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VALIDATING THE COLLECTION OF SKID DATA BY ASSESSING CORRELATION WITH CRASH DATA

Prepared For:

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UNIT CONVERSION FACTORS

*SI is the symbol for the International System of Units. (Adapted from FHWA report template, Revised March 2003)

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EXECUTIVE SUMMARY

Pavement friction is an important pavement surface condition metric, as it is assumed to be associated with traction and thus traffic safety outcomes, due to larger coefficients of road adhesion during vehicle braking. The Utah Department of Transportation (UDOT) measures pavement friction using a standard test that generates a skid number (SN), where larger numbers reflect more friction. However, there is limited existing literature that directly relates skid resistance to safety performance, as measured by models of crash data and crash prediction methods. Therefore, the objective of this project was to determine whether and how skid resistance data can provide meaningful insights regarding the relationship between pavement friction and traffic safety in Utah.

To achieve this objective, this study collected data from an interstate highway (I-15) and a non-interstate highway (US-89) within the state of Utah, covering the years 2016 to 2019. For each segment (0.5 miles or less) on each highway, data collection involved gathering information about traffic volumes, SN values, and roadway geometry (lanes, shoulders, medians, barriers, rumble strips, and curves). These data were then statistically linked to crashes—by dry weather, wet weather, property damage only, injury-related, and all-type crashes—using negative binomial regression models. Through this analysis, safety performance functions and crash modification factors were also generated.

The models found a significant negative association between the SN and crash frequency across all types of crashes and on both interstate and non-interstate highways, even after controlling for many other roadway geometric characteristics that also influence crashes. This finding means that segments with higher pavement friction, indicated by larger SN values, saw fewer crashes of all types. This result implies that skid resistance is an important characteristic of pavement surfaces that contributes to a reduction in crashes on all types of roadways and for all types of crashes.

Specifically, a 10-unit increase in SN (on a 0-100 scale) was linked to a 7% to 8% reduction in dry weather crashes on both non-interstate and interstate highway segments, while the same increase in SN led to a 14% and 21% decrease in wet weather crashes, for non-

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interstate and interstate highway segments, respectively. Notably, the crash reduction potential of an increase in SN was particularly strong on interstate highways for wet weather crashes, suggesting that pavement friction is particularly important for improving safety on interstate highways when the surface condition is wet.

The study results suggest recommendations for implementation. UDOT should continue to collect SN data about pavement roughness on Utah highways, and prioritize data collection on interstate and other higher speed, volume, and/or functional class roadways. Also, when conducting pavement resurfacing work to enhance pavement friction, UDOT should prioritize locations with the greatest potential for crash reduction, including curves and segments with lower SN values and more wet weather crashes.

1.0 INTRODUCTION

1.1 Problem Statement

Pavement surface condition metrics, such as pavement friction and other forms of pavement quality, are extensively used for infrastructure assessments both in the US and worldwide. One commonly used measure for describing pavement friction is the skid number (SN). This measure represents the ratio of horizontal tractive force to vertical load between a vehicle's tires and the pavement surface. The SN is calculated by dividing the horizontal tractive force by the vertical load and then multiplying this ratio by 100 (PennDOT, n.d.). Consequently, a higher SN indicates greater friction and traction between the tire and pavement, as it reflects a larger horizontal tractive force relative to the vertical load. In addition to the skid number, other metrics like grip number (GN) and international roughness index (IRI) (Cafiso et al., 2021) are also used to assess pavement surface quality.

The Utah Department of Transportation (UDOT) has accumulated multiple years of skid resistance data from highways statewide. This data is collected using a specialized trailer that measures pavement friction through a braking tire on wet pavement (see [Figure 1-1\)](#page-13-1), following the ASTM E274 "Standard Test Method for Skid Resistance of Paved Surfaces Using a Full-Scale Tire." UDOT continues to gather this data annually and records it as SN values tied to specific roadway sections. Despite the availability of this valuable data, UDOT faces challenges in effectively analyzing this rapidly accumulating dataset (Smith, 2022). Additionally, UDOT collects supplementary pavement texture metrics to establish thresholds for skid number testing. Some researchers suggest strategic testing based on these texture thresholds to mitigate the high costs associated with skid testing (Allen et al., 2019). To determine the appropriate scale and utilization of Utah's skid number monitoring program, a thorough evaluation of the merits and potential applications of comprehensive skid data collection is essential.

Figure 1-1: UDOT skid data collection truck and trailer (Courtesy of UDOT)

One potential application for these data is in the area of traffic safety. Greater pavement friction (higher SN) is typically assumed to be associated with improved traction and thus improved safety, especially in wet conditions, due to larger coefficients of road adhesion (Mannering & Washburn, 2019). However, in Utah (as in many places throughout the US), this road friction data is not well understood or used, since other data sources exist that are currently used more frequently for safety analysis purposes. Also, there is limited existing literature that directly relates skid resistance to safety performance (as measured by models of crash data and crash prediction methods). Therefore, there exists the following major questions for UDOT and any other transportation agency collecting similar data: Should these skid resistance data continue to be collected? And, more specifically: Can these skid resistance data provide meaningful insights regarding the relationship between pavement friction and traffic safety?

1.2 Objective

The importance of skid data in enhancing traffic safety cannot be overstated, as it offers critical information about road friction, a key component in understanding and improving road safety, allowing vehicles to stop faster and handle more precisely in response to a hazardous situation involving prompt braking or maneuvering. However, the valuable resource that is SN data is often underutilized in safety analyses, overshadowed by more conventional data sources that may not offer as direct a link to crash prevention measures. The underuse of skid resistance data represents a significant gap in current approaches to traffic safety analysis and suggests that there is much to be gained from a more focused application of this information. This leads to

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several pressing questions: Should the collection of skid resistance data continue, despite its current underutilization? More importantly, can this type of data provide meaningful insights into the relationship between pavement friction and traffic safety? These questions highlight a critical point in traffic safety analysis. By exploring the potential of skid resistance data, we open the door to possibly uncovering new strategies for reducing road crashes.

To address these questions, conducting a statistical analysis of the skid data in relation to crash data becomes an essential objective. Such an analysis could illuminate impacts of pavement friction on road safety, offering evidence-based insights into how skid resistance data can be leveraged to mitigate accident risks. This objective not only aims to validate the relevance of skid data in traffic safety analysis but also to quantify its potential contributions to reducing crashes. With this investigation, we can develop more informed strategies for road safety improvements, making a case for the optimized collection and use of skid resistance data in traffic safety efforts. Alternatively, if skid resistance on roadways is not associated with reductions in crashes, then there is one less reason for continuing to collect such data.

1.3 Scope

To achieve this objective, safety performance functions (SPF) and crash modification factors (CMF) were developed to estimate the change in expected crashes based on pavement friction SN values (all other factors remaining constant). These analyses are detailed in the following chapters. As a result of this study, UDOT officials can use the SPFs and CMFs to better utilize Utah's skid data and evaluate safety related to pavement friction, thus helping inform whether to implement safety improvements or mitigation strategies related to pavement conditions, such as high-friction surface treatments (FHWA, 2021).

1.4 Outline of Report

This report is organized into the following chapters:

• Chapter [1.0](#page-12-0) "Introduction" presents the problem statement, objectives, scope, and organization of the report.

- Chapter [2.0](#page-16-0) "Literature Review" offers an in-depth summary of previous literature about how pavement conditions, including roughness, friction, and skid resistance, affect traffic safety. It also discusses the research methodologies used in these studies, and provides brief insights into how various factors influence crash risk.
- Chapter [3.0](#page-19-0) "Data Collection" details the data collection methods used in the study. This involved obtaining traffic and roadway geometry data from UDOT for I-15 and US-89 from 2016 to 2019, including segmented AADT, crash data under various conditions, and highway condition metrics like SN and highway geometric characteristics.
- Chapter [4.0](#page-24-0) "Data Analysis" presents the results of descriptive statistics and statistical analyses of crash frequencies, the development of SPFs and CMFs, and the findings from negative binomial (NB) regression models analyzing various crash types on these highways.
- Chapter [5.0](#page-40-0) "Conclusions" summarizes the study's key findings, acknowledges limitations, and suggests directions for future research.
- Chapter [6.0](#page-42-0) "Recommendations and Implementation" provides suggestions for applying the results of the research, including regarding the continued collection of skid resistance data in Utah.

2.0 LITERATURE REVIEW

2.1 Overview

This literature review chapter provides an overview of the relationships between pavement condition, including roughness, friction, and skid resistance, and their impacts on traffic safety outcomes. Furthermore, this section also discusses the research methodologies employed and brief insights on impacts of various factors on crash risk from prior studies.

2.2 Literature Review

Pavement condition, roughness, friction, and skid resistance can be measured in a variety of ways. As previously mentioned, in Utah, the annual collection of network-level pavement friction data involves measuring SN. In other jurisdictions, different measures may be used, including GN or IRI. A review of these various methods is beyond the scope of this paper; see elsewhere (Mataei et al., 2016). Instead, this brief literature review summarizes evidence from studies investigating the effects of pavement condition, roughness, friction, and skid resistance on traffic safety outcomes. Friction is a critical characteristic of a pavement that affects how vehicles interact with the roadway, including potentially affecting the frequency of crashes. Measuring, monitoring, maintaining, and enhancing pavement friction could prevent many types of traffic crashes, especially in locations where braking is expected, like horizontal curves, ramps, intersection approaches, and crosswalks (FHWA, 2021 & 2022). Given the special importance of road friction under conditions that degrade traction (e.g., rain, snow), this review also summarizes key findings about the impacts of pavement friction on traffic safety under different road surface conditions (e.g., dry vs. wet). Specific studies reviewed are presented in [Table 2-1.](#page-17-0)

Citation	Data	Crash severity	Weather conditions	Other conditions	Methods
Long et al. (2013)	• State-maintained roads \bullet Texas • $2008 - 2011$	\bullet All	• All weather • Wet weather	×	CRR, Hierarchical tree grouping method
Geedipally et al. (2019)	• Two-lane, four-lane rural highways • One southern US state \bullet 2007-2011	Fatal and \bullet injury	• All weather • Wet weather	\bullet Run-off- the-road	SPF, CMF
Geedipally et al. (2020)	• Two-lane, four-lane divided, four-lane undivided \bullet Texas \bullet 2012-2016	Fatal and injury	• Wet Weather	×	SPF, CMF
Cafiso et al. (2021)	• Two-lane rural road \bullet Italy \bullet 2011-2017	Fatal and injury	• Dry pavement • Wet pavement	\bullet Run-off- the-road \bullet Other crashes • Day time \bullet Night time	SPF, CMF
McCarthy et al. (2021)	• Three US states \bullet 2012-2016	\bullet All	• Dry weather • Wet weather	×	SPF
This study	• Interstate highways, non-interstate roads \bullet Utah • 2016-2019	All PDO Fatal and injury	• Dry weather • Wet weather	×	SPF, CMF

Table 2-1: Summary of studies about pavement friction effects on traffic safety

Notes: PDO: Property Damage Only. CRR: Crash Rate Ratio. SPF: Safety Performance Function. CMF: Crash Modification Factor.

Multiple studies have examined the relationship between pavement friction and crash frequency using various methodologies. Cafiso et al. (2021) conducted a study on two-lane rural roads and developed SPFs and CMFs for pavement condition indicators such as GN and IRI. The findings revealed that increased friction (GN) was associated with a decrease in crash frequency. Conversely, increases in road roughness (IRI) were associated with higher crash frequencies. Run-off-the-road (ROR) crashes showed a more pronounced effect from the IRI value, likely due to the fact that irregularities in the road surface can contribute to vehicles losing control during braking and steering. Long et al. (2014) identified a negative exponential relationship between crash risk and skid resistance, further supporting the importance of pavement friction in crash prevention. Moreover, Geedipally et al. (2019, 2020) specifically highlighted an elevated crash risk associated with reduced pavement friction, particularly on horizontal curves. The studies mentioned above have consistently identified pavement friction as a critical factor influencing roadway safety and crash risk, emphasizing the significance of maintaining adequate levels of pavement friction to ensure safer road conditions.

The relationship between pavement surface characteristics, weather, and crash risk has also been the subject of a number of studies, especially in connection with pavement friction. Long et al. (2014) found that wet pavement conditions increased crash risk compared to dry conditions, at least until reaching a relatively high SN. Further evidence of increased wet weather crash risk was demonstrated by Geedipally et al. (2019), who saw larger effects of SN on wet weather and ROR injury and fatal crashes. This points to wet pavement exaggerating the effects of low skid resistance and amplifying crash risk. Cafiso et al. (2021) showed a similar trend of GN having greater influence on wet pavement crashes, as well as ROR and nighttime crashes. This indicates that wet weather and darkness amplify crash risk. McCarthy et al. (2021) confirmed these findings, showing skid resistance had more effect on wet weather crashes across fatal, injury, and property damage (KABCO) crash severity levels. However, they note pavement friction also remains relevant for crashes under dry conditions, given their often-higher frequency (than under wet conditions).

In summary, multiple studies have tended to find increased crash risk, especially for ROR and nighttime crashes, under wet pavement conditions compared to dry. Thus, it seems likely that maintaining adequate skid resistance is particularly important in wet weather to limit the elevated safety risks of reduced pavement friction.

2.3 Summary

From the studies reviewed above, road surface friction appears to be a critical factor influencing traffic safety. However, its association with different crash types and roadways is not fully characterized, including in Utah. To address this knowledge gap, in the following chapters we describe the collection and analysis of data to quantify the differential effects of road friction across crash severities, weather conditions, and highway functional classes. Characterizing these relationships provides essential insights into how factors like weather and road type interact with surface friction to impact crash occurrence.

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3.0 DATA COLLECTION

3.1 Overview

This study collected data from an interstate and a non-interstate highway within the state of Utah, covering the years 2016 to 2019. The interstate highway, I-15, stretches 401 miles from north to south across the state. On the other hand, US-89, classified as a non-interstate highway, also extends from north to south within the state, spanning 501 miles. UDOT provided the necessary data for this study. Specifically, the study required nine types of data: crash, traffic volumes, skid resistance, lanes, shoulders, medians, barriers, rumble strips, and curve data. The subsequent sections describe each data type and their processing required for the analysis.

3.2 Data Preparation

3.2.1 Highway Segments and Traffic Volume Data

The data preparation started by dividing the highways into segments of 0.5-mile length. Segments were distinguished separately for the northbound (NB) and southbound (SB) directions for I-15, whereas both directions were combined into one for US-89 as per data availability. The annual average daily traffic (AADT) volumes for the study highways were collected for the stated study period from UDOT's database (UDOT, 2023), maintained using data collected from continuous and short-term traffic count stations across the state. Since AADT values represent the daily traffic volumes of the segments considering both directions of travel, the AADT values were halved to get the directional AADT values for I-15 segments, whereas total AADT values (both directions, not directional) were kept for US-89 segments. To accurately account for the impact of AADT in the analysis, 0.5-mile segments were further split whenever the AADT values changed. This resulted in 1,854 interstate and 993 non-interstate segments for each year, such that there were 11,388 observations in total. The average AADT values of I-15 and US-89 for the study years are reported later in Section [4.2.](#page-24-2)

3.2.2 Crash Data

The AADT data preparation was followed by crash data processing. Crash data were retrieved from the Utah Department of Public Safety's (UDPS) reported crash database (UDPS, 2023). This database includes detailed information about each crash that was reported on Utah roadways, along with information about its location and conditions. In the current study, particular interest was on dry weather, wet weather, property damage only (PDO), injury-related, and all-type crashes. Thus, the relevant crash information was processed so that the final output consisted of the total number of dry, wet, PDO, injury-related, and all-type crashes that happened on each highway segment in each year. I-15 crashes were associated with the specific directional interstate segments, whereas both directions' crashes were added together for the non-interstate segments of US-89. Since some non-interstate segments pass through urban areas with signalized intersections, intersection-related crashes were completely excluded from the analysis. The total number of crashes for each crash type on each highway type during the study period are reported later in Section [4.2.](#page-24-2)

3.2.3 Skid Resistance Data

The third step in data preparation was the processing of skid resistance data. UDOT provided skid data collected annually on Utah roads. As previously mentioned, UDOT performs the pavement skid assessment using the locked-wheel-skid-trailer method typically from April to November each year. In this method, a truck towing a trailer is run on a test road at a speed of 40 mph, and water is sprayed on the test trailer wheel. The trailer wheel is then locked via a braking mechanism. During this process, the resistance force of the locked wheel is recorded and converted to a unitless SN value. UDOT typically collects the SN measurements at 0.5-mile intervals, though it varies based on road and test conditions. UDOT's skid measurement process classifies the direction of travel for interstate highways, but directional measurements are not done for non-interstate highways. Therefore, as stated above, the I-15 analysis and data were distinguished by direction, whereas they were not for US-89. When multiple skid measurements were present for a segment, the arithmetic mean of the available values was calculated and considered as the single SN for the segment. Similar to AADT and crash data observations, the SN value for each highway segment was prepared for each year over the study period. Out of

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11,388 segment-year combinations, 2,700 (24%) observations had missing SN values. Removing these data would significantly reduce the sample size, potentially decreasing statistical power and introducing bias. Therefore, the missing values were imputed using linear interpolation of the adjacent segments' values for the same year. Finally, the SN of each highway segment for each study year was prepared and summarized later in Section [4.2.](#page-24-2)

3.2.4 Other Covariates

In the final step of data preparation, covariates that might influence the dependent variable, namely crash frequency, were assembled from UDOT's open data portal (UDOT, 2023). Covariates were included in this study primarily to enhance the model's predictive accuracy. Specifically, by including other factors that influence crash frequency in the regression model, the result for SN more clearly captures the unique relationship between skid resistance and crash frequencies. This process involved the assembly and processing of various variables related to roadway geometry as shown in [Table 3-1.](#page-21-1)

Raw variable (s)	Processed variable (s)	Function(s)	
Lanes and shoulders	Multiple:		
• Number of through lanes	• Number of through lanes	• Longest distance	
• Through lane width	• Through lane width	• Longest distance	
• Shoulder width	• Shoulder width	• Distance-weighted	
Median and barriers	Multiple:		
• Median width	• Median width	• Distance-weighted	
• Barrier offset distance • Inverse of barrier offset distance		• Distance-weighted	
• Length of barrier	• Proportion of the segment length with a barrier present	\bullet Sum	
Rumble strips	One:		
• Length of rumble strips	• Proportion of the segment length with a rumble strip present	\bullet Sum	
Horizontal curves	One:		
• Degree of curve	• Curve Impact Factor: (degree of curve) ² \times	\bullet Sum	
• Length of curve	proportion of effective segment length with curve		

Table 3-1: Description of processing other covariates

Notes:

• Barrier offset distance is measured as the lateral distance from the near edge of the shoulder to the face of the barrier.

• If there is no barrier, the inverse of the barrier offset distance is set to 0.

• Proportions of barriers and rumble strips are technically calculated as the sums of the total lengths of barriers and rumble strips within each segment, divided by the length of the segment. Values could exceed 1: e.g., 2.00 if there are barriers and rumble strips the full length of both sides of the roadway.

Regarding the integration of new covariates, the segments initially established in the study—0.5-mile segments further divided based on changes in AADT values—did not align with the segments from the datasets where covariates were collected. Consequently, a stepwise method was employed to successfully merge these datasets based on specific attributes. Initially, segments from the covariate datasets that matched or overlapped those in our study were identified and compiled into a list. From this list, the values of covariates and their respective segment lengths, as used in the covariate dataset, were gathered. Functions (detailed below) were then applied to aggregate values from this list of identified segments (from the covariate datasets) and calculate a single value (for each of this project's segments). Finally, covariate values were prepared, using the functions as specified in [Table 3-1,](#page-21-1) and a summary is presented later in Section [4.2.](#page-24-2)

- *Longest distance function*: This function returns the value which is present for the longest linear distance, tabulated from among all matching segments. This function was used for the number of through lanes and the width of through lanes.
- *Distance-weighted function*: This function multiplies the values by their respective segment lengths, divided by the total length, yielding a distance-weighted average value. This function was utilized for shoulder width, median width, and barrier offset.
- *Sum function*: This function returns the total value by adding all the values together. This function was used for barrier run length, run length of rumble strips, and curve impact factor. Barrier run length and run length of rumble strips were further processed to calculate them as a proportion of the segment length where they were present.

After assembling the data, some segments of non-interstate US-89 had unexpectedly high values for the curve impact factor. Upon further inspection, these were places where US-89 made a sharp left or right turn at an intersection with traffic control (signal or stop sign). Since these locations should not be considered curves, the 13 segments per year were removed from the US-89 dataset prior to analysis.

3.3 Summary

The data collection in this study involved gathering a set of traffic, crash, skid resistance, and roadway geometry data from UDOT for two major highways (I-15 and US-89) from 2016 to 2019. Traffic data included AADT, and segments were 0.5-mile lengths or where AADT values changed. Crash data were compiled from UDOT's crash databases, focusing on different weather conditions and types of crashes, and processed to align with the highway segments. Additionally, highway condition data such as SN measurements were collected, and other relevant roadway geometric characteristics were incorporated. The datasets were then assembled carefully, making sure that segments lined up correctly.

4.0 DATA ANALYSIS

4.1 Overview

This chapter presents the descriptive statistics and results from the statistical analyses of crash frequencies for different types of crashes on interstate and non-interstate highways in Utah from 2016 to 2019. The first section provides the descriptive statistics of assembled data such as crashes and roadway geometry characteristics. The second section describes the analysis methods, including the development of SPFs and CMFs. Later sections report the findings from the NB regression models that examined different types of crashes on interstate and noninterstate highways.

4.2 Descriptive Statistics

The frequency of various types of crashes for the years 2016 to 2019 on I-15 NB, I-15 SB, and US-89 is shown in [Figure 4-1.](#page-25-0) Also, descriptive statistics of the independent variables (traffic volumes, skid number, and highway characteristics) used in the study are summarized in [Table 4-1.](#page-26-1)

Figure 4-1: Frequency of different crash types across study years

	$1-15 NB$ $(3,708$ segments)		$I-15SB$ $(3,708$ segments)		US-89	
Variable					$(3, 912$ segments)	
	Mean	SD	Mean	SD	Mean	SD
Segment length (mi)	0.431	0.134	0.431	0.134	0.421	0.144
AADT						
2016	29,582	32,394	29,582	32,394	10,037	12,353
2017	30,291	32,723	30,291	32,723	10,271	12,666
2018	30,905	33,163	30,905	33,163	10,456	12,866
2019	31,571	33,881	31,571	33,881	10,605	13,076
All years	30,587	33,040	30,587	33,040	10,342	12,740
Skid number						
2016	56.60	7.85	57.80	6.94	52.50	9.63
2017	53.00	8.18	53.10	8.05	57.70	6.58
2018	56.70	7.22	55.20	6.95	50.90	10.30
2019	57.20	7.57	57.10	7.60	53.70	10.50
All years	55.90	7.89	55.80	7.62	53.69	9.71
Through lane width (ft)	12.10	0.26	11.90	0.27	12.09	0.82
Shoulder width (ft)	8.32	2.03	8.45	1.81	5.40	2.67
Median width (ft)	80.80	83.20	81.10	85.50	5.64	28.61
Barrier offset distance (ft)	4.36	7.45	5.16	9.14	1.15	2.24
Proportion of barrier	0.42	0.48	0.75	0.71	0.21	0.43
Proportion of rumble strips	1.30	0.84	1.31	0.85	1.38	1.36
Curve Impact Factor	0.34	0.96	0.31	0.91	8.50	24.72

Table 4-1: Descriptive statistics of the independent variables

Notes: SD: Standard Deviation.

AADT for I-15 NB and I-15 SB are directional values, i.e., total \div 2.

 Proportions of barriers and rumble strips are calculated as the sums of the total lengths of barriers and rumble strips within each segment, divided by the length of the segment. Values could exceed 1: e.g., 2.00 if there are barriers and rumble strips the full length of both sides of the roadway. Curve Impact Factor = (degree of curve)² \times proportion of effective segment length with curve.

4.3 Analysis Method

Before starting the formal analysis, we observed the correlation between road friction, exposure, and highway geometry variables for both interstate (I-15) and non-interstate (US-89) highways in Utah, as shown in [Figure 4-2.](#page-27-0) To avoid the effects of multicollinearity, which could potentially distort the model's estimates and reduce its accuracy, we removed geometric variables having high correlations with friction and exposure. As a result, we excluded shoulder width, the proportion of barriers, and rumble strips when analyzing different types of crashes on interstate highway segments, and the rumble strip variable for non-interstate highway segments. These high correlations could suggest that segments with higher AADT were provided with wider shoulders, a greater proportion of barriers, and a lower proportion of rumble strips in our study area.

Figure 4-2: Correlation matrices

This study developed SPFs and CMFs, based on *Highway Safety Manual (HSM)* methodology (AASHTO, 2010). An SPF is defined as a regression equation that calculates the predicted number of crashes that are likely to occur in a roadway segment for the base conditions for a given period. In contrast, a CMF is a numerical value that is defined as the ratio of the crash frequency at a site under two different road conditions, termed the base and test conditions. This study developed separate SPFs and CMFs for interstate and non-interstate highways, and for dry, wet, PDO, injury-related, and all-type crashes. For this, segment length (L), traffic volume (AADT), skid resistance (SN), through lane width (TLW), shoulder width (SW), median width (MW), barrier offset (BO), proportion of barrier in a segment (BP), and Curve Impact Factor (CIF) were considered as the independent variables potentially related to crash frequencies.

The functional form of the SPFs developed in this study is shown in [Equation 4-1.](#page-27-1)

 $E(N) = e^{-\beta_{SW} \times SW + \beta_{MW} \times MW + \beta_{BO} \times BO + \beta_{BP} \times BP + \beta_{CIF} \times CIF}$ Equation 4-1 $a+\beta_L\times\ln(L)+\beta_{AADT}\times\ln(AADT)+\beta_{SN}\times SN+\beta_{TLW}\times TLW+$

where $E(N)$ is the predicted annual crash frequency, a is the parameter for the intercept, and β_X are the parameters of each of the independent variables $X(L, AADT, SN, TLW, SW, MW, BO,$ BP, and CIF, respectively). The values for AADT and L entered the model as natural logged terms. A perfectly linear relationship between L and crash frequency was imposed on the SPFs by setting the value of $\beta_L = 1$ (called an "offset" in the frequency modeling literature). With this assumption, the predicted crash frequency for a segment increases by 100% when the segment length is also increased by 100% and so on, considering other factors to remain the same.

The error structure of the crash frequency prediction model was assumed to have a NB distribution—hence, a NB model—such that the variance of the predicted annual crash frequency was represented as in [Equation 4-2.](#page-28-0)

$$
Var(N) = E(N) + k \times E(N)^{2}
$$
 Equation 4-2

where $Var(N)$ is the variance of the predicted annual crash frequency, and k denotes the dispersion parameter of the NB distribution.

Next, without changing the functional form of the SPF, [Equation 4-1](#page-27-1) can be rewritten similar to the HSM format, as in [Equation 4-3.](#page-28-1)

$$
E(N) = e^{a} \times L \times AADT^{\beta_{AADT}} \times e^{\beta_{SN} \times SN} \times e^{\beta_{TLW} \times TLW} \times e^{\beta_{SW} \times SW} \times e^{\beta_{MW} \times MW} \times e^{\beta_{BO} \times Bo} \times e^{\beta_{BP} \times BP} \times e^{\beta_{CIF} \times CIF}
$$

Equation 4-3

CMFs are estimated by applying coefficients that were developed from an NB regression model. The CMF for each specific response variable is characterized by an exponential relationship similar to that shown in [Equation 4-4.](#page-28-2) The same method was used by Lord and Bonneson (2007) to estimate CMFs for rural frontage roads in Texas, and by Sando et al. (2014) to estimate lane width CMFs for curb and gutter asymmetric multilane roadways.

$$
CMF_i = e^{\beta_i(i_{test} - i_{base})}
$$
 Equation 4-4

where *i* is the specific response variable; β_i is the regression coefficient for *i*; i_{test} is one of a range of values investigated for *i*; and i_{base} is the baseline value of *i*. In summary, CMF_i

indicates the potential proportional increase/decrease in crash frequency when the value of response variable *i* is changed from i_{base} to i_{test} .

Based on [Equation 4-3](#page-28-1) and [Equation 4-4,](#page-28-2) the predicted annual crash frequency $E(N)$ can be represented in [Equation 4-5.](#page-29-0)

$$
E(N) = e^{a} \times L \times AADT^{b} \times CMF_{SN} \times CMF_{TLW} \times CMF_{SW} \times CMF_{MW} \times CMF_{BO} \times
$$

$$
CMF_{BP} \times CMF_{CIF}
$$
 Equation 4-5

where, CMF_X is the CMF for variables X (SN, TLW, SW, MW, BO, BP, and CIF), represented in the following equations:

$$
CMF_{SN} = e^{\beta_{SN}(SN_{test}-SN_{base})}
$$
 Equation 4-6

$$
CMF_{TLW} = e^{\beta_{TLW}(TLW_{test} - TLW_{base})}
$$
 Equation 4-7

 $CMF_{SW} = e^{\beta_{SW}(SW_{test} - SW_{base})}$ Equation 4-8

 $CMF_{MW} = e^{\beta_{MW}(MW_{test}-MW_{base})}$ Equation 4-9

$$
CMF_{BO} = e^{\beta_{BO}(BO_{test} - BO_{base})}
$$
 Equation 4-10

$$
CMF_{BP} = e^{\beta_{BP}(BP_{test} - BP_{base})}
$$
 Equation 4-11

$$
CMF_{CIF} = e^{\beta_{CIF}(CIF_{test} - CIF_{base})}
$$
 Equation 4-12

In the above equations, β_{BO} is estimated for $BO = 1/Barrier$ of fset distance or $BO = 0$ if there is no barrier. Also, β_{CIF} is estimated for $CIF = \sum_{j=1}^{m} D^2 \times P_{c,j}$, where m is number of horizontal curves in a segment, D is the degree of curve j, and $P_{c,j}$ is proportion of effective segment length with curve j .

The test conditions for all the variables in the study were established based on their range, defined by upper and lower bounds. Since the study involves two different types of highways (interstate and non-interstate), different base values for the response variable were set for each type of highway. Base values were considered based on freeway segments for I-15 and rural

multilane highways with undivided roadway segments for US-89, as per the American Association of State Highway and Transportation Officials (AASHTO) (2010). However, a base value for SN was not provided in AASHTO (2010); therefore, SN_{base} was set to 40 (the average of UDOT's "fair" range of SNs, i.e., between 35 and 45) and several values of SN_{test} ranging from 0 to 100 were examined. The base values for the response variables used in the study are shown in [Table 4-2.](#page-30-1)

Variable	Interstate $(I-15)$	Non-interstate (US-89)
SN_{base}	40	40
TLW_{base}	12 ft	12 ft
SW_{base}	8 ft	6 ft
MW_{base}	60 ft	0 ft
BO_{base}	0 (no barrier)	0 (no barrier)
BP_{base}	0 (no barrier)	0 (no barrier)
CIF_{base}	0 (no horizontal curve)	0 (no horizontal curve)

Table 4-2: Base values for the response variables

4.4 Results

This section presents the findings from the NB regression models (SPFs) that examined different types of crashes on interstate and non-interstate highways. Predictive models were developed separately for five crash categories (dry weather, wet weather, PDO, injury-related, and total crashes) and two highway types (interstate and non-interstate). A 90% significance level ($p < 0.10$) was used to evaluate statistical significance. The models used AADT as exposure, L as an offset (coefficient fixed at 1), SN as the variable of interest, and highway geometry characteristics as control variables. [Table 4-3,](#page-31-0) [Table 4-4,](#page-32-0) and [Table 4-5](#page-33-0) show the NB model results for the various crash types, separately for interstate and non-interstate highway segments, and with and without controlling for roadway geometry.

Table 4-3: NB model (SPF) results for dry and wet weather crash frequencies

Notes: — variable excluded from the model (i.e., not controlling for roadway geometry, or due to multicollinearity).

n.s. variable removed from the model during estimation (i.e., not significant).

Table 4-4: NB model (SPF) results for PDO and injury-related crash frequencies

Notes: — variable excluded from the model (i.e., not controlling for roadway geometry, or due to multicollinearity).

n.s. variable removed from the model during estimation (i.e., not significant).

Table 4-5: NB model (SPF) results for all-type crash frequencies

Notes: — variable excluded from the model (i.e., not controlling for roadway geometry, or due to multicollinearity).

n.s. variable removed from the model during estimation (i.e., not significant).

For all models, exposure and SN were statistically significant predictors of crash frequencies. Also, the NB models controlling for roadway geometry variables provided a better fit than NB models without controlling for roadway geometry. Therefore, the following sections summarize model results for traffic volume, skid number, and other covariates, based on the results when controlling for roadway geometry.

4.4.1 Traffic Volume

The calibrated models showed a significant positive relationship between AADT and crashes. Consistent with previous research, the models showed that higher AADT resulted in increases in the predicted number of crashes (Cafiso et al., 2021; Geedipally et al., 2019, 2020; McCarthy et al., 2021). Based on standard practice in exposure modeling, AADT was logtransformed. As a result, a 1% increase in AADT was associated with a percentage rise in the expected number of crashes equal to the estimated coefficient value. The exposure coefficient for all the crashes (other than wet weather crashes on the interstate) was greater than 1. This indicates that the effect of traffic volume on the crash rate is more exponential than proportional: i.e., a smaller increase in traffic leads to a larger percent increase in crashes. For example, a 10% increase in interstate AADT would be associated with a 14.4% increase in dry weather crashes, according to the model. In contrast, for wet weather crashes on interstate segments, a 10% increase in AADT is associated with only a 9.1% rise in the expected number of crashes, indicating a decrease in the wet weather crash rate effect of traffic.

4.4.2 Skid Number

The SN had a significant impact on crash frequency for all crash types and highway types. In all cases, the coefficient for SN was negative, implying that higher SN values (greater pavement friction) were associated with lower crash frequencies. As an example, for all-type crashes on interstate highway segments, the model predicts that a 10-point increase in the SN would result in a 13% decrease $(1 - e^{(-0.014)(50 - 40)} = 0.13)$ in crashes. Considering a 90% confidence interval, the true coefficient is expected to lie between -0.016 and -0.011, implying that the effect is statistically significant since the interval does not include zero. This means that, with 90% confidence, an increase in SN results in fewer crashes. Furthermore, with 90% confidence, the reduction in crashes is expected to be between 11% and 15% for a 10-point

increase in SN. [Table 4-6](#page-35-0) and [Table 4-7](#page-35-1) report confidence intervals for the effects of SN on crashes, within models of interstate highways and non-interstate highways, respectively.

Crash type	Coef.			Projected crash reduction for a 10-point increase in SN		
	LB $(5%)$	Mean	UB(95%)	LB $(5%)$	Mean	UB(95%)
Dry weather crashes	-0.010	-0.007	-0.004	9%	7%	4%
Wet weather crashes	-0.027	-0.024	-0.020	24%	21%	18%
PDO crashes	-0.016	-0.014	-0.012	15%	13%	11%
Injury-related crashes	-0.013	-0.010	-0.006	12%	10%	6%
All-type crashes	-0.016	-0.014	-0.011	15%	13%	11%

Table 4-6: Confidence intervals for SN increase on interstate highways

Notes: 90% confidence intervals; LB = lower bound (5th percentile); UB = upper bound (95th).

Table 4-7: Confidence intervals for SN increase on non-interstate highways

Notes: 90% confidence intervals; $LB =$ lower bound (5th percentile); $UB =$ upper bound (95th).

Looking across crash/highway categories, some interesting results emerge. Similar to findings from prior studies (Cafiso et al., 2021; Geedipally et al., 2019; Long et al., 2014; McCarthy et al., 2021), the effect of road friction in reducing wet-weather crashes was more pronounced—larger negative coefficients for wet vs. dry weather crashes—on both interstate and non-interstate highways in Utah. This indicates that improving skid resistance through higher SN values can significantly decrease wet-pavement crashes across different highway types. The effect of SN for wet-weather crashes (and difference between wet- and dry-weather crashes) was stronger for interstate highway segments, suggesting an even more beneficial impact of skid resistance on interstate highways during wet conditions.

On interstate highways, SN had a similar mitigating effect on PDO and total (or all-type) crashes, followed by smaller but still significant reductions in injury and dry weather crashes. The similar effect on PDO and all-type crashes likely stems from the higher frequency of these

kinds of crashes (PDO make up a larger portion of total crashes, so there is an overlap in the data of the two models). Although the effect of SN on dry weather crashes is small, the high frequency of dry weather crashes means that improving skid resistance still has relevance for reducing crash risk in dry conditions in Utah. For non-interstate highways, all-type, PDO, and dry weather crashes all exhibited a similar effect of SN. In summary, increased SN correlated strongly with reduced crash frequency on both interstate and non-interstate highway segments, particularly for wet weather crashes.

As noted earlier, coefficients from a NB SPF model equation can be interpreted into various CMFs, depending on the test value. [Figure 4-3](#page-37-1) shows the interpretation of SN coefficients (from [Table 4-3,](#page-31-0) [Table 4-4,](#page-32-0) and [Table 4-5\)](#page-33-0) as CMFs, for various crash types, for interstate and non-interstate highway segments. This study set the baseline SN at 40, so the CMF at 40 is exactly 1 in all cases (because base = test). The downward sloping lines reflect the negative coefficients: As SN increases from 40, the CMF gets smaller (increasingly less than 1), meaning that the expected number of crashes decreases (compared to a base of $SN = 40$). For interstate highway segments (left), the steeper line for wet weather crashes reiterates the finding mentioned in the previous paragraph about how pavement friction matters more for crash risk reduction under wet conditions. The same interpretation applies to the steeper curves for wet weather and injury crashes for non-interstate highway segments (right).

Figure 4-3: Skid number crash modification factors by crash type

4.4.3 Covariates

Though roadway geometry characteristics were not the focus of this study, their results are briefly summarized and discussed in the following subsections.

4.4.3.1 Through Lane Width (TLW)

When significant, through lane width reduced crash frequencies, especially dry weather and PDO crashes on interstates, and wet weather crashes on non-interstate highways. In other words, segments with wider lanes saw fewer crashes. The beneficial effect of TLW on all-type crashes on interstate segments was also significant.

4.4.3.2 Shoulder Width (SW)

Non-interstate highway segments with more SW were also found to have fewer crashes, across all crash types. The effect of SW was more pronounced for wet weather crashes, followed by injury-related crashes. The similar impact on dry weather, PDO, and all-type crashes could be attributed to the higher frequency of these types of crashes, resulting in data overlap between the models. SW was excluded from models of interstate highways due to multicollinearity concerns.

4.4.3.3 Median Width (MW)

MW significantly influenced crash frequencies, but mostly on non-interstate highways, and all effects were fairly small. Non-interstate segments with any or wider medians had slightly fewer crashes of all types. On the other hand, on interstate highways, an increase in MW was associated with a slight but statistically significant increase in the frequency of injury-related crashes, which could be attributed to the large sample size or low variability in the data. The small effect sizes could be because wider medians help to reduce head-on collisions, which are only a small subset of all crashes.

4.4.3.4 Barrier Offset (BO)

BO is measured as the lateral distance from the near edge of the shoulder to the face of the barrier. In the NB models, BO was inverted to predict crash frequency. The positive coefficients for the inverse of BO across most crash types on non-interstate highways (except for non-significant injury-related and wet weather crashes) indicate that a decreased BO (thus increased inverse BO) leads to more crashes. In other words, there were more crashes when there was a shorter distance between the shoulder and the barrier. This effect was most significant (larger positive coefficients) for PDO crashes. These findings highlight the critical role of barrier placement in highway safety. BO was not significantly associated with crashes on interstate highway segments.

4.4.3.5 Proportion of Barrier in a Segment (BP)

BP significantly impacted crash frequencies on non-interstate highways. The negative BP coefficients indicated that increasing BP generally reduced crash frequencies. BP had a more pronounced mitigating effect on injury-related crashes, followed by dry, all-type, PDO, and wet weather crashes. This suggests that barriers are particularly effective in reducing the severity of crashes resulting in injuries on non-interstate highways. As mentioned previously, BP was excluded from interstate highway models due to high correlations.

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4.4.3.6 Curve Impact Factor (CIF)

CIF was calculated to examine the relationship between horizontal curves and crashes. CIF is defined as the product of the square of the degree of the curve and the proportion of the effective segment length that includes the curve. As the degree of the curve increases, the radius decreases, resulting in a sharper curve. Higher CIF values correspond to sharper curves, while lower CIF values indicate gentler curves. Notice how the mean CIF in [Table 4-1](#page-26-1) is much larger for non-interstate highway segments on US-89 than for interstate highway segments on I-15.

