ESTIMATION OF THE SAFETY EFFECT OF PAVEMENT CONDITION
ON RURAL TWO-LANE HIGHWAYS

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ABSTRACT

The condition of the pavement surface can have an important effect on highway safety. For example, skidding crashes are often related to pavement rutting, polishing, bleeding, and dirty pavements. When transportation agencies develop paving schedules for their roadways, they often make decisions based on asset management condition targets but do not explicitly account for the role of pavement condition in roadway safety. The Virginia Department of Transportation (VDOT) began automated pavement condition data collection using digital images and an automated crack detection methodology in 2007. This development enabled the DOT to track historical pavement condition information, and thus facilitates research regarding pavement condition impacts on safety. Information on how pavement condition influences safety could be used to inform paving decisions and better set priorities for maintenance.

The objective of this study is to quantitatively evaluate the safety effectiveness of good pavement conditions versus deficient pavement conditions on rural two-lane undivided highways in Virginia. Using the Empirical Bayes method, it was found that good pavements are able to reduce fatal and injury (FI) crashes by 26 percent over deficient pavements, but do not have a statistically significant impact on overall crash frequency. Further analysis indicated that the safety benefit of pavement condition improvement on FI crashes does not statistically significantly change as the lane or shoulder width increases. In conclusion, improving pavement condition from deficient to good can offer a significant safety benefit in terms of reducing crash severity.
INTRODUCTION

Pavement condition can have an important effect on highway safety. According to the American Association of State Highway and Transportation Official’s (AASHTO) *A Policy on Geometric Design of Highways and Streets*, pavements should enable drivers to steer easily, keep their vehicles moving in the proper path, and provide a level of skid resistance that will accommodate the braking and steering maneuvers that can reasonably be expected for a particular site (1). Skidding crashes, a major concern in highway safety, are usually related to pavement rutting, polishing, bleeding, and dirty pavements (1). Previous research regarding the safety effect of pavement condition usually focused on either maintenance activities such as resurfacing or a certain type of pavement distress. Few studies were able to evaluate the safety effect of the general pavement condition, due in part to a lack of systematic data on overall pavement condition across the roadway network. If this information were available, it could be used for a variety of applications, including prioritizing sites for the agency’s annual paving program or quantifying the benefits of preventative maintenance treatments.

Historically, it has been difficult to evaluate the safety effect of pavement conditions because of the lack of robust and consistent pavement condition measures. The Virginia Department of Transportation (VDOT) began automated pavement condition data collection using digital images and an automated crack detection methodology in 2007, which led to significant improvements in the consistency and efficiency of pavement condition data assessments. Since then, pavement condition information has been updated annually for the entire interstate and primary highway systems and every five years for the secondary system (2). This development has enabled engineers to track historic pavement condition information, and thus facilitates safety research regarding the effect of pavement conditions on crash frequency and severity.

OBJECTIVES AND SCOPE

The intent of this paper is to provide DOTs with information that will allow them to include safety in the pavement management decision making process. It is not intended to be used as a justification to repave a road section that has a demonstrated pavement friction problem. The objective is to quantitatively evaluate the safety effectiveness of good pavement conditions versus deficient pavement conditions. The effect of pavement condition on both overall crash frequency and crash severity was examined. The targeted facility type is segments on rural two-lane primary highways in the Commonwealth of Virginia. The Empirical Bayes (EB) approach was applied using information from VDOT databases containing roadway inventory information, crash history, and pavement condition between 2007 and 2011.

LITERATURE REVIEW

While there has been a longstanding interest in examining the impact of pavement condition on safety, there are relatively few studies that have examined this issue in detail. Initial investigations in the late 1980s examined the effect of resurfacing. A synthesis by Cleveland of published evidence from studies conducted before 1986 found that there was a small, immediate increase in overall crash frequency for rural resurfacing projects conducted to address structural quality or poor ride condition (3). On the other hand, it was found that there was an average reduction of about 20 percent in wet pavement crashes for resurfacing projects conducted due to high numbers of wet pavement crashes (3). In light of these diverse findings, Cleveland concluded that the detrimental effect of resurfacing on safety, if any, is likely to be small. A related hypothesis was that vehicle speed will increase due to the smoother pavement surface after resurfacing, which, in turn, results in more crashes.

A well cited report by Hauer et al applied the Empirical Bayes (EB) approach to evaluate the safety effectiveness of two types of resurfacing projects undertaken in the early 1980s in New York State (4). Crash data and annual average daily traffic (AADT) from 1975 to 1987 were used. The study concluded that non-intersection crashes did increase by 21 percent during the first 30 months after
resurfacing on “fast-track” projects in which no safety improvements accompanied the repaving, while non-intersection crashes did not change on reconditioning and preservation (R&P) projects that included geometric safety improvements. Another conclusion was that within the first 6 to 7 years of pavement life, safety improves as the pavement ages. In this study, no pavement condition data were collected and information about NYDOT’s selection criteria regarding the two types of resurfacing projects were not mentioned.

