ATTACHMENT C

HIGH SPEED UNRESTRICTED $CMF_{ROADSIDE}$

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Table of Contents

TABLE OF TABLES

TABLE OF FIGURES

INTRODUCTION

Harwood *et al.* suggested that well-designed observational before-after studies are the preferred source of data to develop Crash Modification Factors (CMFs). [Harwood00] Furthermore, a study is considered "well-designed" when it observes changes in crash frequency where only one feature has been changed. The same authors also observed that there are very few observational before-after studies for geometric features in the literature. While Harwood *et al.* ultimately collected many CMFs developed using many different methods to represent the effect of geometric features on rural two-lane road crashes, only one subjective CMF was developed to represent the entire influence of the roadside (i.e., the Roadside Hazard Rating). One can only conclude there were even fewer observational before-after studies quantifying the influence of roadside features on highway safety at the time of that publication in 2000. The literature search conducted for this research supports that assessment.

Regrettably, few States maintain road-based roadside feature datasets making cross-sectional studies as problematic as before-after studies of the influence roadside features have on ROR crash severity. Promisingly, the roadside safety community has invested in and incrementally developed over the last four decades a conditional probability model for evaluating roadside safety, most recently packaged under the Roadside Safety Analysis Program version 3 (RSAPv3). This document presents the methods used to develop the $CMF_{ROADSIDE}$ using a cross-sectional study and a simulated before-after study.

RUN-OFF-ROAD CRASH PREDICTION MODEL FORM

The functional form of the Run-off-Road (ROR) prediction method was presented and discussed in Attachment D11. This functional form includes two crash modification functions: $CMF_{ROADWAY}$ and a $CMF_{ROADSIDE}$. Equation 1 shows a very general form for a ROR crash prediction model. The model predicts the number of expected crashes in a year of a particular severity that cross a particular edge of a particular segment.

$$N_{SEVERITY} = SPF_{EDGE} \cdot CMF_{ROADWAY} \cdot CMF_{ROADSIDE} \quad (1)$$

where:

$N_{SEVERITY}$ = Annual number of ROR crashes of a given severity associated with a given roadway segment edge.

SPF_{EDGE} = Safety performance function for an edge of the roadway in crashes per mile of segment edge.

$CMF_{ROADWAY}$ = A crash modification function that adjusts for the alignment and cross-sectional features of the roadway like grade, curvature, lane width and number of lanes.

$CMF_{ROADSIDE}$ = A crash modification function that adjusts for the features of the roadside. Particular crash modification factors used within the roadside CMF are chosen for a particular severity.

More particularly, each of the terms on the right-hand side can be further expanded as follows:

$$SPF_{EDGE} = (365 \cdot AADT \cdot L)^{A1} \cdot e^{A2 \cdot AADT/1000} \cdot e^{A3}$$

$$CMF_{ROADWAY} = \prod_{i=1}^{n} CMF_i$$

$$CMF_{ROADSIDE} = \left[\beta_{SHLD} \cdot X_{SHLD} \cdot \prod_{j=1}^{m1} CMF_j\right] + \left[\beta_{UNSHLD} \cdot X_{UNSHLD} \cdot \prod_{k=1}^{m2} CMF_k\right]$$

where:

CMF_i =Crash modification factors dealing with the roadway features (e.g., horizontal curvature, grade, lane width, access density, etc.)

CMF_j , CMF_k =Crash modification factors dealing with specific roadside features (e.g., utility poles, guardrail type, foreslope, clearzone width, etc.).

A_n and β_n =Regression coefficients.

AADT =Average annual daily traffic (vehicles/day).

L =Segment length (miles).

PT =Percentage of heavy vehicles (percent)

X_{SHLD} =Percent of the segment edge that is covered by longitudinal barriers.

X_{UNSHLD} =Percent of the segment edge that is not shielded by guardrails or other longitudinal barriers.

1 $= X_{SHLD} + X_{UNSHLD}$

The high-speed unrestricted SPF_{EDGE} and $CMF_{ROADWAY}$ were developed and documented in the Second Interim Report. The $CMF_{ROADSIDE}$ is documented herein.

ROADSIDE CRASH MODIFICATION FUNCTION -- $CMF_{ROADSIDE}$

The roadside crash modification function, $CMF_{ROADSIDE}$, is assumed to have the following form:

$$CMF_{ROADSIDE} = \left[\beta_{SHLD} \cdot X_{SHLD} \cdot \prod_{j=1}^{m1} CMF_j\right] + \left[\beta_{UNSHLD} \cdot X_{UNSHLD} \cdot \prod_{k=1}^{m2} CMF_k\right]$$

Where:

X_{SHLD} = Proportion of the segment edge where longitudinal barriers are installed where $0 \leq X_{SHLD} \leq 1$.

X_{UNSHLD} = Proportion of the segment edge where there are unshielded ditches or roadside slopes and other unshielded fixed objects where $0 \leq X_{UNSHLD} \leq 1$.

Condition that: $1 = X_{SHLD} + X_{UNSHLD}$ (100% of the segment edge is accounted for).

β_{SHLD} = A regression coefficient associated with the segment edges where longitudinal barriers are installed.

β_{UNSHLD} = A regression coefficient associated with the segment edges where there are unshielded ditches, roadside slopes or fixed objects like trees, tree lines, utility poles, bridge piers, etc.

CMF_j = Crash modification factors associated with roadside feature j that modify the ROR crashes associated with longitudinal barriers. These CMFs would account for characteristics like barrier type, barrier terminals, barrier transitions, barrier offset, etc.

CMF_k = Crash modification factors associated with roadside feature k that modify the ROR crashes associated with unshielded roadsides. These CMFs would account for characteristics like the presence of ditches, the density of narrow fixed objects, and other unshielded objects.

$CMF_{ROADISDE}$ is an additive form because it considers shielded and unshielded edges independently and these edges must sum to one (i.e.., $X_{SHLD} + X_{UNSHLD}$=1). CMFs that represent characteristics of the longitudinal barriers (i.e., type, offset, etc.) are multiplied only by the first portion of the CMFunction since they would affect only those characteristics. Likewise, characteristics that involve the unshielded fixed objects, roadside ditches and terrain are multiplied only by the second portion of the CMFunction since they only affect the proportion of the segment edge with those characteristics.

MODELING METHODS

The development of the $CMF_{ROADSIDE}$ included the modeling of longitudinal barrier crashes with the percentage of shielding as a variable and the modeling of all other ROR crashes with the percentage of unshielded roadside edges as a variable. Recall that any vehicle that runs off the road in any sequence of events is included in the crash dataset (ROR).

A longitudinal barrier crash (LB) subset of the complete run-off road dataset (ROR) was defined as any crash where the longitudinal barrier is the first object struck off the road. In other words, if a vehicle runs of the road to the left and hits a w-beam, it is a longitudinal barrier crash. If a vehicle side-swipes another vehicle then runs off the road to the right and hits a longitudinal barrier, it is still a longitudinal barrier crash. On the other hand, if a vehicle runs of the road to the right and hits a tree then a longitudinal barrier, it is an "other" ROR crash (OC). Using these definitions for LB and OC, the P(LB) and P(OC) are mutually exclusive events. In other words, the same vehicle cannot be counted as a LB and an OC crash, but only as an LB or an OC crash. Therefore, $P(LB \cup OC) = P(LB) + P(OC)$. The P(LB) and P(OC) will be determined individually and added together to find the P(ROR). Recall this dataset is only ROR crashes, therefore the P(ROR) is equal to unity and the P(LB) and P(OC) are some fraction of one. This relationship is the basis for $CMF_{ROADSIDE}$ (i.e., $CMF_{ROADSIDE}$ = P(ROR))

The P(LB) is assumed to be a function of the percent of shielding on the segment (X_{SHLD}) was found using the log odds of the probability (P). The odds of an event occurring are simply the probability of an event (P) occurring divided by the probability of the event not occurring (1-P). [Hilbe11]

$$Odds = \frac{successes}{failures} = \frac{P}{1-P}$$

The limited range of probability (i.e., 0 to 1) present a problem when used directly in regression, therefore the odds, $\frac{P}{1-P}$, are used. For example, if the probability of snow in November is 0.25, the odds of having snow in November are $\frac{0.25}{1-0.25} = 0.3333 = 1/3$. A person gambling on snow in November would say there is a 1 in 3 chance it will snow in November or a 3 to 1 chance it will not snow in November.

Using these definitions for ROR, LB, and OC, the relationships used to determine $CMF_{ROADSIDE}$ can be conceptualized as follows:

Where:

SPF_{EDGE}	= Safety performance function for an edge of the roadway in crashes per length of segment edge. The SPF_{EDGE} predicts all ROR crashes per edge per mile.
LB+OC=ROR	= Total ROR crashes per edge are equal to all LB crashes plus all other ROR crashes.
$\frac{LB}{ROR-LB}$	= Odds of a longitudinal barrier crash to all ROR crashes.
$\frac{OC}{ROR-OC}$	= Odds of a non-longitudinal barrier crash (i.e., other crash) to all ROR crashes.

Simple logistic regression is an appropriate tool when considering one nominal variable with two values (i.e., longitudinal barrier crash, other ROR crash) and one measurement variable (i.e., amount of shielding on the segment). In this case, the nominal variable is the dependent variable and the measurement variable is the independent variable. "One goal is to see whether the probability of getting a particular value of the nominal variable is associated with the measurement variable; the other goal is to predict the probability of getting a particular value of the nominal variable, given the measurement variable." [McDonald14]

Log odds provide a more suitable variable for regression, modeling a line fit using the maximum-likelihood method. When β_{SHLD} is the slope and ε is the intercept, the model takes this form and can be rewritten to find the probability, as shown here:

$$ln\left(\frac{\mathrm{LB}}{\mathrm{ROR}-\mathrm{LB}}\right) = \mathrm{a} + \mathrm{bX}$$

Rewritten as:

$$ln\left(\frac{\mathrm{P(LB)}}{1-\mathrm{P(LB)}}\right) = \varepsilon + \beta_{\mathrm{SHLD}}\mathrm{X}_{\mathrm{SHLD}}$$

Applying the same concepts, a series of simple logistic regression models were used on the same dataset to determine the probability of longitudinal barrier crashes across different severities (i.e., $P(LB_{SEVi})$) and the probability of other ROR crashes across different severities (i.e., $P(OC_{SEVi})$).

Where:

$\frac{LB_{severity\ i}}{ROR-LB_{severity\ i}}$	=Odds of longitudinal barrier crash of a particular severity to all ROR crashes

$$\frac{OC_{severity\ i}}{ROR - OC_{severity\ i}}$$ = Odds of a non-LB crash (i.e., other crash) of particular severity to all ROR crashes.

Throughout the derivation of β_{SHLD} and β_{UNSHLD}, CMF_j and CMF_k are taken to be unity since the modelling at this point is based on the mean roadside condition of the base segments. The sections that follow include the technical documentation of the datasets used and the models developed for β_{SHLD} and β_{UNSHLD}. At the close of the document, β_{SHLD} and β_{UNSHLD} are tabulated for each severity considered.

DEVELOP B_{SHLD} AND B_{UNSHLD}

Road-based datasets were used to develop β_{SHLD} and β_{UNSHLD}. These road-based datasets included information about the frequency and location of crashes relative to the highway geometry, posted speed limit, traffic mix, etc. Only a few States maintain equivalent road-based datasets (i.e., inventories) for roadside features. The states of Ohio and Washington maintain a longitudinal barrier inventory which can be linked to each State's HSIS data. These longitudinal barrier inventories were used to determine the percentage of longitudinal barrier for segments and subsequently the percentage of unprotected roadside (i.e., X_{SHLD} and X_{UNSHLD}).

Unfortunately, the inventories do not include specification information about the barriers located in the medians of divided highway. Specifically, it was not clear from the inventories if the barriers present are median barriers or single-faced barriers. Single-faced barriers struck from behind do not function as a longitudinal barrier is intended to function and single-faced barriers placed in the median are subject to these types of non-designed collisions. Due to this lack of information on barriers located in the medians, the analysis was only conducted for primary right edge (PRE) and opposing right edge (ORE) crashes. Limiting the analysis to right edges eliminated the need to understand the type of barriers located in the median. It is recommended that the findings for the right edge be used for the left edges (i.e., median edges) until better information is available for barriers located within the median.

The roadside conditions were not measured and modeled in the development of the SPF. There are, therefore, a certain amount of roadside conditions "built" into SPF_{EDGE} and its coefficients. In essence, β_{SHLD} and β_{UNSHLD} represent the "typical" roadsides associated with the straight, flat roads in Ohio and Washington. The objective of this task was to determine β_{SHLD} and β_{UNSHLD} for base conditions. CMF_j and CMF_k have therefore been set to unity for this part of the analysis:

$$CMF_{ROADSIDE|SEVERITY} = \left[B_{SHLD} \cdot X_{SHLD} \cdot \prod_{j=1}^{m1} CMF_j\right] + \left[B_{UNSHLD} \cdot X_{UNSHLD} \cdot \prod_{k=1}^{m2} CMF_k\right]$$

$$CMF_{ROADSIDE|SEVERITY} = [B_{SHLD} \cdot X_{SHLD}] + [B_{UNSHLD} \cdot X_{UNSHLD}] \text{ for } CMF_j = CMF_k = 1$$

Table 1and Table 2 provide the descriptive statistics for the filtered divided and undivided datasets respectively. Each table includes the statistics for segment length in miles (L), annual average daily traffic (AADT), and portion of the primary right edge which is shielded

(X_{SHLD} on PRE) at the top of the table. The table then includes descriptive crash frequency statistics for crashes occurring on the primary right edge (PRE) for each severity combination. As defined above, any vehicle that runs off the road in any sequence of events is included in the crash dataset (ROR). Longitudinal barrier crashes (LB) are defined as any crash where the longitudinal barrier is the first object struck off the road. Other ROR crashes (OC) is essentially all ROR crashes minus LB crashes for each segment. As with the other analyses, all opposing direction events have been transposed to be primary direction events. The results of the analyses are applicable to either right edge.

These data show that for both the divided and undivided segments, fatal LB crashes have a mean of zero, indicating that the longitudinal barriers are preforming as intended.

Table 1. Descriptive Statistics for Rural Divided Dataset.

Continuous Variables	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
L	0.1	0.19	0.36	0.548	0.78	2
AADT	710	8250	11710	12769	15360	43950
X_{SHLD} on PRE	0	0	0.10	0.242	0.393	1
Crashes of any severity (KABCOU)						
ROR crash on PRE	0	0	0	0.251	0	7
LB crash on PRE	0	0	0	0.080	0	4
OC crash on PRE	0	0	0	0.171	0	6
Fatal & Injury Crashes (F+I or KABC)						
ROR crash on PRE	0	0	0	0.092	0	5
LB crash on PRE	0	0	0	0.024	0	2
OC crash on PRE	0	0	0	0.068	0	4
Fatal & Serious Injury Crashes (KAB)						
ROR crash on PRE	0	0	0	0.070	0	3
LB crash on PRE	0	0	0	0.018	0	2
OC crash on PRE	0	0	0	0.052	0	3
Fatal & Severe (KA)						
ROR crash on PRE	0	0	0	0.019	0	2
LB crash on PRE	0	0	0	0.003	0	1
OC crash on PRE	0	0	0	0.016	0	2
Fatal Crashes (K)						
ROR crash on PRE	0	0	0	0.003	0	2
LB crash on PRE	0	0	0	0.000	0	1
OC crash on PRE	0	0	0	0.003	0	2

Table 2. Descriptive Statistics for Rural Undivided Dataset.

Continuous Variables	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
L	0.1	0.14	0.21	0.33	0.38	2
AADT	40	2656	4320	4860	6020	27540
X_{SHLD} on PRE	0	0	0	0.125	0.13	1
Crashes of any severity (KABCOU)						
ROR crash on PRE	0	0	0	0.126	0	6
LB crash on PRE	0	0	0	0.013	0	6
OC crash on PRE	0	0	0	0.112	0	5
Fatal & Injury Crashes (F+I or KABC)						
ROR crash on PRE	0	0	0	0.057	0	4
LB crash on PRE	0	0	0	0.004	0	3
OC crash on PRE	0	0	0	0.052	0	4
Fatal & Serious Injury Crashes (KAB)						
ROR crash on PRE	0	0	0	0.043	0	4
LB crash on PRE	0	0	0	0.003	0	2
OC crash on PRE	0	0	0	0.039	0	4
Fatal & Severe (KA)						
ROR crash on PRE	0	0	0	0.012	0	2
LB crash on PRE	0	0	0	0.001	0	1
OC crash on PRE	0	0	0	0.011	0	2
Fatal Crashes (K)						
ROR crash on PRE	0	0	0	0.002	0	2
LB crash on PRE	0	0	0	0.000	0	1
OC crash on PRE	0	0	0	0.002	0	2

MODELS

The development of the $CMF_{ROADSIDE}$ comprises a multi-sage process to find the probability of a longitudinal barrier crash of a particular severity to all other ROR crashes as a function of the percent of shielding on the segment (X_{SHLD}) and the probability of any non-longitudinal barrier ROR crash (OC) of a particular severity to all other ROR crashes as a function of the percent of the segment which is unshielded (X_{UNSHLD}). Different models were therefore developed for different combinations of severities (i.e., KABCOU, KABC, KAB, KA, and K.). This modeling was also completed for both divided and undivided roadways. Initially a binomial error structure was assumed for the undivided data, however, the unshielded models were found to be overdispersed (i.e., residual deviance/degrees of freedom > 1). The undivided unshielded models were refit using a quasibinomial to account for the overdispersion. Quasibinomial models were used for the divided data for the same reason. A total of thirty models (i.e., 2 shielding conditions x 5 severities x [divided + bionomial undivided + quasibinomial undiv] = 30 models) were developed and simplified to a single $CMF_{ROADSIDE}$ with an accompanying table of model coefficients. Table 4 through Table 6 summarize the undivided binomial and quasibinomial models developed while Table 7 and Table 8 summarize the divided models.

Table 3. Example of Final $CMF_{ROADSIDE}$ Presentation.

$CMF_{ROADSIDE\|SEVERITY} = [\beta_{SHLD} \cdot X_{SHLD}] + [\beta_{UNSHLD} \cdot X_{UNSHLD}]$					
		all severity (KABCOU)	F+I (KABC)	Serious injuries only (KAB)	Severe injuries only (K+A)
Undivided	β_{SHLD}	TBD	TBD	TBD	TBD
	β_{UNSHLD}	TBD	TBD	TBD	TBD
Divided	β_{SHLD}	TBD	TBD	TBD	TBD
	β_{UNSHLD}	TBD	TBD	TBD	TBD

P-values of 0.05 or greater are considered significant. The statistical null hypothesis is that the particular value of P(LB) is not associated with X_{SHLD}. A P-value greater than 0.05 would reject the null hypothesis.

Table 4. Undivided Longitudinal Barrier to All Other ROR Crashes Binomial Modeling Results.

$$\frac{LB_{severity}}{ROR - LB_{severity}} \sim X_{SHLD}$$

	Estimate	Std. Error	z value	Pr(|z|)
$LB_{severity}$=KABCOU				
	Estimate	Std. Error	z value	Pr(|z|)
(Intercept)	-2.77898	0.09131	-30.43	<2e-16
X_{SHLD}	4.12129	0.27211	15.15	<2e-16
p-value:	6.62E-55		AIC:	1398.2
Null deviance: 1548.8 on 2018 degrees of freedom				
Residual deviance: 1305.2 on 2017 degrees of freedom				
$LB_{severity}$=KABC				
	Estimate	Std. Error	z value	Pr(|z|)
(Intercept)	-3.8103	0.146	-26.094	< 2e-16
X_{SHLD}	2.87	0.3615	7.939	2.04E-15
p-value:	8.07E-13		AIC:	664.44
Null deviance: 671.99 on 2018 degrees of freedom				
Residual deviance: 620.73 on 2017 degrees of freedom				
$LB_{severity}$=KAB				
	Estimate	Std. Error	z value	Pr(|z|)
(Intercept)	-4.0232	0.1637	-24.57	< 2e-16
X_{SHLD}	2.4664	0.4227	5.835	5.39E-09
p-value:	1.90E-07		AIC:	551.94
Null deviance: 548.84 on 2018 degrees of freedom				
Residual deviance: 521.70 on 2017 degrees of freedom				
$LB_{severity}$=KA				
	Estimate	Std. Error	z value	Pr(|z|)
(Intercept)	-5.7037	0.3698	-15.422	< 2e-16
X_{SHLD}	2.5333	0.8846	2.864	0.00419
p-value:	0.012388		AIC:	153.19
Null deviance: 150.61 on 2018 degrees of freedom				
Residual deviance: 144.35 on 2017 degrees of freedom				
$LB_{severity}$=K				
	Estimate	Std. Error	z value	Pr(|z|)
(Intercept)	-8.331	1.356	-6.143	8.10E-10
X_{SHLD}	2.718	3.056	0.889	0.374
p-value:	0.441511		AIC:	21.033
Null deviance: 17.625 on 2018 degrees of freedom				
Residual deviance: 17.033 on 2017 degrees of freedom				

Table 5. Undivided Unshielded ROR Crashes to All other ROR Crashes Binomial Modeling Results.