On interstate highways, higher values of CIF were associated with an increase in crash frequencies, with a more pronounced effect on wet weather crashes. However, on non-interstate highways, the effect of CIF was significant only for wet weather and injury-related crashes. Specifically, sharper curves increased wet weather and injury-related crashes. Overall, horizontal curves had a greater impact on crash frequencies on interstate highways than on non-interstate highways. Perhaps this is the result of risk compensating behavior: drivers might expect and prepare more for sharp curves on US-89 than on I-15.

4.5 Summary

This section summarizes findings from the NB regression models that analyzed various crash types on both interstate and non-interstate highways, producing SPFs and CMFs. The models differentiated crash categories—dry weather, wet weather, PDO, injury-related, and total crashes—across two types of highways. Key variables included AADT, L, and highway geometry, with SN being a specific variable of interest. The findings revealed that AADT and SN were significant predictors of crash frequency across all categories. Models that incorporated roadway geometry variables provided a better fit than those that did not, indicating the importance of these factors in crash frequency analysis. Overall, segments with higher SN values (more pavement friction) saw fewer crashes; effects were stronger for interstate highways and wet weather crashes. These results indicate the safety benefits of greater pavement friction, especially during wet conditions.

5.0 CONCLUSIONS

5.1 Summary

Pavement friction is crucial for road safety, especially in adverse weather conditions. This study investigated the relationship between pavement friction—quantified by SN—and the frequency of crashes on Utah interstate (I-15) and non-interstate (US-89) highways. Chapter [2.0](#page-16-0) reviewed literature on the impact of pavement friction on roadway safety, summarizing key findings and their relevance. The data collection methods, described in detail in Chapter [3.0,](#page-19-0) involved gathering traffic and roadway geometry data from UDOT for I-15 and US-89 from 2016 to 2019. This included AADT (broken into 0.5-mile segments, adjusted for directional flows on I-15) and crash data categorized by different crash types. Road condition data specifically skid resistance measured using the locked-wheel-skid-trailer method—and other geometric characteristics of the highway were also assembled and aligned ensuring segments' consistency. Chapter [4.0](#page-24-0) described and reported on the analysis of assembled data using NB models to develop SPFs and CMFs for both interstate and non-interstate highways. This chapter summarizes the key findings from the research project and discusses study limitations.

5.2 Findings

5.2.1 Impacts of Pavement Friction on Road Safety

Recall this study's key objective: to determine whether and how skid resistance data can provide meaningful insights regarding the relationship between pavement friction and traffic safety. The analysis utilized NB models to generate SPFs and CMFs for various types of crashes, including those occurring in dry and wet conditions, injuries and PDO incidents, as well as allcrash types. The findings consistently indicated a significant negative association between the SN and crash frequency across all types of crashes and on both interstate and non-interstate highways, even after controlling for many other roadway geometric characteristics that also influence crashes. This finding means that segments with higher pavement friction, indicated by larger SN values, saw fewer crashes of all types. This result implies that skid resistance is an

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important characteristic of pavement surfaces that contributes to a reduction in crashes on all types of roadways and for all types of crashes.

Notably, increasing skid resistance was particularly effective in reducing wet weather crashes across different types of highways, compared to dry weather crashes. A 10-unit increase in SN was linked to a 7% to 8% reduction in dry weather crashes on both non-interstate and interstate highways segments, while the same increase in SN led to a 14% and 21% decrease in wet weather crashes, for non-interstate and interstate highway segments, respectively. Even though the impact of SN on dry weather crashes was less pronounced (but still measurable and significant), the larger share of dry weather crashes in Utah underscores the importance of improved skid resistance for reducing crash risks in such conditions. Notably, the crash reduction potential of an increase in SN was particularly strong on interstate highways for wet weather crashes, suggesting that pavement friction is particularly important for improving safety on interstate highways when the surface condition is wet.

These results make intuitive sense. Higher SN reflects greater pavement friction, which means vehicles are able to stop more quickly and maneuver more easily when faced with a hazardous situation. The greater benefit of SN in wet weather conditions is also reasonable, since that is when improved roadway friction is of particular importance. In conclusion, the study reveals that enhanced pavement friction, as measured by SN, has significant potential to reduce crashes, especially in wet conditions, across both interstate and non-interstate highways.

5.3 Limitations and Challenges

While useful, the results from this study could be improved through future work. This study found differences in how SN affects crashes between wet and dry weather, and between interstate and non-interstate roads. However, examining more specific types of crashes or locations (e.g., urban versus rural) could also be useful. For example, studying segments where pavement friction is crucial—like curves, ramps, and intersections—might show whether SN has a stronger impact on crashes in these areas. Future research could offer more specific advice on how improving road friction and skid resistance can enhance traffic safety.

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6.0 RECOMMENDATIONS AND IMPLEMENTATION

6.1 Recommendations

This research project found that the measure of pavement friction currently used in Utah—SN, measured through a standard field test—is statistically linked to road safety. Specifically, segments of interstate (I-15) and non-interstate (US-89) highways with higher SN values saw fewer crashes of all types than would have otherwise been expected. The beneficial effects of pavement friction were especially stronger for reducing the number of wet weather crashes and on interstate highway segments. These results offer the following potential recommendations:

- Continue to collect SN data about pavement roughness on Utah highways.
	- o Prioritize data collection on roadways with higher speeds, higher traffic volumes, and/or of a higher functional class.
- Conduct pavement resurfacing maintenance work in places where additional pavement friction would be most beneficial for reducing crashes.
	- o Prioritize roadway segments with lower current SN values, more crashes occurring during wet weather conditions, and interstate highways.

6.2 Implementation Plan

Implementation of the first recommendation—continue collecting SN data—will likely require no new resources or staffing, as it reflects a continuation of current practices. The second recommendation—enhance pavement friction where beneficial—is also likely already taking place. Additional work could involve staff from UDOT's Traffic and Safety Division analyzing crash data and coordinating with other UDOT divisions and regional offices to prioritize sites for resurfacing projects to increase pavement friction and ultimately reduce crashes.

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