SHRP2 Safety Implementation Assistance Program (IAP) – Round 4 Concept to Countermeasures – Research to Deployment Using the SHRP2 Safety Data

Research Title: Evaluation of the interaction between horizontal and vertical alignment on rural two lane roads: An investigation using the SHRP2 naturalistic driving study

Phase 1: January 28, 2015 to September 30, 2015

Final Report for Phase 1 and Proposal for Phase 2

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ABSTRACT

This study used data from the RID and NDS to study driver performance associated with different alignment combinations. The study included the development of an algorithm that used the RID to identify vertical curves. This algorithm was also validated using *ground-truth* data from Washington. The analysis of the NDS data included performance measures related to speed and lane deviation. The analysis of the NDS data showed that the alignment categories that include a horizontal curve have the worst performance in terms of the lane deviation measures. In addition, sharper horizontal curves are associated with the higher absolute values of lane deviation. The analysis was conducted using both disaggregate and aggregate methods. Comparison of the CMFs from Bauer and Harwood (2014) with the performance measures indicates a good match with the lane deviation measures, indicating that the lane deviation measures could serve as good surrogates for crash propensity.

BACKGROUND AND MOTIVATION

Many studies have shown that on rural roads, horizontal and vertical curves and grades are associated with more crashes compared to tangent level sections. A common crash type under these conditions is a lane departure crash. For many states, including North Carolina, lane departure crashes are of very high priority. In fact, Chapter 10 of the 1st edition of the Highway Safety Manual (HSM) provides crash modification factors (CMFs) for horizontal curvature and grade on rural two lane roads. However, the HSM treats horizontal and vertical alignment as independent entities assuming that there is no interaction between them. Recent work sponsored by the Federal Highway Administration (FHWA) as part of the Highway Safety Information Systems (HSIS) effort investigated the safety effects of horizontal curve and grade combinations on two lane roads using roadway and crash data from the state of Washington (Bauer and Harwood, 2014). As part of their effort, Bauer and Harwood (2014) conducted a review of the design criteria in the AASHTO Policy on Geometric Design of Highways and Streets (AASHTO, 2011) (also called the green book), and previous studies that had tried to estimate CMFs for horizontal and vertical curves. For horizontal curves, the primary design parameters are radius (R) (lower values imply sharper horizontal curves), length of the horizontal curve (L_c), superelevation, and transition design. For vertical grades, grade (G) is the primary design parameter. Vertical curves occur when the grade changes and usually involves a parabolic curve that joins two sections of different grade (say, G_1 and G_2). For vertical curves, the primary design parameters include the difference in grade between the two sections (i.e., abs($G_1 - G_2$)), length of the vertical curve (L_v), and the ratio of the length of the vertical curve to the algebraic difference between the grades, which is a measure of the sharpness of the vertical curve (K) (lower K values imply sharper vertical curves). Figure 1 shows the different types of vertical curves discussed in the AASHTO green book.

Bauer and Harwood (2014) estimated crash modification functions for property damage only (PDO) and injury and fatal (FI) crashes for the following situations:

- Horizontal curves and tangents on straight grades
- Horizontal curves and tangents at type 1 crest vertical curves
- Horizontal curves and tangents at type 1 sag vertical curves
- Horizontal curves and tangents at type 2 crest vertical curves

- Horizontal curves and tangents at type 2 sag vertical curves

Although CMFs provide valuable information about the safety risk associated with different roadway characteristics and traffic control devices, they do not necessarily provide insight into why certain conditions are higher risk. Data from naturalistic driving studies would be able to provide this insight that studies based only on crash data cannot easily provide. This research is expected to provide valuable information about how drivers interact with roadways under various combinations of vertical and horizontal alignment.

STUDY OBJECTIVES

The overall goal of this effort was to examine driver performance under different combinations of horizontal and vertical alignment and determine countermeasures that may be effective in reducing crashes at these locations. The primary aim of Phase 1 was to determine whether useful data and results can be produced in this effort and if further work is likely to provide insights into crash causality or countermeasures effectiveness. In Phase 1, the intent was to obtain sample data from sites with different combinations of horizontal and vertical alignment and determine if certain combinations are associated with better or worse driving performance. Another objective was to compare the performance measures with the CMFs that were estimated from Bauer and Harwood (2014), with the intent of obtaining insight into the reliability of these surrogate performance measures in the context of predicting crash propensity. The primary performance measures are related to speed and lane position, and combinations of these two measures. Phase 2 is intended to examine driver performance associated with different countermeasures and roadway features that could not be examined in Phase 1, and identify potential countermeasures.

OVERVIEW OF METHODOLOGY AND APPROACH

The following tasks provide an overview of the methodology that was adopted for this study:

1. <u>Literature Review and IRB Approval</u>. Apart from reviewing the crash based studies on this topic, the review also included studies that used Naturalistic Driving Study (NDS) type data in the past including Hallmark et al., (2014), Gordon et al., (2013), Davis and Hourdos (2012), and Jovanis et al., (2012). The intent of this review was to obtain insight into the methods that have been used to analyze NDS type data and the performance measures that have been used as surrogates for crash propensity. Hallmark et al., (2014), was especially useful because it dealt with a closely related topic (lane departures on rural two lane roads). The other three references provided useful information about modeling approaches that could be used with the NDS data. While conducting the literature review, the UNC project team had the study design approved by the UNC institutional review board (IRB).
2. <u>Identify Study Sites</u>. Since the intent of the study was to examine horizontal and vertical curves, it was important to identify segments tangent sections, straight grades, horizontal curves, vertical curves, and combinations. The roadway information database (RID) was used to identify the sites. The next section provides more details regarding the process that was undertaken to identify the study sites.
3. <u>Obtain time series and forward video data</u>. The time series data included the kinematics variables such as speed, acceleration, lane position, distance from left and right lane markings, and steering wheel position. The forward video provided the driver's

viewpoint. The forward video was used to record events such as presence of lead vehicle, presence of vehicle in the opposing vehicle, and other intrusions from vehicles and other road users.

4. Obtain eye glance and secondary task data. The eye glance data provided information on where a driver was looking every fraction of a second. The UNC team was interested in the relationship between eye glance and the driver performance data. The secondary task summary provided information on what other activities drivers were involved in apart from driving.
5. Data reduction and analysis. The intent of this task was to examine the relationship between driver performance, alignment characteristics, and CMFs from Bauer and Harwood (2014).
6. Results and Conclusions. Develop a final report based on the findings

Tasks 2 through 6 are discussed further below. Following the discussion of results from Phase 1, the Phase 2 Research Plan and Proposal are presented.

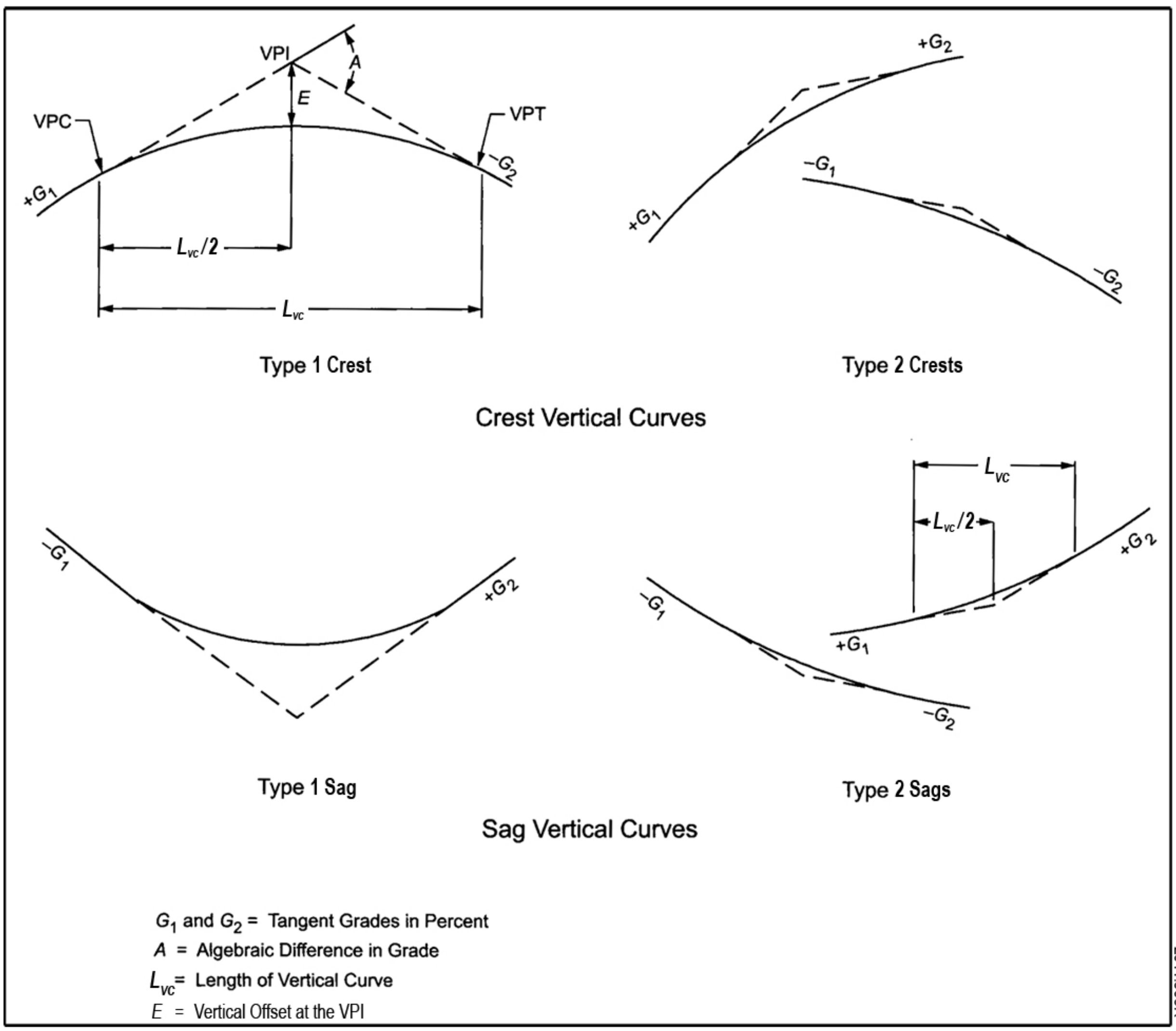

Figure 1: Types of Vertical Curves (Bauer and Harwood, 2014)

IDENTIFY STUDY SITES

The site selection included the following steps:

1. Select routes

The RID spatial files were used to select potential routes (before obtaining the RID, the UNC team signed a terms of use agreement with Iowa State University outlining the scope of the project). In identifying the routes, the following selection criteria were considered:

- **Two-lane roads (critical)** – The preliminary selection of two-lane roads was done using the "Lanes" layer from the RID. However, it was necessary to further refine that selection from aerial image inspection due to the fact that the RID provides through lanes in both directions for undivided roads but separately in each direction for divided roads. Thus, a screening for "Number of lanes = 2" would select two-lane undivided roads and four-lane divided roads. The UNC team spot checked the selected routes by viewing aerial photography to verify that the road was actually a two-lane road. However, it was discovered later that some routes changed cross-sections from two-lane to four-lane at various places that were not detected in the visual inspection. Thus, some of the NDS data collected was for multilane roads, and was not used in the analysis. Based on this experience, future identification of two-lane roads in Phase 2 will not rely on the number of through lanes from the "Lanes" layer, but will rather focus on other variables present in the RID, such as the directional lanes values in the "Links" layer.
- **Rural area type (critical)** – Rural areas were loosely defined as areas that appeared to be largely outside of semi-dense suburban development. This was assessed through a visual assessment of the road network as well as subsequent aerial image inspection. Routes were chosen that fit this criterion.
- **Moderately high number of trips (preferred)** – To maximize the efficiency of the NDS data collection, the UNC team sought to identify roads that had more than a minimal number of trips. This was accomplished through referencing the trip density maps provided on the NDS InSight website. The UNC team selected routes that had at least 20 trips.
- **Promising amount of vertical and horizontal curvature (preferred)** – Since the focus of this study is on curvature, the UNC team wanted to ensure that potential routes would have a fair potential for both horizontal and vertical curvature. Following a conversation with Iowa State University, the UNC team began by focusing on the RID data from New York and Pennsylvania, since these were assumed to have the greatest number of curves on rural roads. Routes that appeared to have a relatively high amount of horizontal curvature (based on the RID "Alignment" layer) and vertical grade *variation* (based on the RID "Location" layer) were prioritized in the selection. At this stage, it was not yet possible to determine which routes had vertical curves.

Based on these criteria, the UNC team selected four "routes" (as defined by RouteID in the RID):

- New York, Route 132 (21 total miles)
- Pennsylvania, Route 587, (24 total miles)
- Pennsylvania, Route 779 (3.6 total miles)
- Pennsylvania, Route 914 (23 total miles)

2. Identify sections of interest based on alignment data

Once the potential routes were identified, alignment files were developed for each route to indicate the beginning and ending points of horizontal or vertical curvature along the route. This information was used to dynamically segment the route into unique sections representing combinations such as “Vertical crest curve on horizontal tangent” or “Vertical sag curve on horizontal curve”. These sections would later serve as the unit of analysis when NDS driver behavior data were obtained. For this step, the UNC team developed a method to identify vertical curves. The method and its development are described below.

<u>Method to Identify Vertical Curves</u>

The topic of this study required the identification of the presence and location of both horizontal and vertical curves along the selected routes. Determining the start and end points of horizontal curves was straightforward. The “Alignment” layer of the RID is segmented into horizontal tangents and curves. Basic curve attributes are also provided, such as curve radius. However, determining the start and end points of vertical curves was challenging.

There was a need for a method to assess the grade data to determine the location and extent of vertical curves. This was not a straightforward task, since the RID does not explicitly define vertical curvature in the data. Rather, it provides grade data (in percent) approximately every 25 feet, collected by an instrumented vehicle which drove all roads in the study area. It was necessary to develop a method for extracting vertical curve information from the grade data. The basic approach taken to assessing the grade data for identifying vertical curves was to conduct a “sliding window” analysis. This approach would begin with the first segment of the route and evaluate the group of adjacent grades within a certain designated window distance to determine if the trend of the values indicated that a vertical curve had been encountered. After each evaluation, the window would slide down the road by one grade section (in the direction of increasing mileposts) and the evaluation would be repeated until the end of the route was reached.

The team first attempted a method to identify vertical curves using a difference in average grades. This method compares the average of all grades in a window distance upstream of the segment of interest to the average of all grades in a window downstream of the segment of interest. If the difference in the two grades exceeds a designated threshold amount, then the segment of interest is determined to lie within a vertical curve. Adjacent curve sections are later grouped as a distinct curve. However, initial assessments of the method showed some issues when attempting to identify both short (sharp) vertical curves and long (flat) curves on the same route. Over the same distance in length, long curves have less change in grade than sharp curves, making it difficult to select a grade difference threshold that will evaluate both correctly. Any particular threshold value would underestimate the length of long curves but overestimate the length of sharp curves.

A second method was developed out of a desire to address the main drawback with the first method. That is, a method was needed that could equally assess and identify both sharp and flat curves. The answer to this need was found in the common design standards used for all vertical curves. The similarity in sharp and flat curves is that they both follow a parabola (or similar curve within some tolerance for deviations in construction and/or older curve designs). Mathematically, the first derivative of a parabola is a straight line (Equation 2). If the derivative of the roadway curve could be compared to a straight line, it would be possible to determine how similar the curve is to a parabola.

$$y = ax^2 + bx + c \qquad \text{(Equation 1)}$$

$$y' = 2ax + b \qquad \text{(Equation 2)}$$

Conveniently, the RID provides the first derivative of the roadway curve by providing the grade at every 25 to 30 foot interval. If the road were exactly constructed as a perfect parabola (and the grade data were perfectly collected), the trend of the grade values would be a straight line. Thus, this method examines the trend of the grade values within a window distance of the segment of interest and calculates a correlation value that reflects the degree to which the grades form a linear trend. The higher the correlation value, it is more likely that the segment of interest lies within a vertical curve (i.e., a parabolic group). A correlation value of 1.0 would reflect a straight line. Even for curves that are not parabolic (e.g., a constant radius circular arc), the trend of the grades is fairly close to a straight line. Setting a correlation threshold to a value somewhat less than 1.0 allows for tolerances in the noise of the data or variations in real-world construction.

This method calculates a linear correlation value for the grades of all segments within a designated window distance downstream and upstream of the segment of interest. A linear correlation value is calculated for the grade values captured in the windows. If the trend of the grades is linear within a certain tolerance (linear correlation threshold, such as 0.9), the segment is deemed to be within a vertical curve. TABLE 1 uses an excerpt of actual RID grade values to demonstrate the second method. It uses an example threshold of 0.9 for the linear correlation and a window consisting of six segments downstream and upstream.

The user-specified parameters of this method are: 1) the value of the linear correlation threshold, and 2) the number of segments to use as the window distance upstream and downstream of the segment of interest. In order to calibrate these parameters (i.e., find the best values to use for identifying vertical curves) a comparison to a real world dataset was critical. Since state of Washington maintains an inventory of vertical curves as part of their roadway inventory files, one of the routes from Washington (40-mile portion of US 2 containing 37 vertical curves), was selected as the real work dataset for evaluating the method. The quantitative assessment of the methods was done using counts of false positives and false negatives. If a method indicated that a segment was not in a curve, when ground truth indicated that it was, this represented a false negative. Conversely, if a method indicated that a segment was in a curve when ground truth indicated that it was not, this represented a false positive. These false positives and negatives were summed across the entire 40 mile test route to determine how well the methods compared to ground truth. The linear correlation threshold parameter was adjusted in a trial-and-error fashion to hone in on the optimal value (lowest resulting counts of false positives and negatives). This revealed that a linear correlation of 0.9 performed best. Further discussion of the ground truth validation method and the findings is available in a paper that is <u>under review</u> for possible presentation at the 2016 TRB Annual Meeting.

Identify Segments
Once the segments of each route were classified into horizontal and vertical curves or tangents, the team selected certain segments from each route. This selection was targeted at sections that occurred on vertical and horizontal curves, but also included segments that occurred on horizontal tangents or vertical straight grades in order to serve as a baseline comparison. The selected segments comprised a total of a little over 6 miles, in the following breakdown:

- New York, Route 132 (3.08 miles selected)
- Pennsylvania, Route 587, (1.3 miles selected)
- Pennsylvania, Route 779 (0.95 miles selected)
- Pennsylvania, Route 914 (0.85 miles selected)

Data Use Agreement with VTTI
During this task, the UNC team also negotiated a data use agreement with VTTI. The agreement discussed the scope of the research study including the objectives, the data elements that are requested, sample size (i.e., number of trips), who will be compiling the data including information that potential personal identifiers (e.g., eye glance information), how long the data should be kept at UNC after the completion of the study, and a copy of the UNC IRB application. This agreement was later modified to obtain vehicle width data and driver demographics data.

TABLE 1 Example of Linear Correlation Method Using a 0.9 Correlation Threshold

Segment ID	Segment Grade	Linear Correlation Using Six Segment Window	Segment is in Vertical Curve (Correlation Meets Threshold)?
1	-1.2	0.243	No
2	-1.4	0.280	No
3	-1.4	0.512	No
4	-1.3	0.773	No
5	-1.0	0.888	No
6	-1.4	0.882	No
7	-1.6	0.881	No
8	-1.5	0.906	**Yes**
9	-1.7	0.947	**Yes**
10	-1.9	0.976	**Yes**
11	-2.0	0.986	**Yes**
12	-2.4	0.984	**Yes**

3. Send LINK IDs to VTTI to Obtain NDS Data

Throughout Steps 1 and 2, the team worked with the curve and grade files from the RID (Alignment and Location). However, the NDS data maintained by VTTI is stored on the basis of LinkIDs as defined in the Links layer of the RID. Thus, based on the selection of road segments in Step 2, the team identified the corresponding links by LinkID in the Links layer. This compilation of LinkIDs was submitted to VTTI as the basis of the request for the driver behavior data from the NDS.

OBTAIN TIME SERIES AND FORWARD VIDEO DATA

For each study site that was provided to VTTI, VTTI provided a list of trips that traversed these sites. The information provided for each trip included trip id, participant id, time of day, duration of the trip, the sequence of LinkIDs in the trip, number of crashes, and number of near crashes in the trip. None of the trips had any crashes or near crashes. From this list, VTTI asked UNC to randomly select trips for which the time series, eye glance, and secondary task data would be extracted. Based on the data use agreement with VTTI, a total of 1250 LinkID-trips were selected.

After the trips were selected and provided to VTTI, VTTI provided the time series data and the forward video in two batches: one in June 2015 and the second in July 2015. The time series data included the kinematics variables such as speed, lane position offset, distance to edge and centerlines, heading, acceleration, steering, latitude, and longitude.

The forward video was used to determine the presence of lead vehicles, vehicles in the opposing lane approaching the subject vehicle, weather conditions, lighting/time of day, construction and maintenance, and intrusions from vehicles and other road users. Lead vehicles within a 3 second headway in front of the subject was assumed to affect the speed of the subject vehicle, and hence, timestamps associated with this time period was noted. Similarly, vehicles in the opposing lane were assumed to affect the lane position of the vehicle for about 2 seconds before it passed the subject vehicle.

OBTAIN EYE GLANCE AND SECONDARY TASK DATA

VTTI provided the eye glance and secondary task data in August 2015. The eye glance data provided information on whether the driver was looking forward into the roadway, rear view or side mirrors, or inside the vehicle, including passenger, interior object, cell phones, windshield, etc. In addition, there was also an indication on whether the driver's eye glance was in transition. In some cases, the eye glance data were not available because of glare or when drivers were using sunglasses.

The secondary task information was provided as summaries for each LinkID for each trip. The secondary task file included information on the activities that drivers were doing apart from driving. The main purpose for requesting this information was to determine if the analysis should look at drivers that were not involved in secondary tasks apart from the driving task. A review of the secondary task file indicated that in over 65% of trips, drivers were involved in other activities in addition to the driving task. Hence, analysis using just the drivers without any secondary tasks would have been based on a very small sample, and probably not very useful. Consequently, the secondary task file was not used further in the analysis.

DATA REDUCTION

The first step in the data reduction was to combine the time series data, eye glance data, and the data that were coded from the forward video. During this process, it was found that for some of the trips, the start and end timestamps of the time series data were significantly different from the start and end timestamps of the eye glance data. VTTI indicated that this match was due to "errored export" and happened due to "different portions of the same file being exported as part of the process". VTTI provided the corrected time series data for the affected trips on September 11, 2015, allowing the UNC team to proceed with further data reduction and analysis. VTTI also assured the UNC team that this error is not a common occurrence and has been resolved. They also indicated that there was no reason to believe that this issue affected the other trips where there was a good match between the timestamps of the eye glance data and the times series data.

Merging the time series, eye glance, and coded data from the forward video presented a few other challenges as well. The time series data were provided at a frequency of 10 Hz (every 0.1 second). However, the eye glance data and the coded data from the forward video were available more frequently, i.e., every 0.066 or 0.067 seconds. The UNC team wrote a computer program to combine the different data sets together to match the frequency in the time series data. Before analyzing the data, some observations had to be removed due to the following reasons:

- As mentioned earlier, some of the segments were multilane roads instead of two-lane roads.
- The lane position data were either missing or incorrect, e.g., there were a series of observations where the distance to the right side and left side lane markings from the center of vehicle were both zero for the same observation.
- The latitude and longitude information was missing for some observations. Since UNC provided VTTI with LinkIDs in order to extract the NDS data, and these LinkIDs often included multiple tangent sections and curves, without latitude and longitude, it was not possible to link the time series data with specific curves or tangents.

ANALYSIS AND RESULTS

As discussed earlier, the intent of the analysis was to determine the relationship between alignment and driver performance. The performance measures that we investigated included mean speed, speed variance, mean absolute value of the lane deviation (defined as the absolute value of the distance between the center of vehicle and the center of the lane), variance of lane deviation, probability of lane encroachments (i.e., probability that any part of a vehicle was outside the lane on either side), and mean absolute value of lateral acceleration. The analysis included both disaggregate (i.e., including data from each timestamp) and aggregate where the data were aggregated over homogenous segments (based on alignment) for each driver and trip. The disaggregate analysis included linear regression for mean speed, mean absolute value of the lane position, and mean absolute value of lateral acceleration. Probability of lane encroachments was investigated using logistic regression. The independent variables included alignment category, presence of a lead vehicle, presence of a vehicle in the opposing lane, weather conditions, time of day category, driver's glance location, age category, and gender. In some cases, models were estimated after eliminating outliers based on the Cook's distance (Cook's D) criterion (Cook, 1979). For the models that used the lane deviation information, only those observations where the lane marker probability value for the left and right lane marking was greater than or equal to 512[1] was used.

[1] This parameter has a maximum value of 1024 and based on Hallmark et al., (2014), a cutoff value of 512 was chosen.

For the disaggregate analysis, a fixed effects model was estimated by including individual specific indicator variables for each driver to account for serial correlation due to repeated measures from each driver. A more sophisticated analysis approach would have been use time series analysis methods to account for correlation between observations from the same driver. However, that proved to be a bit challenging because of the gaps in the data that were introduced due to removing parts of the data due to errors and missing information. We plan to investigate time series analysis methods if funding for Phase 2 becomes available. All the models were estimated using PROC GENMOD in SAS by maximizing log-likelihood estimation.

In the aggregate analysis, for each homogenous segment, a CMF was calculated using the equations from Bauer and Harwood (2014), to compare them to the performance measures for that segment. The intent of this comparison was not to necessarily validate the CMFs from Bauer and Harwood (2014), but to obtain insight into the relationship between performance measures and crash propensity.

Overall, data were available for 85 drivers that took 317 trips. 42% of drivers in the sample were female and 56% were male. About 29% of the drivers were younger than 30, 43% were between 30 and 64 years old, and 26% were 65 years or older. Gender and age was missing for a couple of drivers.

Results from Disaggregate Analysis

Results from some the disaggregate analysis are shown below in Tables 2 and 3. These models were based on about 60,000 observations. For brevity, only the parameter estimates for the alignment related variables from the models are shown in the tables. The following abbreviations are used to describe the different alignment categories:

- Flat tangent (reference level)
- Grade: Straight grade without horizontal or vertical curve
- HC_C1: Horizontal curve and Crest 1 vertical curve
- HC_C2: Horizontal curve and Crest 2 vertical curve
- HC_S1: Horizontal curve and Sag 1 vertical curve
- HC_S2: Horizontal curve and Sag 2 vertical curve
- HC_STR: Horizontal curve without any vertical curve (includes curves with and without straight grades)
- HT_C1: Tangent and Crest 1 vertical curve
- HT_C2: Tangent and Crest 2 vertical curve
- HT_S1: Tangent with Sag1 vertical curve
- HT_S2: Tangent with Sag 2 vertical

<u>Linear Regression with Absolute Value of Lane Deviation</u>

TABLE 2 shows the results of the linear regression model that was estimated for the absolute value of lane deviation. Lane deviation is the distance between the center of the lane and the center of the vehicle, and is measured in centimeters. A positive coefficient implies that compared to a flat tangent section, vehicles were driven farther away from the center of lane. Similarly, a negative coefficient implies that compared to a flat tangent section, vehicles were driven closer to the center of lane. Assuming that driving closer to the center of the lane is associated with safer driving behavior, all the alignment categories with horizontal curves do worse compared to flat tangents with and without vertical curves. At the same time, surprisingly, tangents with crest 2 and sag curves seem to be doing better compared to flat tangent sections. Models estimated using the absolute value of the lateral acceleration were very similar to the lane position models, and hence, are not shown here.

TABLE 2: Results for absolute value of lane deviation

Variable	Estimate	Standard Error
Intercept	13.8732	0.8621
Flat Tangent	----	------
Grade	-1.0742	0.2457
HC_C1	3.7402	0.4784
HC_C2	2.8922	0.8072
HC_S1	4.9875	0.4732
HC_S2	0.7109*	1.0648
HC_STR	6.9464	0.2506
HT_C1	-0.2276*	0.3513
HT_C2	-3.6833	0.6885
HT_S1	-1.8173	0.3067
HT_S2	-2.1768	0.4274

Note: *Not statistically significant at the 0.05 level. Only the alignment variables from the model are shown.

Logistic Regression for Probability of Lane Encroachment

TABLE 3 shows the results of the logistic regression. The parameter estimates can be used to estimate the log of the odds of lane encroachment associated with a particular alignment category (overall, about 7.5% of observations had a lane encroachment). A positive coefficient implies that the probability of encroachment is higher for that alignment category compared to a flat tangent section. Consistent with the lane position model, the alignment categories that include a horizontal curve have a higher probability of an encroachment compared to a flat tangent section. However, unlike the lane position model, tangents with sag curves and straight grades have a higher probability of encroachment compared to a flat tangent section. This model also indicated the probability of lane encroachment was higher for the youngest drivers and decreased with increase in age.

TABLE 3: Results for probability of lane encroachment

Variable	Estimate	Standard Error
Intercept	-4.7046	0.1421
Flat Tangent	----	-----
Grade	0.8546	0.0947
HC_C1	0.2972*	0.2005
HC_C2	1.7665	0.1651
HC_S1	1.6418	0.1237
HC_S2	1.2792	0.2643
HC_STR	1.9685	0.0918
HT_C1	0.2021*	0.1440
HT_C2	0.1462*	0.2744
HT_S1	0.7310	0.1082
HT_S2	1.0558	0.1223

Note: *Not statistically significant at the 0.05 level. Only the alignment variables from the model are shown.

Linear Regression with Mean Speed

The models estimated for mean speed indicated that horizontal tangents with sag 2 vertical curves (HT_S2) were associated with highest values and horizontal curve with crest 1 vertical curves (HC_C1) were associated with the lowest values. These models are not shown here for the sake of brevity. In addition, mean speed may not be relevant unless it is considered along with other factors including speed limit and specific geometric features.

Models with Curve Radius and K Values

In addition to the models that were estimated with alignment categories, models were also estimated using radius of horizontal curve (R) and the K value for vertical curves. The models indicated that horizontal curves with smaller radii (i.e., sharper horizontal curves) were associated with higher absolute values of the lane deviation and higher encroachment probabilities. The results regarding the effect of K on lane deviation were not as consistent; some models showed lower K values associated with higher lane deviations, while others showed the reverse. Again, these models are not shown here for the sake of brevity.

Results from Aggregate Analysis

Table 4 shows the results of the aggregate analysis. For each homogenous segment, CMFs for fatal and injury crashes were calculated based on the equations in Bauer and Harwood (2014); depending on the alignment category, the CMFs are a function of R, K, L_c, and L_v. Similarly, the performance measures were also calculated for each homogenous segment[2]. Then, for each alignment category, a weighted average was calculated (using the number of observations as the weight) to determine an overall average for each alignment category. For each column in Table 4, the alignment categories with the three highest values are highlighted in **bold** and the four lowest values are highlighted in *italics*. The three alignment categories with the highest CMFs are HC_C2, HC_S1, and HC_STR. The three alignment categories with the highest absolute value of lane deviation and lane encroachment proportion are also HC_C2, HC_S1, and HC_STR.

The four alignment categories with the lowest CMFs are Flat Tangent, HT_C1, HT_C2, and HT_S2. The four alignment categories with the lowest absolute value of lane deviation are HT_C1, HT_C2, HT_S1, and HT_S2. Similarly, the four alignment categories with the lowest lane encroachment proportions are Flat tangent, HT_C1, HT_C2, and HC_C1. Again, there is a good match between the alignment categories with the lowest CMFs and the alignment categories with the lowest values for the lane deviation measures.

[2] Unlike the disaggregate analysis, the aggregate did not specifically account for the presence of lead vehicles or vehicles in the opposing lane. Hence, the two sets of results may not be completely consistent with each other.

TABLE 4: CMFs and Performance Measures

Alignment Category	CMF	Speed	Speed variance	Absolute value of lane deviation	Variance of lane deviation	Lane encroachment proportion	Horizontal acceleration
Flat Tangent	*1.000*	**91.9**	2.373	22.5	**332.2**	*0.019*	*0.018*
Grade	1.235	83.9	**6.453**	22.3	218.4	0.055	*0.022*
HC_C1	1.505	*81.1*	2.592	26.3	309.1	*0.021*	0.064
HC_C2	**1.527**	*78.5*	*0.659*	**33.2**	312.4	**0.091**	0.047
HC_S1	**1.919**	**88.9**	*1.071*	**31.2**	**329.0**	**0.106**	**0.083**
HC_S2	1.393	87.0	1.319	26.9	*132.0*	0.055	**0.077**
HC_STR	**1.782**	*81.9*	**5.737**	**33.0**	**502.2**	**0.139**	**0.072**
HT_C1	*1.000*	*81.7*	2.556	*21.3*	*186.9*	*0.023*	*0.020*
HT_C2	*1.000*	87.8	*0.738*	*18.8*	*43.7*	*0.023*	*0.023*
HT_S1	1.176	84.9	**3.528**	*22.3*	294.6	0.049	0.025
HT_S2	*1.000*	**88.3**	*0.782*	*20.1*	*56.6*	0.084	0.028

CONCLUSIONS FROM PHASE 1

The analysis of the NDS data has shown that the alignment categories that include a horizontal curve have the worst performance in terms of the lane deviation measures. In addition, sharper horizontal curves are associated with the higher absolute values of lane deviation. The analysis was conducted using both disaggregate and aggregate methods. Comparison of the CMFs from Bauer and Harwood (2014) with the performance measures indicates a good match with the lane deviation measures, indicating that the lane deviation measures could serve as good surrogates for crash propensity. The UNC team was also successful in developing an algorithm that used the RID to identify vertical curves. This algorithm was also validated using ground truth data from Washington.

PHASE 2 RESEARCH PLAN AND PROPOSAL

The results from Phase 1 demonstrated the value in conducting further research on this topic to investigate driver performance associated with the combination of horizontal and vertical alignment and identify potential countermeasures. Phase 2 will be conducted by the same team members at UNC including Raghavan Srinivasan, Daniel Carter, and Bo Lan. The proposed approach in Phase 2 is quite similar to the approach in Phase 1, but with some important modifications:

- Sample size. The sample of LinkID-trips will be about 5 times higher than the LinkID-trips investigated in Phase 1. About 6000 LinkID-trips are being targeted. VTTI indicated that 6000 is probably the maximum that they can handle due to “limitations in the computing cost of generating exports, within the time constraints typically present in these projects”. Data for more trips can be the requested if the request is limited to less frequent information (e.g., 1 Hz instead of 10 Hz). However, at this time, we feel that less frequent data may not provide the necessary level of detail for the analysis, especially for some performance measures such as lane deviation.

- Identifying rural two lane roads. As discussed earlier, in Phase 1, some portions of the road sections were multilane roads rather than rural two lane roads. We have refined our approach for identifying rural two lane roads, and identification of two-lane roads in Phase 2 will not rely on the number of through lanes from the "Lanes" layer, but will focus on other variables present in the RID, such as the directional lanes values in the "Links" layer.
- Use of radar data. Radar data will be used to obtain more accurate information about lead vehicles. Based on Hallmark et al., (2014), we were reluctant to use the radar data in Phase 1, and used the forward video to determine if a lead vehicle could have impacted the speed of the subject vehicle. However, communication with VTTI has revealed that the radar data are quite reliable in providing information about the lead vehicle.
- Combinations of alignment categories. Conversations with the North Carolina Department of Transportation (NCDOT) has revealed anecdotal information about the safety issues regarding certain combinations, e.g., crest vertical curve followed by a horizontal curve to the left have been associated with a large number of crashes involving motorcycles. Although motorcycles are not part of the SHRP2 data, such combinations may be associated with safety problems for cars and trucks as well. Another issue that will be investigated is the distance between curves, i.e., isolated curves versus closely spaced curves. Most previous studies, including the Bauer and Harwood (2014), have not considered the combined effect of multiple roadway features that are adjacent to each other.
- Other States. Phase 1 only included data from Pennsylvania and New York. Phase 2 will include data from at least one other state (North Carolina).
- Countermeasures and roadside data. The results from Bauer and Harwood (2014) are most useful if an agency is considering changes to roadway alignment, which are obviously expensive changes. So, agencies are looking for low cost countermeasures that could be effective in reducing crashes. In Phase 1, countermeasures could not be investigated partly due to the limited time for analyzing the data. In Phase 2, information on countermeasures will be an important component of the study. In addition, data from the roadside will be compiled and included in the analysis.
- More sophisticated statistical analysis. Due to the limited time that was available for the analysis, the analysis methods in Phase 1 were limited to linear regression and logistics regression. Phase 2 would involve the use of more sophisticated analysis techniques including time series and Bayesian methods.

Tasks

Following is the list of tasks that are proposed for Phase 2:

1. Obtain IRB approval from UNC IRB. This is the first task that will be conducted. Since, UNC will not be directly handling any of the personal identifying information from the NDS data, quick approval is expected, as in the case of Phase 1.

2. Review of Literature. The primary purpose of this task is to review any recent studies that have used NDS data. The intent is to get some insights into any new statistical methods that may have been used to analyze the NADS data and new measures of

performance that may have been used as surrogates for crashes. The outcome from this task will be an initial list of performance measures and statistical methods that could be applied in Phase 2.

3. Refine Work Plan. This task will be done in consultation with NCDOT and VTTI. This task will focus on the following issues:
    a. *Sample size of LinkID-trips*. As mentioned earlier, the UNC team is planning to request data for 6000 LinkID-trips due to limitations mentioned earlier. However, VTTI is continuing to work on other alternatives that may allow a larger number of LinkID-trips to be exported, and this will be discussed as part of Task 2.
    b. *Scope of the eye glance data collection*. The UNC team has already had some discussion with VTTI about the cost implications of two options for compiling the eye glance data. The first option is to compile the eye glance data only for a sample of the LinkID-trips (say, for about 30% of the LinkID-trips). The second option is to compile the eye glance data for all the trips.
    c. *Combination of alignment categories*. The analysis of the driver performance data is expected to provide insight into the safety aspects of the combination of alignment categories. However, if anecdotal or other evidence regarding certain combinations are available, that may guide the UNC team in looking for certain combinations, e.g., crest vertical curve followed by a horizontal curve to the left, which was mentioned above.
    d. *List of site characteristics*. A final decision will be made on the list of site characteristics that will be compiled including roadway and roadside characteristics. In addition to the RID, the sources will include extracting information from the forward video, aerial photographs, and google maps. Examples include information that can be used to estimate a roadside hazard rating (RHR), traffic control devices and signs (including posted speed), and treatments such as reflectorized pavement markings (RPMs) and rumble strips. Many of these variables including traffic signs/traffic control devices, rumble strips, guardrail presence, and shoulder width/type are available in RID. Other features such as RHR and pavement markings can be compiled through the forward video and other venues such as google earth.

During Task 3, UNC and VTTI will negotiate a data sharing agreement with VTTI. The agreement is expected to be very similar to the one that was signed for Phase 1. The agreement will indicate the scope of the research study including the objectives, the data elements that are requested, who will be compiling the data including information that potential personal identifiers (e.g., eye glance information), how long the data should be kept at UNC after the completion of the study, the security procedures for the data at UNC, and a copy of the UNC IRB application.

4. Identify Study Sites. The intent is to identify sites in rural two lane roads by using the directional lanes values in the "Links" layer. As in Phase 1, different types of sites including tangent, horizontal curve, sag and crest type 1, and combinations will be identified. The method developed in Phase 1 will be used to determine the parameters and boundaries of vertical curves. In addition, the UNC team will also seek to identify

sites where curves are next to each other, e.g., horizontal curve followed by vertical curve, or vice versa. Similar to Phase 1, sites with at least 20 trips will be identified. In Phase 1, the VTTI InSight website was used to determine the range of trips on each route. VTTI has indicated that a GIS layer of this trip file is now available and can be used in Phase 2. As in Phase 1, many of the sites are expected to be from New York and Pennsylvania, but sites from North Carolina will be included as well.

5. <u>Provide Study Sites to VTTI.</u> As discussed earlier, in Phase 1, the UNC team initially worked with the curve and grade files from the RID (Alignment and Location). However, since the NDS data maintained by VTTI is stored on the basis of LinkID as defined in the Links layer of the RID, the team identified the corresponding links by LinkID in the Links layer. The approach is expected to be similar in Phase. However, the UNC team will also explore the possibility of providing the data using “GIS buffers”.

6. <u>Obtain List of Trips.</u> As in Phase 1, VTTI is expected to provide UNC with the list of trips along with basic summary information about each trip including the number of crashes and near misses, time of day, and participant ID, and the list of LinkIDs that each trip traversed. UNC will select trips from this list and provide it to VTTI. Trips involving crashes and near misses are of specific interest to the UNC team (there were no crashes or near misses in Phase 1).

7. <u>Obtain Time Series, Forward Video, and Eye Glance Data.</u> VTTI is expected to provide the time series and eye glance data as in Phase 1. As in Phase 1, this information may be provided in batches. The eye glance data is expected to be available later because extracting that data is a manual process.

8. <u>Data Reduction and Coding.</u> The forward video will be used to code information on the presence of vehicles in the opposing lane (which may affect the lane position of the subject vehicle), lighting, intrusions from vehicles and other road users, construction and maintenance activities, and other roadway/roadside characteristics not available from the RID. At the same time, the UNC team will check for consistency between the time series data and the eye glance data to ensure that there are no obvious errors. Following this, the time series data, the RID data, the eye glance data, and the coded data from the forward video will be merged into one file. This may require the UNC team to use the computer program that was written in Phase 1 to combine the different data sets together to match the frequency in the time series data.

9. <u>Statistical Analysis.</u> As in Phase 1, the UNC team will conduct analysis at two levels: disaggregate and aggregate. The disaggregate data will make use of the frame by frame (i.e., every 0.1 second) data using time series methods that specifically account for the correlation between successive observations. The analysis will use random or fixed effects to account for repeated measures from the same driver and the same trip. The primary dependent variables for this disaggregate analysis will include speed, lane deviation, whether there was a lane encroachment on the right or left side, and lateral acceleration. The independent variables will include site characteristics (including geometry), any treatments/countermeasures implemented at a site, driver characteristics,

roadside characteristics, time of day, presence of lead vehicles (from radar), and presence of vehicles in the opposing lane (based on coded data from the forward video). Speed, lane deviation, and lateral acceleration will be analyzed using linear regression methods with appropriate transformations. The encroachment variable will be analyzed through logistic regression.

The aggregate analysis will be based on combining the data over homogenous segments for each driver and trip and using the summary information (mean and variance of speed, mean and variance of lane deviation, proportion of the section where there was a lane encroachment, maximum lateral acceleration within that section) as dependent variables. As in the case of the disaggregate analysis, random and fixed effects will be explored to account for repeated measures from the same driver and the same site. Linear regression and logistic regression models will again be used.

10. <u>Conclusions and Final Report.</u> Based on the results from aggregate and disaggregate analysis, we expect to determine the following:
    - Relationship between performance measures and crash propensity (based on the CMFs in Bauer and Harwood, 2014). This is expected to provide insight on the appropriate surrogates that could be used in future research.
    - Combinations of horizontal and vertical alignment associated with inferior driving performance and potentially higher risk of crashes
    - Potential effectiveness of countermeasures in affecting driver performance and behavior

    The results and conclusions from the effort will be prepared in the form of a final report.

PHASE 2 PROJECT SCHEDULE

A 24 month project schedule is proposed. The project schedule by task is shown below.

	Months from Beginning of Contract																							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Task 1	■																							
Task 2	■																							
Task 3		■	■																					
Task 4				■	■	■	■																	
Task 5								■	■															
Task 6										■	■													
Task 7												■	■	■	■	■								
Task 8															■	■	■	■						
Task 9																	■	■	■	■	■	■		
Task 10																						■	■	■

REFERENCES

Bauer, K.M. and Harwood, D.W. (2014), *Safety Effects of Horizontal Curve and Grade Combinations on Rural Two-Lane Highways*, Report FHWA-HRT-13-077, Washington, DC.

Cook, R. D. (1979), Influential Observations in Linear Regression, *Journal of the American Statistical Association*, 74, 169–174.

Davis, G. and Hourdos, J. (2012), *Development of Analysis Methods Using Recent Data*, SHRP2 Report S2-S01A-RW-1, TRB, Washington, DC.

Gordon, T.J. et al. (2013), *A Multivariate Analysis of Crash and Naturalistic Driving Data in Relation to Highway Factors*, SHRP2 Report S2-S01C-RW-1, TRB, Washington, DC.

Hallmark, S.L., Oneyear, N., Tyner, S., Wang, B., Carney, C., and McGehee, D. (2014), *Analysis of Naturalistic Driving Study Data: Roadway Departures on Rural Two-Lane Curves*, SHRP2 Safety Project S08D, TRB, Washington, DC.

Jovanis, P., Shankar, V., Aguero-Valverde, J., Wu, K.-F., and Greenstein, A. (2012), *Analysis of Existing Data: Prospective Views on Methodological Paradigms,* SHRP2 Report S2-S01B-RW-1, TRB, Washington, DC.

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