<table>
<tr><td colspan="5">$\frac{\mathrm{OC_{severity}}}{\mathrm{ROR - OC_{severity}}} \sim X_{SHLD}$</td></tr>
<tr><td colspan="5">$\mathbf{OC_{severity}}$=KABCOU</td></tr>
<tr><td></td><td>Estimate</td><td>Std. Error</td><td>z value</td><td>Pr(|z|)</td></tr>
<tr><td>(Intercept)</td><td>-1.3423</td><td>0.2228</td><td>-6.025</td><td>1.69E-09</td></tr>
<tr><td>X_{UNSHLD}</td><td>4.1213</td><td>0.2721</td><td>15.146</td><td>< 2e-16</td></tr>
<tr><td>p-value:</td><td>6.62E-55</td><td></td><td>AIC:</td><td>1398.2</td></tr>
<tr><td colspan="5">Null deviance: 1548.8 on 2018 degrees of freedom</td></tr>
<tr><td colspan="5">Residual deviance: 1305.2 on 2017 degrees of freedom</td></tr>
<tr><td colspan="5">$\mathbf{OC_{severity}}$=KABC</td></tr>
<tr><td></td><td>Estimate</td><td>Std. Error</td><td>z value</td><td>Pr(|z|)</td></tr>
<tr><td>(Intercept)</td><td>-1.2087</td><td>0.2078</td><td>-5.816</td><td>6.03E-09</td></tr>
<tr><td>X_{UNSHLD}</td><td>0.9636</td><td>0.2278</td><td>4.231</td><td>2.33E-05</td></tr>
<tr><td>p-value:</td><td>1.36E-05</td><td></td><td>AIC:</td><td>3025</td></tr>
<tr><td colspan="5">Null deviance: 2780.0 on 2018 degrees of freedom</td></tr>
<tr><td colspan="5">Residual deviance: 2761.1 on 2017 degrees of freedom</td></tr>
<tr><td colspan="5">$\mathbf{OC_{severity}}$=KAB</td></tr>
<tr><td></td><td>Estimate</td><td>Std. Error</td><td>z value</td><td>Pr(|z|)</td></tr>
<tr><td>(Intercept)</td><td>-1.3953</td><td>0.2218</td><td>-6.291</td><td>3.15E-10</td></tr>
<tr><td>X_{UNSHLD}</td><td>0.6592</td><td>0.2428</td><td>2.715</td><td>0.00663</td></tr>
<tr><td>p-value:</td><td>0.005378354</td><td></td><td>AIC:</td><td>2783.8</td></tr>
<tr><td colspan="5">Null deviance: 2564.1 on 2018 degrees of freedom</td></tr>
<tr><td colspan="5">Residual deviance: 2556.3 on 2017 degrees of freedom</td></tr>
<tr><td colspan="5">$\mathbf{OC_{severity}}$=KA</td></tr>
<tr><td></td><td>Estimate</td><td>Std. Error</td><td>z value</td><td>Pr(|z|)</td></tr>
<tr><td>(Intercept)</td><td>-2.0664</td><td>0.3174</td><td>-6.51</td><td>7.50E-11</td></tr>
<tr><td>X_{UNSHLD}</td><td>-0.3649</td><td>0.3537</td><td>-1.032</td><td>0.302</td></tr>
<tr><td>p-value:</td><td>0.3124112</td><td></td><td>AIC:</td><td>1329.2</td></tr>
<tr><td colspan="5">Null deviance: 1240.1 on 2018 degrees of freedom</td></tr>
<tr><td colspan="5">Residual deviance: 1239.1 on 2017 degrees of freedom</td></tr>
<tr><td colspan="5">$\mathbf{OC_{severity}}$=K</td></tr>
<tr><td></td><td>Estimate</td><td>Std. Error</td><td>z value</td><td>Pr(|z|)</td></tr>
<tr><td>(Intercept)</td><td>-3.6465</td><td>0.6619</td><td>-5.509</td><td>3.61E-08</td></tr>
<tr><td>X_{UNSHLD}</td><td>-0.5267</td><td>0.7431</td><td>-0.709</td><td>0.478</td></tr>
<tr><td>p-value:</td><td>0.4941893</td><td></td><td>AIC:</td><td>396.5</td></tr>
<tr><td colspan="5">Null deviance: 379.44 on 2018 degrees of freedom</td></tr>
<tr><td colspan="5">Residual deviance: 378.98 on 2017 degrees of freedom</td></tr>
</table>

Table 6. Undivided Unshielded ROR Crashes to All other ROR Crashes Quasibinomial Modeling Results.

$$\frac{\mathrm{OC}_{\mathrm{severity\ i}}}{\mathrm{ROR}-\mathrm{OC}_{\mathrm{severity\ i}}} \sim X_{SHLD}$$

$OC_{severity}$=KABCOU				
	Estimate	Std. Error	t value	Pr(|t|)
(Intercept)	-1.3423	0.2151	-6.24	5.32E-10
X_{UNSHLD}	4.1213	0.2627	15.69	< 2e-16
p-value:	6.62E-55		α:	0.9323308
Null deviance: 1548.8 on 2018 degrees of freedom				
Residual deviance: 1305.2 on 2017 degrees of freedom				
$OC_{severity}$=KABC				
	Estimate	Std. Error	t value	Pr(|t|)
(Intercept)	-1.2087	0.2097	-5.764	9.49E-09
X_{UNSHLD}	0.9636	0.2298	4.193	2.88E-05
p-value:	1.36E-05		α:	1.018177
Null deviance: 2780.0 on 2018 degrees of freedom				
Residual deviance: 2761.1 on 2017 degrees of freedom				
$OC_{severity}$=KAB				
	Estimate	Std. Error	t value	Pr(|t|)
(Intercept)	-1.3953	0.2245	-6.216	6.19E-10
X_{UNSHLD}	0.6592	0.2458	2.682	0.00737
p-value:	0.005378354		α:	1.024421
Null deviance: 2564.1 on 2018 degrees of freedom				
Residual deviance: 2556.3 on 2017 degrees of freedom				
$OC_{severity}$=KA				
	Estimate	Std. Error	t value	Pr(|t|)
(Intercept)	-2.0664	0.319	-6.478	1.17E-10
X_{UNSHLD}	-0.3649	0.3554	-1.027	0.305
p-value:	0.3124112		α:	1.010033
Null deviance: 1240.1 on 2018 degrees of freedom				
Residual deviance: 1239.1 on 2017 degrees of freedom				
$OC_{severity}$=K				
	Estimate	Std. Error	t value	Pr(|t|)
(Intercept)	-3.6465	0.6813	-5.352	9.69E-08
X_{UNSHLD}	-0.5267	0.7649	-0.689	0.491
p-value:	0.4941893		α:	1.059528
Null deviance: 379.44 on 2018 degrees of freedom				
Residual deviance: 378.98 on 2017 degrees of freedom				

Table 7. Divided Longitudinal Barrier to All Other ROR Crashes Quasibinomial Modeling Results.

$\frac{\mathrm{LB}_{\mathrm{severity}}}{\mathrm{ROR} - \mathrm{LB}_{\mathrm{severity}}} \sim X_{SHLD}$				
$LB_{severity}$=KABCOU				
	Estimate	Std. Error	t value	Pr(|t|)
(Intercept)	-1.5798	0.0898	-17.59	<2e-16
X_{SHLD}	3.2141	0.2445	13.14	<2e-16
p-value:	3.30E-49		α:	1.075334
Null deviance: 1574.7 on 1132 degrees of freedom				
Residual deviance: 1357.3 on 1131 degrees of freedom				
$LB_{severity}$=KABC				
	Estimate	Std. Error	t value	Pr(|t|)
(Intercept)	-2.8595	0.1323	-21.618	< 2e-16
X_{SHLD}	2.1122	0.2795	7.556	8.53E-14
p-value:	1.07E-12		α:	0.9379199
Null deviance: 766.63 on 1132 degrees of freedom				
Residual deviance: 715.92 on 1131 degrees of freedom				
$LB_{severity}$=KAB				
	Estimate	Std. Error	t value	Pr(|t|)
(Intercept)	-3.1306	0.1545	-20.266	< 2e-16
X_{SHLD}	1.9412	0.3239	5.993	2.76E-09
p-value:	8.01E-09		α:	0.9976478
Null deviance: 652.94 on 1132 degrees of freedom				
Residual deviance: 619.66 on 1131 degrees of freedom				
$LB_{severity}$=KA				
	Estimate	Std. Error	t value	Pr(|t|)
(Intercept)	-5.0182	0.3954	-12.691	< 2e-16
X_{SHLD}	2.2217	0.7385	3.008	0.00268
p-value:	0.002140761		α:	1.157971
Null deviance: 203.25 on 1132 degrees of freedom				
Residual deviance: 193.83 on 1131 degrees of freedom				
$LB_{severity}$=K				
	Estimate	Std. Error	t value	Pr(|t|)
(Intercept)	-6.1021	0.8792	-6.94	6.57E-12
X_{SHLD}	-3.566	5.2468	-0.68	0.497
p-value:	0.3716122		α:	1.095845
Null deviance: 30.496 on 1132 degrees of freedom				
Residual deviance: 29.698 on 1131 degrees of freedom				

Table 8. Divided Unshielded ROR Crashes to All other ROR Crashes Quasibinomial Modeling Results.

$\frac{\mathrm{OC}_{\mathrm{severity}}}{\mathrm{ROR} - \mathrm{OC}_{\mathrm{severity}}} \sim X_{SHLD}$				
$OC_{severity}$=KABCOU				
	Estimate	Std. Error	t value	Pr(|t|)
(Intercept)	-1.6343	0.1901	-8.596	<2e-16
X_{UNSHLD}	3.2141	0.2445	13.143	<2e-16
p-value:	3.30E-49		α:	1.075334
Null deviance: 1574.7 on 1132 degrees of freedom				
Residual deviance: 1357.3 on 1131 degrees of freedom				
$OC_{severity}$=KABC				
	Estimate	Std. Error	t value	Pr(|t|)
(Intercept)	-2.613	0.2469	-10.584	< 2e-16
X_{UNSHLD}	2.0276	0.2875	7.054	3.03E-12
p-value:	1.90E-15		α:	1.060844
Null deviance: 1421.2 on 1132 degrees of freedom				
Residual deviance: 1358.0 on 1131 degrees of freedom				
$OC_{severity}$=KAB				
	Estimate	Std. Error	t value	Pr(|t|)
(Intercept)	-2.7722	0.2688	-10.312	< 2e-16
X_{UNSHLD}	1.7788	0.3122	5.698	1.54E-08
p-value:	2.02279E-10		α:	1.052714
Null deviance: 1245.4 on 1132 degrees of freedom				
Residual deviance: 1205.0 on 1131 degrees of freedom				
$OC_{severity}$=KA				
	Estimate	Std. Error	t value	Pr(|t|)
(Intercept)	-4.0536	0.4779	-8.482	< 2e-16
X_{UNSHLD}	1.6535	0.5476	3.02	0.00259
p-value:	0.000598923		α:	1.070552
Null deviance: 607.25 on 1132 degrees of freedom				
Residual deviance: 595.47 on 1131 degrees of freedom				
$OC_{severity}$=K				
	Estimate	Std. Error	t value	Pr(|t|)
(Intercept)	-4.9832	0.8873	-5.616	2.45E-08
X_{UNSHLD}	0.7843	1.0469	0.749	0.454
p-value:	0.4150291		α:	1.08402
Null deviance: 185.03 on 1132 degrees of freedom				
Residual deviance: 184.36 on 1131 degrees of freedom				

$CMF_{ROADSIDE}$ COEFFICIENTS

Table 4 through Table 8 report β_{SHLD} and β_{UNSHLD} as the log odds for each severity of crash as a function of shielding and other ROR crashes as a function of non-shielded segments. The log odds are transformed back to probability using the original relationship: $P(LB_{severity\ i}) = \frac{e^{\beta_{SHLD}}}{1+e^{\beta_{SHLD}}}$ or $P(OC_{severity\ i}) = \frac{e^{\beta_{UNSHLD}}}{1+e^{\beta_{UNSHLD}}}$. Table 9 summarizes these findings along with the 95% confidence intervals.

Table 9. Derived $CMF_{ROADSIDE}$ Coefficients.

$$CMF_{ROADSIDE} = [\beta_{SHLD} \cdot X_{SHLD}] + [\beta_{UNSHLD} \cdot X_{UNSHLD}]$$

Highway Type	Coefficient	Value	95% Confidence Range	
all severity (KABCOU)				
Undivided	β_{SHLD}	0.9840	0.9733	0.9906
	β_{UNSHLD}	0.9840	0.9737	0.9905
Divided	β_{SHLD}	0.9614	0.9395	0.9759
	β_{UNSHLD}	0.9614	0.9395	0.9759
F+I (KABC)				
Undivided	β_{SHLD}	0.9463	0.8954	0.9726
	β_{UNSHLD}	0.7238	0.6270	0.8055
Divided	β_{SHLD}	0.8921	0.8268	0.9346
	β_{UNSHLD}	0.8837	0.8143	0.9313
Serious injuries only (KAB)				
Undivided	β_{SHLD}	0.9218	0.8331	0.9635
	β_{UNSHLD}	0.6591	0.5464	0.7597
Divided	β_{SHLD}	0.8745	0.7860	0.9291
	β_{UNSHLD}	0.8555	0.7657	0.9176
Severe injuries only (KA)				
Undivided	β_{SHLD}	0.9264	0.6489	0.9847
	β_{UNSHLD}	*0.4098**	*0.2620*	*0.5894*
Divided	β_{SHLD}	0.9022	0.6744	0.9749
	β_{UNSHLD}	0.8394	0.6548	0.9424

*recommend excluding due to poor model fit.

$CMF_{ROADSIDE}$ is represented graphically in Figure 1 and Figure 2 to allow for a visual assessment. Figure 1 and Figure 2 are the individual components of the undivided and divided CMF for the full severity distributions. Notice that when shielding on the x-axis increases, crashes related to shielding increase while crashes related to unshielded edges decrease. Figure 3 and Figure 4 are the $CMF_{ROADSIDE}$ for each severity distribution of undivided and divided roadways. Notice in each figure that higher severity crashes have a lower proportion of the crashes as would be expected.

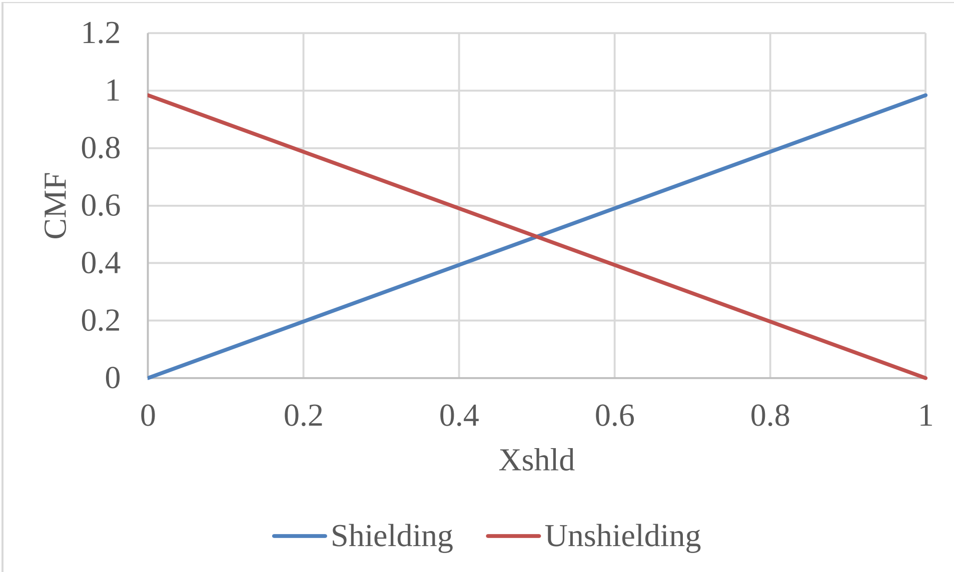

Figure 1. Shielded and Unshielded Components of $CMF_{ROADSIDE}$ for the Full Severity Distribution of Undivided Roadway Edges.

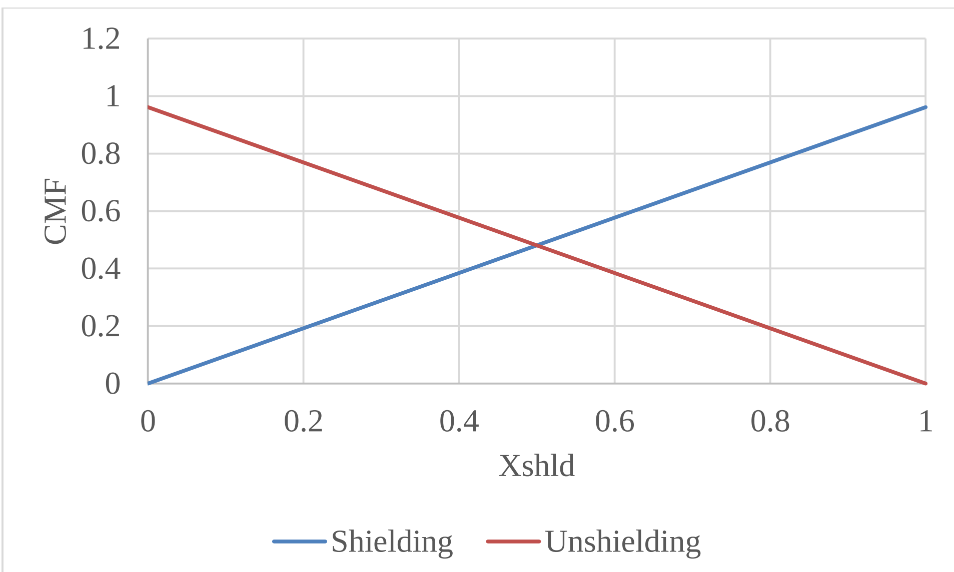

Figure 2. Shielded and Unshielded Components of $CMF_{ROADSIDE}$ for the Full Severity Distribution of Divided Roadway Edges.

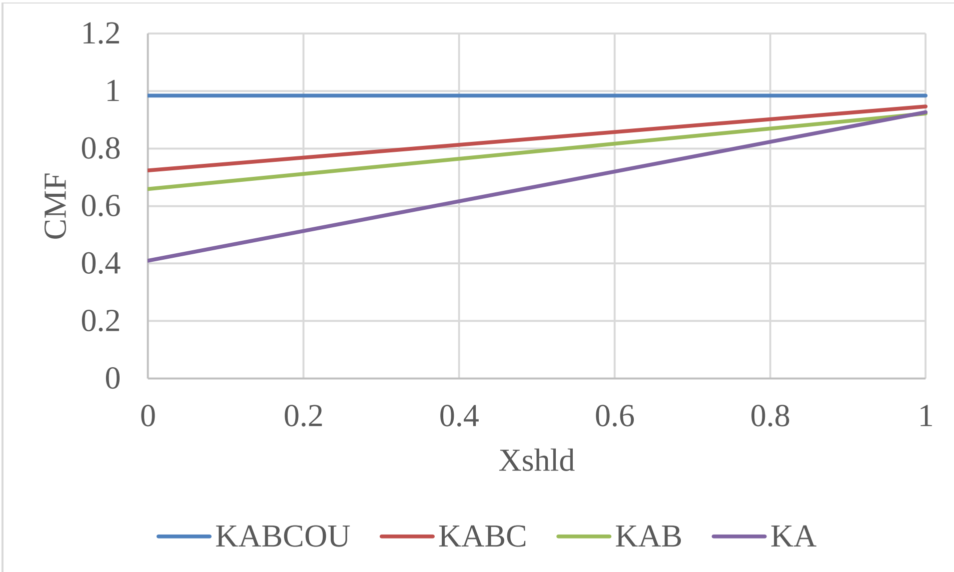

Figure 3. $CMF_{ROADSIDE}$ for the Each Severity Distribution of Undivided Roadway Edges.

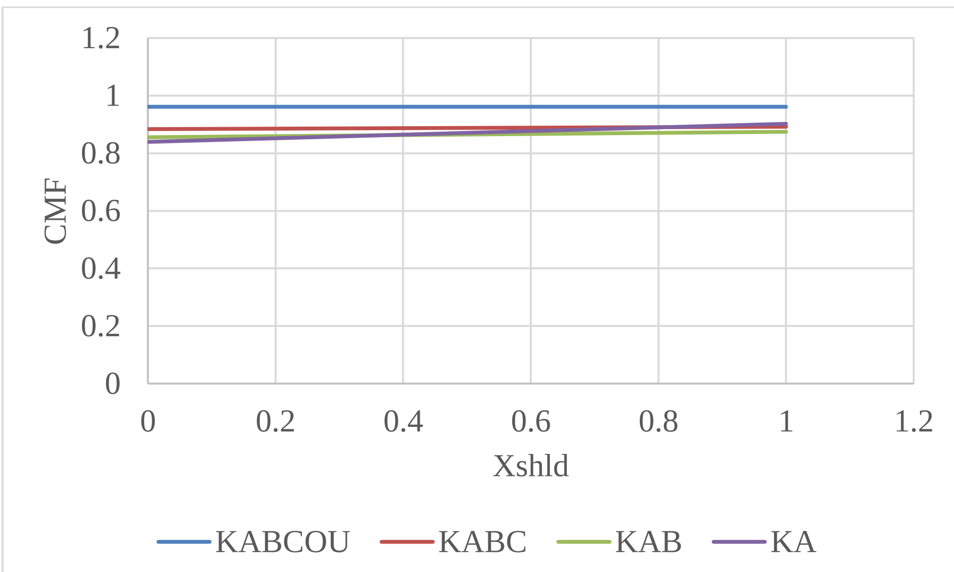

Figure 4. $CMF_{ROADSIDE}$ for the Each Severity Distribution of Divided Roadway Edges.

In summary, the coefficients shown in Table 10 to accompany $CMF_{ROADSIDE}$ were developed from well fit models with minimal error. It is recommended that $CMF_{ROADSIDE}$ be included in the HSM as a function with CMF_j and CMF_k as companions. The development of CMF_j and CMF_k will be documented separately.

Table 10. $CMF_{ROADSIDE}$ Recommended for Inclusion in the HSM.

$$CMF_{ROADSIDE|SEVERITY} = [B_{SHLD} \cdot X_{SHLD}] + [B_{UNSHLD} \cdot X_{UNSHLD}]$$

		All severity (KABCOU)	F+I (KABC)	Serious injuries only (KAB)
Undivided	**β_{SHLD}**	0.9840	0.9463	0.9218
	β_{UNSHLD}	0.9840	0.7238	0.6591
Divided	**β_{SHLD}**	0.9614	0.8921	0.8745
	β_{UNSHLD}	0.9614	0.8837	0.8555

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