To confirm or refine the Hauer et al study results, a larger study was undertaken in NCHRP project 17-9 (2), which involved five states: Washington, California, Minnesota, New York, and Illinois (5). The EB approach was used. Generally, there were five-years of before data and three-years of after data. The results were inconclusive, as there was not a single consistent pattern of safety effectiveness of resurfacing among and within the states. Crashes were found to increase after resurfacing in some states, but to decline in others. In addition, no explanation was found for these state-to-state variations.

Given the hypothesis that smoother pavement surfaces following resurfacing lead to higher vehicle speeds, another NCHRP study evaluated the effect of resurfacing, restoration, and rehabilitation (RRR) projects on travel speed (6). Speed data were collected before and after resurfacing at 39 sites on rural two-lane highways of five states: Maryland, Minnesota, New Mexico, New York, and West Virginia. The results indicated that overall there was a small but statistically significant increase of approximately 1.6 km/h (1 mph) in both the mean speed and 85th percentile speed after resurfacing. However, this effect varied substantially from site to site. No explanation was found for these site-to-site variations. In addition, no further analysis was conducted regarding the relationship between the change in speed and the change in crashes.

A 2010 study applied the cross-sectional method to investigate the efficacy of roadway improvements in terms of crash reduction on various subclasses of rural two-lane highways (7). Data were collected from 540 rural two-lane highway segments in the state of Indiana. The factors in the crash prediction model included lane width, shoulder width, pavement surface friction, pavement condition, and horizontal and vertical alignments. The effect of pavement friction in crash reduction was found to be significant for rural major collectors and rural minor arterials, but insignificant for rural principal arterial two-lane roads. It was also found that increased skid resistance impacted severe crashes more than non-severe crashes as the roadway functional class increased. The Present Serviceability Index (PSI), on a scale of 0 to 5, was used to represent pavement condition. The model results showed that better pavement condition significantly reduced crashes for rural two-lane principal arterials, but the effect was insignificant for the two lower road classes. One concern about this study is that there may be a multicollinearity issue in the models as pavement condition may correlate with pavement friction and this issue was not discussed in the paper.

In summary, most of the previous studies were event-driven, focusing specifically on the activity of resurfacing. The previous studies were not able to quantitatively track the pavement condition before and after the resurfacing projects due to lack of data, so the impact of remediating different levels of pavement distress could not be determined. Instead, some studies assumed the pavement conditions were consistent before the repaving project across sites. Since the pavement condition is sensitive to pavement age, traffic load, and other factors, this assumption could be problematic, especially when the duration of the before period is long. Also some previous studies assumed that the safety effectiveness is the same across facility types. However, the safety effectiveness of a change in pavement condition on rural two-lane highways could be very different with that on urban highways. Thanks to progress in the automated collection of quantitative pavement condition data, it is now possible to link the pavement condition information to crash history and other roadway features. It provides an excellent opportunity to investigate the safety effectiveness of pavement condition, which could inform many DOT investments in pavement maintenance. Some recent research had examined this topic by including pavement condition as a crash factor in crash prediction models, but this approach cannot account for regression-to-the-mean effects. In addition, inaccurate results may be derived from the regression models due to inappropriate model forms, omitted variable bias, or correlation among variables (8).
METHODOLOGY

Observational before-after studies have been considered the industry standard for the safety evaluation of treatments such as developing Crash Modification Factors (CMFs). Harwood et al. documented that there are three common ways to carry out a before-after study: naïve before-after evaluations, comparison group evaluations, and the Empirical Bayes (EB) approach (9). Of these three methods, the EB approach was recommended in the first edition of Highway Safety Manual (HSM) (10).

According to Hauer, the EB method is able to account for regression-to-the-mean effects, as well as traffic volume and other roadway characteristic changes, by combining safety performance function (SPF) estimates with the observed count of crashes (8, 11). Regression-to-the-mean is the natural tendency of observed crashes to regress (return) to the mean in the year following an unusually high or low crash count. This advantage allows the EB approach to overcome the limitations faced by the other two evaluation methods and provide more accurate estimates of safety effects. Moreover, VDOT conducts many pavement rehabilitation/resurfacing projects every year and maintains a comprehensive pavement condition database. Generally, the pavements before the rehabilitation/resurfacing projects are deficient while the conditions become good after the project is completed, allowing the research team to find an adequate sample of sites to study. Because of these factors, the EB method was selected as the most suitable approach for this study.

The methodology for this project consisted of three major phases, which are discussed below:

- