing the bias in all of the other observed covariates. The variables with significant bias remaining were included in each of the CMF models (added as predictor variables) to account for the differences in the CGT and comparison intersections. By adding the variables with significant remaining bias to the regression model as a predictor variable, the regression model adjusts for the remaining differences in the data for the treated and untreated intersections.

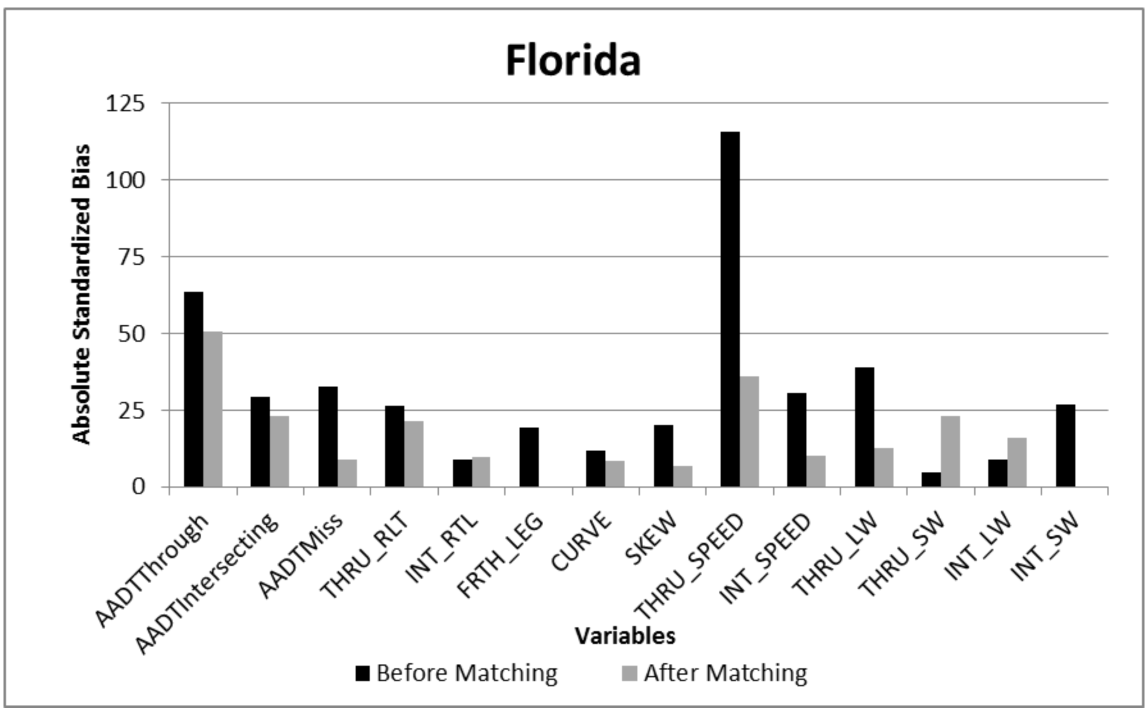


Figure 18. Graph. Absolute standardized bias for covariates in Florida.

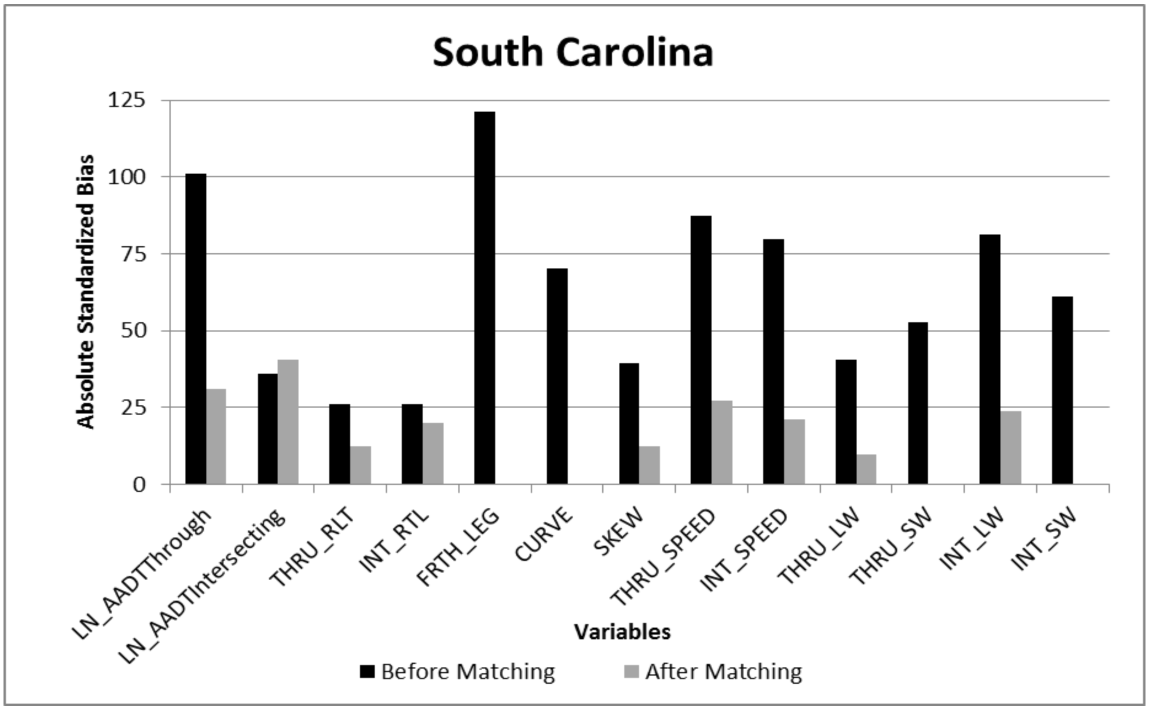


Figure 19. Graph. Absolute standardized bias for covariates in South Carolina.

Since there were still a number of covariates that were not balanced based on the standardized bias measures, genetic matching was also implemented to improve the matching. K-S tests were then done using the entire sample (both states combined) to help determine the level of covariate balance (for both matching methods and the unmatched data). The results of the tests are shown in table 12.

Table 12. K-S test results.

Matching Scheme	**AADTThrough**	**AADTIntersecting**	**AADTMiss**	**THRU_SPEED**	**INT_SPEED**	**INT_LW**	**INT_SW**
Unmatched	**< 0.0001**	**0.009**	0.237	**< 0.0001**	**0.032**	0.077	0.097
Mahalanobis matching	**< 0.0001**	**0.04**	0.713	**< 0.0001**	0.06	0.617	0.577
Genetic matching	0.081	0.083	0.104	0.073	**0.05**	0.801	0.098
Matching scheme	IntNumLane	THRU_LW	THRU_SW	ThruNumLane	FRTH_LEG	CURVE	DEFLECTION
Unmatched	0.265	**0.001**	0.133	**< 0.0001**	**0.003**	0.676	**0.007**
Mahalanobis matching	0.052	0.053	0.051	**< 0.0001**	0.126	1	**0.036**
Genetic matching	0.259	0.078	0.627	**< 0.0001**	**0.02**	0.955	0.133

Bold = Statistically significant difference (i.e., *p*-Value ≤ 0.05).

As shown in table 12, the K-S tests indicate that the following variables were all significantly different at the 95-percent confidence level using Mahalanobis matching:

- AADTThrough.
- AADTIntersecting.
- THRU_SPEED.
- ThruNumLane.
- DEFLECTION.

The following variables were all marginally different when using Mahalanobis matching:

- INT_SPEED.
- IntNumLane.
- THRU_LW.
- THRU_SW.

When using genetic matching, the covariate balance was improved over the Mahalanobis matching. The results of the genetic matching indicate that the only variables that were significantly different between the two groups were INT_SPEED, TruNumLane, and FRTH_LEG.

CHAPTER 7. CMF ESTIMATION

Due to the small sample sizes of the two datasets, the data from both States were combined to estimate CMFs for CGT intersections. The resulting CMFs indicated the average safety effect of the CGT intersections between the two states. CMFs for total, fatal and injury, and target crashes (rear-end, angle, and sideswipe) are described in the following subsections.

Variable selection and model specification were based on the crash prediction model forms found in the HSM.[31] In addition, matching was used to remove the correlation between the treatment (CGT) and other variables in the model. The potential outcomes models considered these same variable forms, as well as the standardized bias, to further minimize the correlation between the treatment and other variables in the model. If the K-S test found that the difference was statistically significant, the variable was included in the regression model to adjust for the remaining correlation between it and the treatment (for both matching methods and the unmatched data). Failing to account for this correlation produces biased treatment effect estimates.[15,35] The decision to use indicator variables for the posted speed limit on the continuous flow lane was made to fully account for the correlation in the full distribution of posted speed limits between the CGT and comparison group. If the posted speeds were grouped into ranges (e.g., lower than 50 mi/h and greater than or equal to 50 mi/h), the aggregation led to bias resulting from correlation between the posted speed indicator variables and the treatment.

As discussed in the Methods section, mixed effects negative binomial or Poisson regression was used to estimate the CMFs whenever possible. The optimal weights found using the genetic matching could not be accommodated using mixed effects regression, so weighted standard negative binomial regression with robust standard errors was used with the genetic matching results. The regression models for estimating the CMFs, along with the CMFs and 95-percent CIs, are shown in table 13 and table 14 for the genetic and Mahalanobis matching, respectively. For table 13, there were 297 observations used in the analysis. A weighted standard negative binomial regression model, with robust standard errors, was used to estimate the CMFs. The log-likelihood for the total, fatal and injury, and target crashes was -717.62695, -491.9991, and -599.30626, respectively. For table 14, there were 434 observations and 73 group (i.e., intersections) used in the analysis. A mixed-effects negative binomial regression model was used to estimate the CMF for total crashes, which had a log-likelihood of -938.44178. A mixed-effects Poisson regression model was used to estimate the CMF for fatal and injury crashes, which had a log-likelihood of -805.2616. Finally, a mixed-effects negative binomial regression model was used to estimate the CMF for target crashes, which had a log-likelihood of -665.20078.The statistical modeling output for the potential outcomes models for each crash type shown in table 13 and table 14 is provided in appendix A.

Table 13. Genetic matched regression models and CMF estimates.

Variable	Total Crash		Fatal and Injury Crash		Target (Rear-End, Angle, and Sideswipe) Crash	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Treated	-0.043	0.110	-0.167	0.133	-0.084	0.129
LN_AADTThrough	***0.492***	***0.146***	*0.303*	*0.172*	***0.563***	***0.169***
LN_AADTIntersecting	***0.216***	***0.039***	***0.191***	***0.044***	***0.225***	***0.044***
Thru_Spd_40	-0.106	0.327	0.048	0.363	-0.466	0.404
Thru_Spd_45	0.211	0.282	0.169	0.310	-0.089	0.345
Thru_Spd_50	*-0.647*	*0.362*	-0.224	0.419	***-1.248***	***0.489***
Thru_Spd_55	0.326	0.303	0.335	0.342	-0.177	0.360
Int_Spd_25	0.290	0.354	0.149	0.394	0.257	0.506
Int_Spd_30	0.460	0.326	0.457	0.357	0.673	0.480
Int_Spd_35	0.494	0.343	0.260	0.385	0.638	0.502
Int_Spd_40	0.311	0.382	0.195	0.405	0.198	0.555
Int_Spd_45	*0.680*	*0.354*	0.386	0.387	*0.905*	*0.516*
Int_Spd_55	0.461	0.399	0.352	0.451	0.443	0.563
Florida	***-0.636***	***0.163***	*-0.332*	*0.196*	***-1.174***	***0.214***
ThruLane5Up	***-1.066***	***0.213***	**-0.585**	**0.275**	***-1.448***	***0.342***
IntShoulder	***-0.295***	***0.124***	-0.233	0.167	***-0.508***	***0.170***
ThruShoulder	-0.566	0.472	-0.705	0.564	***-1.921***	***0.726***
Thru5UpShoulder	**1.115**	**0.518**	0.937	0.627	***2.537***	***0.792***
FRTH_LEG	*-0.241*	*0.138*	-0.253	0.183	-0.274	0.176
Constant	***-4.542***	***1.448***	**-3.636**	**1.696**	***-4.831***	***1.645***
Overdispersion Parameter	***0.239***	***0.041***	***0.077***	***0.045***	***0.284***	***0.063***
CMF	0.958		0.846		0.920	
CMF 95-percent Upper Bound	1.189		1.099		1.185	

Variable	Total Crash		Fatal and Injury Crash		Target (Rear-End, Angle, and Sideswipe) Crash	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
CMF 95-percent Lower Bound	0.772		0.651		0.714	

Italics = Significant at the 90-percent confidence level.
Bold = Significant at the 95-percent confidence level.
Bold and italics = Significant at the 99-percent confidence level.

Table 14. Mahalanobis matched regression models and CMF estimates.

Model Type	Mixed-Effects Negative Binomial		Mixed-Effects Poisson		Mixed-Effects Negative Binomial	
	Total Crash		Fatal and Injury Crash		Target (Rear-End, Angle, and Sideswipe) Crash	
Variable	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
Treated	-0.046	0.160	-0.134	0.139	-0.034	0.192
LN_AADTThrough	***0.591***	***0.058***	**0.443**	**0.185**	**0.527**	**0.250**
LN_AADTIntersecting	***0.183***	***0.058***	**0.116**	**0.052**	***0.195***	***0.071***
Thru_Spd_40	0.102	0.322	0.429	0.292	-0.017	0.398
Thru_Spd_45	0.305	0.246	*0.405*	*0.222*	0.384	0.301
Thru_Spd_50	-0.246	0.379	0.107	0.340	-0.199	0.459
Thru_Spd_55	0.724	0.323	***0.881***	***0.284***	*0.663*	*0.393*
Thru_Spd_60	-0.352	0.613	-0.653	0.690	-0.425	0.786
ThruLane5Up	*-0.614*	*0.316*	*-0.519*	*0.278*	**-0.820**	**0.379**
SKEW	0.009	0.006	0.004	0.005	0.010	0.007
Florida	***-0.724***	***0.149***	-0.191	0.132	***-1.158***	***0.177***
Constant	***-5.541***	***1.969***	***-4.805***	***1.751***	**-5.134**	**2.361**
Overdispersion Parameter	***0.028***	***0.004***	—	—	***0.039***	***0.006***
$\boldsymbol{\sigma}^2$	***0.212***	***0.048***	***0.102***	***0.036***	***0.284***	***0.067***
CMF	0.955		0.874		0.967	
CMF 95 percent Upper Bound	1.307		1.148		1.407	
CMF 95 percent Lower Bound	0.697		0.666		0.664	

— Indicates that no estimate of this parameter for the given model.
Italics = Significant at the 90-percent confidence level.
Bold = Significant at the 95-percent confidence level.
Bold and italics = Significant at the 99-percent confidence level.

The weighted negative binomial model was used for total crashes, fatal and injury crashes, and target crashes (rear-end, angle, and sideswipe) using the genetic matched data. The models shown in table 13 included all independent variables that, theoretically, correlated with total, fatal and injury, or target crashes (based on the K-S tests in table 12). Variables that were not statistically significant in the negative binomial models were included in the model because Mannering and Bhat pointed out that parsimonious models are biased, are fundamentally flawed, and have little practical value.[36] Thus, the statistical models estimated in this evaluation were not specified based on statistical significance at the 95-percent confidence level.

The coefficients for all of the models were consistent with engineering intuition. The purpose of CGT intersections is to improve traffic operations. The results indicate that there were no statistically significant differences (at the 95-percent confidence level) between signalized T intersections without continuous flow lanes and CGT intersections in terms of total, fatal and injury, or target crashes (rear-end, angle, and sideswipe). It is worth noting, however, that the point estimates of the CMFs for total, fatal and injury, and target crashes were all less than 1, suggesting that there is a potential reduction in crash frequency associated with the CGT intersection relative to the conventional signalized-T intersection and that the lack of statistical significance is likely due to the small sample size rather than the lack of an effect. Thus, it is concluded that CGT intersections can have a beneficial effect on crash frequency. The CGT CMFs for each crash type and severity, with the associated 95-percent CIs, are shown in table 13.

The signs and magnitudes of the coefficients for traffic volumes are consistent with the major and minor road coefficients for at-grade intersections found in the HSM.[31] For the through street posted speed limit, the baseline condition was a posted speed limit of 35 mi/h. For the intersecting street posted speed limit, the baseline condition was a posted speed limit of 20 mi/h. A positive coefficient indicates that the expected number of crashes is higher for the speed limit shown relative to the baseline condition. The posted speed limit indicator variables, while mostly insignificant, were retained in the model to minimize bias associated with the covariates in the matched data used to estimate the potential outcomes model that were not balanced after matching. The indicator variable for Florida indicated that there were fewer crashes in Florida than in South Carolina, which matches the descriptive statistics. The indicator variable for five or more through lanes was used because using individual indicator variables for the individual number of through lanes resulted in estimates that were nearly identical for any indicator variables for five or more lanes. The negative signs that indicate whether there were shoulders on the through and intersecting roads are logical because shoulders provide a recovery area for vehicles that leave the travel lanes. The variable Thru5UpShoulder is an interaction variable between five or more through lanes and the existence of a shoulder. The positive value indicates that intersections with five or more through lanes and shoulders on the through street did not receive the same safety benefits from the shoulders as intersections with fewer than five lanes on the through street. Finally, the presence of a fourth leg at the intersection that only allowed right-in and right-out movements correlated with lower crash frequencies. This was likely due to the fourth leg only being allowed on intersections with specific characteristics that were not collected as a part of this study but that are associated with lower crash frequencies.

Since traffic volume data were missing for several of the Florida intersections, a sensitivity analysis was performed by varying the traffic volumes for the missing locations. Traffic volumes of 500, 1,000, and 3,000 vehicles per day were tested. (As mentioned in the Data Collection section, a local jurisdiction performed a traffic count for one of the missing locations and found the AADT to be 500 vehicles per day; most missing minor street approaches had similar land use characteristics.) The difference in results was minimal when using 500, 1,000, and 3,000 vehicles per day for the missing minor street approach traffic volumes. Thus, only the results with the missing traffic volumes set at 500 vehicles per day are provided in this report.

The mixed effects negative binomial model was used for total crashes and target crashes (rear-end, angle, and sideswipe) using the Mahalanobis matched data. For fatal and injury crashes, the overdispersion parameter was not statistically significant when the mixed effects negative binomial was used, so the mixed effects Poisson was used for the final model. The random intercept was statistically significant in all of the models.

The results of the models in table 14 indicate that there were no statistically significant differences (at the 95-percent confidence level) between signalized T intersections without continuous flow lanes and CGT intersections in terms of total, fatal and injury, or target crashes (rear-end, angle, and sideswipe). As with the results from the genetic matching, the point estimates of the CMFs for total, fatal and injury, and target crashes are all less than 1.0, suggesting that there is a potential reduction in crash frequency associated with the CGT intersection relative to the conventional signalized T intersection. The lack of statistical significance is likely due to the small sample size rather than the lack of an effect. The CGT CMFs for each crash type and severity, with the associated 95-percent confidence level, are shown in table 14.

The signs and magnitudes of the coefficients for traffic volumes are consistent with the major and minor road coefficients for at-grade intersections found in the HSM.[31] For the posted speed limit, the baseline condition is a posted speed limit of 35 mi/h. A positive coefficient indicates that the expected number of crashes is higher for the speed limit shown relative to the baseline condition. The posted speed limit indicator variables, while mostly insignificant, were retained in the model to minimize bias associated with the covariates from the Mahalanobis matched data that were significantly different (based on the K-S tests in table 12).

The sensitivity analysis for the missing traffic volumes that was used with the genetic matching CMF models was also performed with the Mahalanobis CMF models. The results were the same, and the missing traffic volumes were set to 500 vehicles per day.

The models in table 14 also indicate that crash frequency increased as intersection skew angle increased. This is consistent with the HSM.[31] The finding that the expected crash frequency in Florida was lower than in South Carolina was consistent with the descriptive statistics.

As noted earlier, the propensity scores-potential outcomes framework reduced the overall sample size from the original data due to matching (i.e., some intersections are dropped). As such, cross-sectional models using the unmatched data were also estimated for comparison. The CMFs estimated using the full, unmatched database were provided to show the magnitude of bias that the CMFs would have had if matching was not used. The regression models and CMFs for total, fatal and injury, and the target crashes using the full dataset (i.e., no matching) are shown in table 13. The statistical modeling outputs for the models shown in table 13 and table 14 are provided in appendix A. The statistical modeling outputs for the models shown in table 15 are provided in appendix B. For table 15, there were 516 observations and 104 groups (i.e., intersections) used in the analysis. A mixed-effects negative binomial regression model was used to estimate the CMF for total crashes, which had a log-likelihood of -1134.5724. A mixed-effects Poisson regression model was used to estimate the CMF for fatal and injury crashes, which had a log-likelihood of -795.8822. Finally, a mixed-effects negative binomial regression model was used to estimate the CMF for target crashes, which had a log-likelihood of -960.89489.

The CMFs estimated using the unmatched data are more likely to be biased than the estimates using the matched data, so the CMFs from the latter should be regarded as more robust. It is encouraging that the CMFs estimated using the unmatched data are similar to the CMFs from the matched data, although the safety benefit estimated with both sets of models is statistically insignificant. Based on the K-S test results, the genetic matching resulted in the best covariate balance. Thus, the CMFs estimated from the genetic matching are preferred over the other two methods.

Table 15. CMF models for unmatched cross-sectional data.

Model Type	Mixed-Effects Negative Binomial		Mixed-Effects Poisson		Mixed-Effects Negative Binomial	
	Total Crash		Fatal and Injury Crash		Target (Rear-End, Angle, and Sideswipe) Crash	
Variable	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Treated	-0.065	0.145	-0.126	0.147	-0.186	0.165
LN_AADTThrough	***0.883***	***0.150***	***0.788***	***0.154***	***0.904***	***0.172***
LN_AADTIntersecting	**0.114**	**0.052**	**0.133**	**0.053**	**0.117**	**0.060**
Thru_Spd_30	-0.066	0.647	0.391	0.675	1.081	0.951
Thru_Spd_35	0.119	0.619	0.230	0.655	1.168	0.927
Thru_Spd_40	0.301	0.642	0.528	0.677	1.465	0.946
Thru_Spd_45	0.379	0.638	0.643	0.673	1.642	0.942
Thru_Spd_50	-0.358	0.704	0.234	0.738	0.805	1.001
Thru_Spd_55	0.611	0.692	1.068	0.723	*1.700*	*0.990*
Thru_Spd_60	0.447	0.964	0.028	1.067	1.461	1.297
Int_Spd_25	0.407	0.466	0.309	0.477	0.394	0.566
Int_Spd_30	0.625	0.446	0.489	0.457	0.671	0.545
Int_Spd_35	0.640	0.450	0.326	0.462	0.630	0.550
Int_Spd_40	0.604	0.491	0.525	0.501	0.478	0.597
Int_Spd_45	*0.929*	*0.479*	0.434	0.488	*1.092*	*0.577*
Int_Spd_55	*0.912*	*0.529*	0.598	0.540	0.968	0.631
THRU_LW	0.134	0.117	0.093	0.123	0.107	0.138
ThruLane5Up	**-0.431**	**0.204**	*-0.382*	*0.210*	**-0.554**	**0.234**
FRTH_LEG	-0.053	0.151	-0.191	0.156	0.002	0.170
SKEW	0.008	0.005	0.002	0.005	0.007	0.006
Florida	***-0.588***	***0.159***	-0.224	0.164	***-1.004***	***0.179***
Constant	***-10.382***	***2.288***	***-10.227***	***2.353***	***-11.668***	***2.714***
Overdispersion Parameter	***0.061***	***0.013***	—	—	***0.088***	***0.012***
σ^2	***0.216***	***0.042***	***0.158***	***0.043***	***0.246***	***0.054***

Model Type	Mixed-Effects Negative Binomial		Mixed-Effects Poisson		Mixed-Effects Negative Binomial	
	Total Crash		Fatal and Injury Crash		Target (Rear-End, Angle, and Sideswipe) Crash	
Variable	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
CMF	0.937		0.882		0.830	
CMF 95 percent Upper Bound	1.245		1.176		1.146	
CMF 95 percent Lower Bound	0.705		0.661		0.602	

— Indicates that no estimate of this parameter for the given model.
Italics = Significant at the 90-percent confidence level.
Bold = Significant at 95-percent confidence level.
Bold and italics = Significant at the 99-percent confidence level.

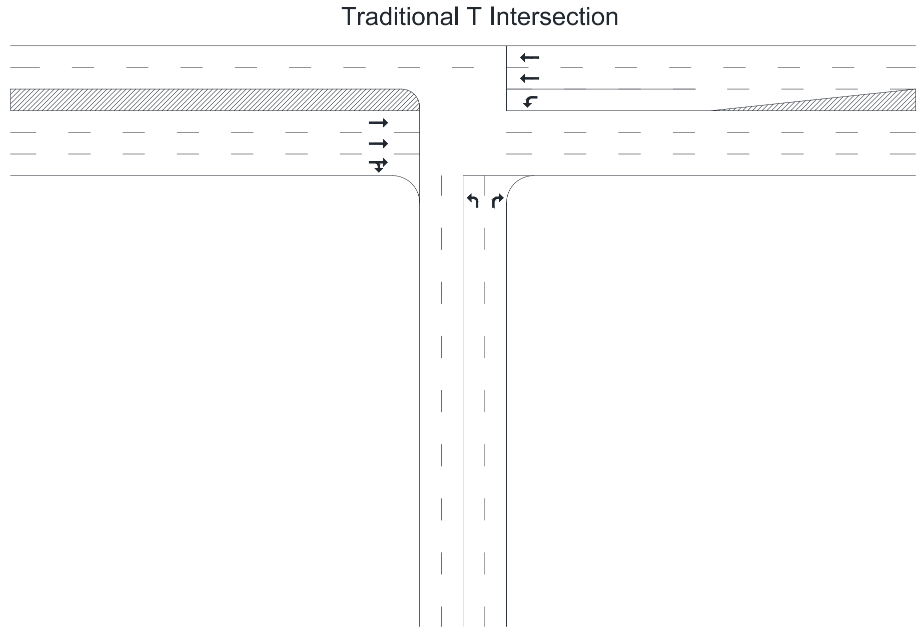
CHAPTER 8. ECONOMIC ANALYSIS

A B/C analysis compared the safety benefits with the construction costs of a CGT relative to a conventional signalized three-leg intersection. This chapter describes the assumptions used in the analysis, describes the differences in the construction costs between the CGT and the conventional signalized three-leg intersection, derives the safety benefits associated with the CGT, and computes the B/C ratio for the CGT relative to a conventional signalized three-leg intersection.

ASSUMPTIONS

Because this study was unable to use an observational before-after study methodology, the B/C analysis presented in this report compared two different intersection forms (CGT versus conventional three-leg signalized intersection). To complete the B/C analysis, the following assumptions were made:

- The median width was as wide as the left-turn lane adjacent to the continuous flow lane on the major street.
- The median was unpaved.
- There were shoulders on both the major and minor streets.
- There was no fourth leg at the intersection.
- There were fewer than five through lanes.
- The comparison intersection was a signalized T intersection.
- The pavement design life was 20 years.
- The average traffic volume for the comparison group was constant over the 20-year period (to be used for predictions).
- All safety benefits were derived using the South Carolina data, so the Florida indicator variable in table 13 was set equal to zero. It should be noted that the Florida indicator variable was negative, so the B/C ratios for Florida were larger than those computed using the South Carolina data.
- There were no maintenance costs because the project design life was equivalent to the pavement design life.
- The existing traffic signals could be used for the CGT intersection.
- The only cost associated with the treatment was the additional pavement for the acceleration lane, as shown in figure 20.



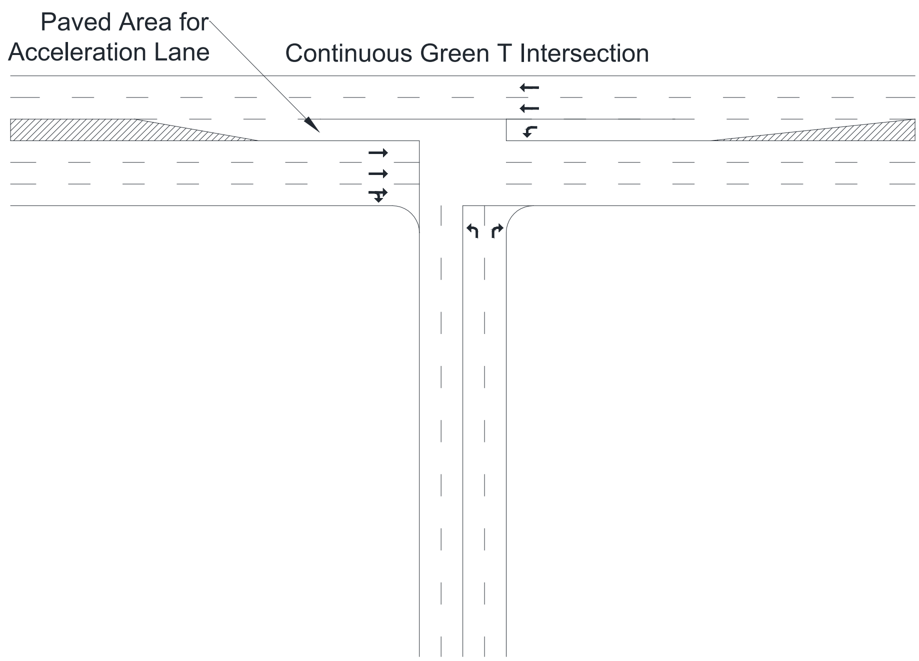


Figure 20. Schematic. Traditional and CGT intersections.

The CMFs used for the evaluation were those estimated using the propensity scores-potential outcomes framework (genetic matching results (table 13)). The treatment cost was dependent on the posted speed limit. A minimum (35 mi/h on the major road) and maximum (55 mi/h on the major road) cost for the treatment are estimated in figure 21 and figure 22.

For the new pavement, the low (posted speed = 35 mi/h) value required is as follows:

- 210 ft to the beginning of the taper at 12 ft wide = 210 x 12 = 2,520 ft^2.
- 125-ft taper with an average of 6 ft wide = 125 x 6 = 750 ft^2.

$$\textit{Total Pavement Required} = 2{,}520 \text{ ft} + 750 \text{ ft} = 3{,}270 \text{ ft}^2 = 363 \text{ yd}^2$$

Figure 21. Equation. Total pavement required for low posted speed.

For the new pavement, the high (posted speed = 55 mi/h) value required is as follows:

- 435 ft to the beginning of the taper at 12 ft wide = 435 x 12 = 5,220 ft^2.
- 540-ft taper with an average of 6 ft wide = 540 x 6 = 3,240 ft^2.

$$\textit{Total Pavement Required} = 5{,}220 \text{ ft} + 3{,}240 \text{ ft} = 8{,}460 \text{ ft}^2 = 940 \text{ yd}^2$$

Figure 22. Equation. Total pavement required for high posted speed.

The cost for asphalt pavement used for the analysis was \$28/yd^2. The cost for concrete pavement was \$70/yd^2. Thus, the cost for 35 mi/h was \$10,173.33 for asphalt and \$25,433.33 for concrete. The cost for 55 mi/h was \$26,320 for asphalt and \$65,800 for concrete.[35]

The number of crashes (total, fatal and injury, and property damage only (PDO)) with and without the CGT, using the average AADTs from the comparison group, were predicted for the 20-year service life. For example, the total expected number of crashes for the untreated intersections were computed using the equation in figure 23, assuming that the posted speed limit on the major road was 35 mi/h (indicator variable for Thru_Spd was set equal to zero because it is the baseline value), minor (intersecting) roadway was 35 mi/h (indicator variable for Int_Spd_35 in table 13 was 0.494), the site was a comparison site (treated variable was set equal to zero), and the intersection was located in South Carolina (Florida indicator was zero).

$$N_{total} = e^{-4.542} \times AADT_{throug\,h}^{0.492} \times AADT_{intersecting}^{0.216} \times e^{0} \times e^{0.494} \times e^{-0.295} \times e^{-0.566}$$

Figure 23. Equation. Total number of expected crashes for untreated intersections.

N_{total} = Total number of expected crashes.
e = The exponential function.
through = The subscript related to through street traffic volume (veh/day).
intersecting = The subscript related to the intersecting road traffic volume (veh/day).

The descriptive statistics for the South Carolina comparison group are shown in table 8 and table 9, and the average through and intersecting roadway AADT volumes are 22,452 and 8,452 vehicles per day, respectively. Inputting these values produced the expected number of total crashes per year, as seen in figure 24.

$$N_{total} = e^{-4.542} \times 22{,}452^{0.492} \times 8{,}462^{0.216} \times e^{0} \times e^{0.494} \times e^{-0.295} \times e^{-0.566} = 720 \text{ crashes/year}$$

Figure 24. Equation. Total number of expected crashes per year for the untreated intersections.

As such, the expected annual total crash frequency for the South Carolina comparison group sites was 7.20 crashes per year, as shown in table 16. Multiplying the annual crash frequency by 20 years produces 144 crashes. The number of property damage only (PDO) crashes was estimated by subtracting the number of fatal and injury crashes from the total crashes. The treated crash frequency predictions were derived by applying the CMFs shown in table 13. The total treated crash frequency estimates were derived by multiplying 144 crashes (untreated crashes) times the CMF for total crashes. This resulted in 144 times 0.958, which equals 137.95 crashes over a 20-year period. All of the predicted crash frequency estimates for the untreated and treated intersections are shown in table 16.

Table 16. Annual predicted crash frequencies.

Posted Speed (mi/h)	Untreated			Treated			Reduction (Untreated - Treated)		
	Total	Fatal and Injury	PDO	Total	Fatal and Injury	PDO	Total	Fatal and Injury	PDO
35	7.20	1.57	5.63	6.90	1.33	5.57	**0.30**	**0.24**	**0.06**
55	9.97	2.19	7.78	9.55	1.85	7.70	**0.42**	**0.34**	**0.08**

Bold = Reduction in annual crash frequencies.

The comprehensive crash costs used for this analysis were derived using 2001 dollar values from Council et al.(38) As suggested by the authors, the crash cost values were multiplied by the ratio of the Consumer Price Index for 2001 and 2014. This ratio was 2.425. The 2001 comprehensive crash costs were \$129,418 for fatal and injury crashes and \$10,249 for PDO crashes on roads with posted speed limits below 50 mi/h. The 2001 comprehensive crash costs were \$146,281 for fatal and injury crashes and \$4,015 for PDO crashes on roads with posted speed limits equal to or above 50 mi/h. This produces crash cost savings of \$1,536,250 for the 35 mi/h posted speed and \$2,427,752 for the 55 mi/h posted speed limit for the 20-year project life. The annual benefits (from crash costs) were \$76,813 for the 35 mi/h posted speed limit major roads and \$121,388 for the 55 mi/h posted speed limit major roads. Thus, the B/C ratio, by pavement type and posted speed limit, were estimated and are provided in table 17.

Table 17. B/C ratios for different pavement types.

Posted Speed Limit (mi/h)	Asphalt Pavement	Concrete Pavement
35	76,813/956.30 = 80.3	76,813/2,390.70 = 32.1
55	121,388/2,474.10 = 49.1	121,388/6,185.20 = 19.6

The annual costs (based on the initial paving costs and no maintenance over the 20-year project life), discounted at 7 percent over the 20-year project life, were $956.30 for asphalt and $2390.70 for concrete pavements at 35 mi/h intersections and $2474.10 for asphalt and $6185.20 for concrete at 55 mi/h intersections, respectively.

Sensitivity Analysis

In order to test the sensitivity of the B/C ratios to variability in the safety benefits, the upper and lower bound of the 95-percent CI of the CMF estimate for total crashes in table 13 was applied to the safety benefit estimates shown in table 17. This produced B/C ratios that ranged from 62.0 to 95.5 for the 35 mi/h posted speed limit on asphalt pavements and from 37.9 to 58.4 for the 55 mi/h posted speed limit on asphalt pavement. The B/C ratio ranged from 24.8 to 38.2 for 35 mi/h posted speed limits on concrete pavements and from 15.1 to 23.3 for 55 mi/h posted speed limits on concrete pavements.

Further sensitivity analysis was done to determine the construction costs that would still achieve a B/C ratio of 2.0 (lower bound) for the 35 and 55 mi/h posted speed limits. (The crash costs were equal for asphalt and concrete pavements.) For the 35 mi/h posted speed limit, a B/C ratio of 2.0 could be achieved with annual construction costs up to $38,407. For a 55 mi/h posted speed limit, annual construction costs up to $60,694 produce a B/C ratio up to 2.0.

CHAPTER 9. SUMMARY AND CONCLUSIONS

The objective of this study was to evaluate the safety impacts of CGT intersections. Total, fatal and injury, and target (rear-end, angle, and sideswipe) crash types were considered. Data from Florida and South Carolina were used for this study to estimate CMFs for CGT intersections relative to conventional signalized T intersections. The propensity scores—potential outcomes—was used to estimate the CMFs. Genetic matching provided better matching results than NN or Mahalanobis matching. The CMFs were estimated using weighted negative binomial regression with the genetic matched data.

Based on the propensity scores-potential outcomes results (with genetic matching), the CMF point estimates for total, fatal and injury, and target crashes were 0.958, 0.846, and 0.920, respectively, suggesting that there was a potential reduction in crash frequency associated with the CGT intersection relative to the conventional T signalized intersection. Although the results were not statistically significant, it was likely due to the small sample rather than the lack of an effect. Because the CGT was not expected to compromise safety performance relative to a conventional signalized T intersection but affords improved traffic operational performance and fewer environmental impacts (lower vehicle emissions), it should be considered as a candidate alternative intersection form when conditions exist to effectively implement.

Based on the findings of this research and the literature review, CGT intersections are likely to be favorable over traditional signalized intersections when there are high through traffic volumes on the major street approach on the far side of the intersection (opposite the minor street approach). This approach could function as the continuous flow lane. The CGT intersection is also likely to be a favorable form if there is low cyclist demand and either no pedestrian demand or an alternative pedestrian crossing nearby.

The B/C analysis confirmed that the CGT is a cost-effective intersection design alternative to the conventional signalized T intersection (based on the point estimates of the CMFs). The B/C ratios for both asphalt and concrete pavements, as well as 35 and 55 mi/h posted speed limits on the major road, produced B/C ratios that significantly exceeded 1.0.

Potential Issues with CGT Intersections

Throughout the course of the present study, it was learned that several CGT intersections were being converted to conventional signalized T intersections in Florida. Anecdotal feedback indicated that non-motorized users at these locations have expressed concern with the high-speed, continuous flow lanes on the major approach. Pedestrians and bicyclists wishing to cross from the minor street approach to the far side of the high-speed continuous flow lanes may have difficulty identifying adequate gaps. As such, implementation of the CGT intersections at locations with anticipated pedestrian and bicycle users should be weighed against the operational and environmental benefits.

APPENDIX A. MATCHED DATA MODELS

This appendix contains the regression output for the models using the matched data (genetic and Mahalanobis matching). These models were used to develop the CMFs.

GENETIC MATCHING

```
Total Crashes

Negative binomial regression                      Number of obs   =        297
Dispersion           = mean                       Wald chi2(19)   =     287.53
Log pseudolikelihood = -717.62695                 Prob > chi2     =     0.0000

------------------------------------------------------------------------------
             |               Robust
         TOT |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     Treated |  -.0425862   .1101659    -0.39   0.699    -.2585075    .1733351
    LNAADTMaj |   .4923199   .1459936     3.37   0.001     .2061778    .7784621
    LNAADTMin |   .2154684   .0385375     5.59   0.000     .1399363    .2910006
     Florida |  -.6362596    .162479    -3.92   0.000    -.9547125   -.3178067
 ThruLane5Up |  -1.065885    .212755    -5.01   0.000    -1.482878   -.6488932
 IntShoulder |  -.2946033   .1243796    -2.37   0.018    -.5383828   -.0508239
ThruShoulder |  -.5656151   .4716386    -1.20   0.230     -1.49001    .3587795
Thru5UpShlder |   1.115338   .5175464     2.16   0.031     .1009653     2.12971
   FRTH_LEG |  -.2411121   .1375897    -1.75   0.080     -.510783    .0285588
             |
   INT_SPEED |
         25  |   .2900747    .354013     0.82   0.413    -.4037781    .9839275
         30  |   .4594779    .326298     1.41   0.159    -.1800544     1.09901
         35  |   .4942091   .3434051     1.44   0.150    -.1788526    1.167271
         40  |   .3111814   .3817203     0.82   0.415    -.4369766    1.059339
         45  |   .6799561   .3540597     1.92   0.055    -.0139882      1.3739
         55  |   .4608651   .3985745     1.16   0.248    -.3203266    1.242057
             |
  THRU_SPEED |
         40  |  -.1062967   .3269923    -0.33   0.745    -.7471898    .5345964
         45  |   .2109157   .2818383     0.75   0.454    -.3414772    .7633087
         50  |  -.6465204   .3619147    -1.79   0.074     -1.35586    .0628194
         55  |   .3262764   .3029884     1.08   0.282     -.26757     .9201229
             |
       _cons |  -4.541765   1.447841    -3.14   0.002    -7.379481   -1.704048
-------------+----------------------------------------------------------------
    /lnalpha |  -1.429498   .1727079                     -1.767999   -1.090997
-------------+----------------------------------------------------------------
       alpha |    .239429   .0413513                      .1706741    .3358815
------------------------------------------------------------------------------
```

Fatal and Injury Crashes

```
Negative binomial regression                      Number of obs   =        297
Dispersion           = mean                       Wald chi2(19)   =      56.78
Log pseudolikelihood = -491.09991                 Prob > chi2     =     0.0000

------------------------------------------------------------------------------
             |               Robust
          FI |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     Treated |  -.1669481   .1334598    -1.25   0.211    -.4285246    .0946283
   LNAADTMaj |   .3027534   .1719295     1.76   0.078    -.0342222    .6397291
   LNAADTMin |   .1910633   .0442966     4.31   0.000     .1042436     .277883
     Florida |  -.3316629   .1961931    -1.69   0.091    -.7161943    .0528685
 ThruLane5Up |  -.5849208   .2753746    -2.12   0.034    -1.124645   -.0451965
 IntShoulder |   -.232926   .1670391    -1.39   0.163    -.5603168    .0944647
ThruShoulder |  -.7050994   .5639856    -1.25   0.211    -1.810491     .400292
Thru5UpShlder |   .9365371   .6267288     1.49   0.135    -.2918288    2.164903
    FRTH_LEG |  -.2530672   .1826752    -1.39   0.166    -.6111041    .1049696
             |
   INT_SPEED |
         25  |   .1490696   .3936889     0.38   0.705    -.6225465    .9206857
         30  |   .4573904   .3566774     1.28   0.200    -.2416845    1.156465
         35  |   .2598806   .3846343     0.68   0.499    -.4939888     1.01375
         40  |    .195327   .4051539     0.48   0.630    -.5987601    .9894141
         45  |   .3861851   .3871922     1.00   0.319    -.3726977    1.145068
         55  |   .3522804   .4505391     0.78   0.434      -.53076    1.235321
             |
  THRU_SPEED |
         40  |    .047759   .3633107     0.13   0.895    -.664317     .759835
         45  |   .1691577   .3103545     0.55   0.586    -.439126     .7774414
         50  |  -.2235057   .4191268    -0.53   0.594    -1.044979    .5979676
         55  |   .3347177   .3418134     0.98   0.327    -.3352244     1.00466
             |
       _cons |  -3.635727   1.696434    -2.14   0.032    -6.960676   -.3107779
-------------+----------------------------------------------------------------
    /lnalpha |  -2.569357   .5916134                     -3.728898   -1.409816
-------------+----------------------------------------------------------------
       alpha |   .0765848   .0453086                      .0240193    .2441883
------------------------------------------------------------------------------
```

Target Crashes

Negative binomial regression　　Number of obs = 297
Dispersion = mean　　Wald chi2(19) = 324.75
Log pseudolikelihood = -599.30626　　Prob > chi2 = 0.0000

Target	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
Treated	-.0835338	.1294228	-0.65	0.519	-.3371979	.1701303
LNAADTMaj	.562835	.1689981	3.33	0.001	.2316047	.8940652
LNAADTMin	.2251839	.0441408	5.10	0.000	.1386696	.3116982
Florida	-1.173519	.2142147	-5.48	0.000	-1.593372	-.7536656
ThruLane5Up	-1.448441	.3416042	-4.24	0.000	-2.117973	-.7789092
IntShoulder	-.5076138	.1700634	-2.98	0.003	-.840932	-.1742957
ThruShoulder	-1.920895	.7262517	-2.64	0.008	-3.344322	-.4974676
Thru5UpShlder	2.536511	.7922779	3.20	0.001	.9836746	4.089347
FRTH_LEG	-.273681	.1758453	-1.56	0.120	-.6183315	.0709695
INT_SPEED						
25	.256837	.5060215	0.51	0.612	-.734947	1.248621
30	.6727153	.4797619	1.40	0.161	-.2676008	1.613031
35	.6383726	.5020733	1.27	0.204	-.3456729	1.622418
40	.1977973	.5548589	0.36	0.721	-.8897061	1.285301
45	.9045994	.5159448	1.75	0.080	-.1066339	1.915833
55	.4433076	.5625622	0.79	0.431	-.659294	1.545909
THRU_SPEED						
40	-.4655281	.4043569	-1.15	0.250	-1.258053	.3269969
45	-.0891576	.3453978	-0.26	0.796	-.7661249	.5878096
50	-1.248241	.4890602	-2.55	0.011	-2.206782	-.2897009
55	-.1768242	.3604577	-0.49	0.624	-.8833083	.5296598
_cons	-4.831303	1.644516	-2.94	0.003	-8.054495	-1.60811
/lnalpha	-1.257409	.2205592			-1.689697	-.8251205
alpha	.2843901	.0627248			.1845755	.4381822

MAHALANOBIS MATCHING

Total Crashes

Mixed-effects nbinomial regression　　Number of obs = 434
Overdispersion: mean
Group variable: Location　　Number of groups = 73

Wald chi2(11) = 76.07
Log likelihood = -938.44718　　Prob > chi2 = 0.0000

TOT	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Treated	-.0464587	.160353	-0.29	0.772	-.3607448	.2678274
LNAADTMaj	.5911802	.2070058	2.86	0.004	.1854563	.9969041
LNAADTMin	.1827335	.0580069	3.15	0.002	.0690421	.2964249
THRU_SPEED						
40	.1020133	.322451	0.32	0.752	-.5299791	.7340057
45	.3045244	.2456019	1.24	0.215	-.1768465	.7858953
50	-.2461067	.3788936	-0.65	0.516	-.9887245	.4965112
55	.7239126	.3226377	2.24	0.025	.0915543	1.356271
60	-.3522544	.6128105	-0.57	0.565	-1.553341	.8488322
ThruLane5Up	-.6136113	.3164582	-1.94	0.053	-1.233858	.0066354
DEFLECTION	.008991	.0058116	1.55	0.122	-.0023995	.0203816
Florida	-.7244923	.1486832	-4.87	0.000	-1.015906	-.4330787
_cons	-5.541216	1.969354	-2.81	0.005	-9.401079	-1.681353
/lnalpha	-3.567961	.4746443	-7.52	0.000	-4.498246	-2.637675

	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Location						
var(_cons)	.2120851	.0475991			.1366066	.3292674

LR test vs. nbinomial regression:chibar2(01) = 133.20 Prob>=chibar2 = 0.0000

Fatal + Injury Crashes

Mixed-effects Poisson regression   Number of obs = 434
Group variable: Location   Number of groups = 73

Wald chi2(11) = 33.52
Log likelihood = -665.20078   Prob > chi2 = 0.0004

FI	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Treated	-.1341782	.1386713	-0.97	0.333	-.405969	.1376126
LNAADTMaj	.4430583	.1845915	2.40	0.016	.0812656	.8048511
LNAADTMin	.1164183	.0520172	2.24	0.025	.0144663	.2183702
THRU_SPEED						
40	.4292983	.2915357	1.47	0.141	-.1421011	1.000698
45	.4049865	.2221222	1.82	0.068	-.0303651	.840338
50	.1067951	.3398837	0.31	0.753	-.5593647	.772955
55	.880773	.2837816	3.10	0.002	.3245713	1.436975
60	-.6526719	.6898198	-0.95	0.344	-2.004694	.6993501
ThruLane5Up	-.5191403	.2780189	-1.87	0.062	-1.064047	.0257668
DEFLECTION	.0038474	.0051373	0.75	0.454	-.0062215	.0139162
Florida	-.1913353	.1319369	-1.45	0.147	-.4499269	.0672564
_cons	-4.805059	1.750959	-2.74	0.006	-8.236877	-1.373242
Location						
var(_cons)	.1022855	.0363784			.0509425	.2053754

LR test vs. nbinomial regression:chibar2(01) = 24.23 Prob>=chibar2 = 0.0000
Target Crashes

Mixed-effects nbinomial regression   Number of obs = 433
Overdispersion: mean
Group variable: Location   Number of groups = 73

Wald chi2(11) = 91.98
Log likelihood = -805.26016   Prob > chi2 = 0.0000

Target	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Treated	-.0337268	.1915727	-0.18	0.860	-.4092025	.3417488
LNAADTMaj	.5266724	.2497115	2.11	0.035	.0372468	1.016098
LNAADTMin	.1948996	.0712121	2.74	0.006	.0553264	.3344728
THRU_SPEED						
40	-.0171329	.398288	-0.04	0.966	-.7977631	.7634973
45	.3838796	.3013736	1.27	0.203	-.2068017	.974561
50	-.1985112	.4589208	-0.43	0.665	-1.097979	.700957
55	.6631016	.393477	1.69	0.092	-.108099	1.434302
60	-.4246656	.7859793	-0.54	0.589	-1.965157	1.115826
ThruLane5Up	-.8200212	.3790982	-2.16	0.031	-1.56304	-.0770024
DEFLECTION	.0100721	.0069324	1.45	0.146	-.0035152	.0236594
Florida	-1.158089	.1774422	-6.53	0.000	-1.505869	-.8103083
_cons	-5.133955	2.36076	-2.17	0.030	-9.76096	-.5069502
/lnalpha	-3.240642	.5155851	-6.29	0.000	-4.251171	-2.230114
Location						
var(_cons)	.2840945	.0674521			.1783871	.4524413

LR test vs. nbinomial regression:chibar2(01) = 108.78 Prob>=chibar2 = 0.0000

APPENDIX B. UNMATCHED DATA MODELS

This appendix contains the regression output for the models using the unmatched data. These models were used to develop the CMFs.

Total Crashes

```
Mixed-effects nbinomial regression              Number of obs      =       516
Overdispersion:             mean
Group variable:         Location                Number of groups   =       104


                                                Wald chi2(21)      =    121.79
Log likelihood = -1134.4724                     Prob > chi2        =    0.0000
------------------------------------------------------------------------------
         TOT |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     Treated |  -.0651048   .1452097    -0.45   0.654    -.3497105     .219501
   LNAADTMaj |   .8827815   .1499963     5.89   0.000     .5887942    1.176769
   LNAADTMin |   .1138795   .0520072     2.19   0.029     .0119472    .2158118
             |
  THRU_SPEED |
         30  |  -.0663538   .6472018    -0.10   0.918    -1.334846    1.202138
         35  |   .1191612   .6194883     0.19   0.847    -1.095014    1.333336
         40  |   .3005828   .6417147     0.47   0.639    -.9571549    1.558321
         45  |   .3793965   .6377301     0.59   0.552    -.8705315    1.629325
         50  |  -.3578762   .7042309    -0.51   0.611    -1.738143    1.022391
         55  |   .6114627   .6921769     0.88   0.377     -.745179    1.968104
         60  |   .4465226   .9637542     0.46   0.643    -1.442401    2.335446
             |
   INT_SPEED |
         25  |     .40674   .4660948     0.87   0.383     -.506789    1.320269
         30  |     .62461   .4456572     1.40   0.161     -.248862    1.498082
         35  |   .6398991   .4503864     1.42   0.155    -.2428419     1.52264
         40  |   .6039956   .4907412     1.23   0.218    -.3578394    1.565831
         45  |   .9291992   .4785334     1.94   0.052     -.008709    1.867107
         55  |   .9122952    .528974     1.72   0.085    -.1244748    1.949065
             |
     THRU_LW |   .1335091   .1174843     1.14   0.256    -.0967559    .3637741
 ThruLane5Up |  -.4314039   .2038598    -2.12   0.034    -.8309617    -.031846
   FRTH_LEG  |  -.0529904   .1514085    -0.35   0.726    -.3497457    .2437649
  DEFLECTION |   .0075639   .0051582     1.47   0.143     -.002546    .0176739
     Florida |  -.5879068    .158542    -3.71   0.000    -.8986434   -.2771703
       _cons |  -10.38209   2.287736    -4.54   0.000    -14.86597   -5.89821
-------------+----------------------------------------------------------------
    /lnalpha |  -2.793322   .3145283    -8.88   0.000    -3.409786   -2.176858
-------------+----------------------------------------------------------------
Location     |
   var(_cons)|   .2162566   .0420769                      .1476902    .3166556
------------------------------------------------------------------------------
LR test vs. nbinomial regression:chibar2(01) =   112.31 Prob>=chibar2 = 0.0000
```

```
Fatal + Injury Crashes

Mixed-effects Poisson regression                 Number of obs      =       516
Group variable:        Location                  Number of groups   =       104


                                                 Wald chi2(21)      =     69.20
Log likelihood =  -795.8822                      Prob > chi2        =    0.0000
------------------------------------------------------------------------------
          FI |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     Treated |  -.1258947   .1468064    -0.86   0.391    -.4136299    .1618406
   LNAADTMaj |   .7880994   .1538588     5.12   0.000     .4865418    1.089657
   LNAADTMin |   .1330427   .0530407     2.51   0.012     .0290847    .2370006
             |
  THRU_SPEED |
         30  |   .3913529   .6747264     0.58   0.562    -.9310865    1.713792
         35  |   .2297819   .6552667     0.35   0.726    -1.054517    1.514081
         40  |   .5284284   .6771754     0.78   0.435    -.7988111    1.855668
         45  |   .6428837   .6733534     0.95   0.340    -.6768647    1.962632
         50  |   .2340186   .7384256     0.32   0.751    -1.213269    1.681306
         55  |   1.067968   .7230297     1.48   0.140    -.3491446     2.48508
         60  |   .0281176   1.067012     0.03   0.979    -2.063187    2.119422
             |
   INT_SPEED |
         25  |   .3085697   .4771768     0.65   0.518    -.6266796    1.243819
         30  |   .4888562   .4565184     1.07   0.284    -.4059034    1.383616
         35  |   .3264459     .46244     0.71   0.480    -.5799198    1.232812
         40  |   .5251068   .5007958     1.05   0.294    -.4564349    1.506648
         45  |   .4338082   .4880265     0.89   0.374    -.5227062    1.390323
         55  |   .5979823   .5404798     1.11   0.269    -.4613386    1.657303
             |
     THRU_LW |   .0928152   .1228663     0.76   0.450    -.1479983    .3336287
 ThruLane5Up |  -.3819944   .2096644    -1.82   0.068    -.7929291    .0289403
   FRTH_LEG  |   -.191284   .1558754    -1.23   0.220    -.4967942    .1142263
  DEFLECTION |   .0018598   .0053054     0.35   0.726    -.0085386    .0122583
     Florida |  -.2244251   .1642601    -1.37   0.172     -.546369    .0975188
       _cons |  -10.22665   2.353285    -4.35   0.000      -14.839   -5.614294
-------------+----------------------------------------------------------------
Location     |
    var(_cons)|     .15825   .0429838                      .0929268    .2694924
------------------------------------------------------------------------------
LR test vs. nbinomial regression:chibar2(01) =    33.71 Prob>=chibar2 = 0.0000
```

```
Target Crashes

Mixed-effects nbinomial regression              Number of obs      =       515
Overdispersion:           mean
Group variable:       Location                  Number of groups   =       104


                                                Wald chi2(21)      =    161.72
Log likelihood = -960.89489                     Prob > chi2        =    0.0000
------------------------------------------------------------------------------
      Target |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     Treated |  -.1857775   .1645152    -1.13   0.259    -.5082214    .1366663
   LNAADTMaj |   .9044383   .1715841     5.27   0.000     .5681397    1.240737
   LNAADTMin |   .1174335    .059866     1.96   0.050     .0000983    .2347687
             |
  THRU_SPEED |
         30  |   1.081438   .9507476     1.14   0.255    -.7819933    2.944869
         35  |   1.167648   .9267098     1.26   0.208    -.6486698    2.983966
         40  |   1.464637   .9456078     1.55   0.121    -.3887202    3.317994
         45  |   1.642442   .9423246     1.74   0.081    -.2044807    3.489364
         50  |   .8048887   1.001211     0.80   0.421    -1.157449    2.767226
         55  |   1.700048   .9904233     1.72   0.086    -.2411461    3.641242
         60  |   1.461301   1.296715     1.13   0.260    -1.080214    4.002816
             |
   INT_SPEED |
         25  |       .394   .5664751     0.70   0.487    -.7162708    1.504271
         30  |   .6714898   .5448975     1.23   0.218    -.3964897    1.739469
         35  |   .6295828   .5501377     1.14   0.252    -.4486673    1.707833
         40  |   .4781859   .5966062     0.80   0.423    -.6911408    1.647513
         45  |    1.09181   .5774279     1.89   0.059    -.0399283    2.223548
         55  |    .967884   .6306965     1.53   0.125    -.2682584    2.204026
             |
     THRU_LW |   .1072025   .1375266     0.78   0.436    -.1623447    .3767496
  ThruLane5Up |  -.5540126    .234327    -2.36   0.018    -1.013285    -.09474
    FRTH_LEG |   .0024002   .1702609     0.01   0.989    -.3313051    .3361054
  DEFLECTION |   .0072983   .0057975     1.26   0.208    -.0040647    .0186612
     Florida |  -1.003687   .1794622    -5.59   0.000    -1.355426   -.6519472
       _cons |  -11.66765   2.713689    -4.30   0.000    -16.98638   -6.348917
-------------+----------------------------------------------------------------
    /lnalpha |  -2.431527   .3402199    -7.15   0.000    -3.098346   -1.764709
-------------+----------------------------------------------------------------
Location     |
   var(_cons)|   .2455567   .0538776                      .1597311    .3774975
------------------------------------------------------------------------------

LR test vs. nbinomial regression:chibar2(01) =    75.34 Prob>=chibar2 = 0.0000
```

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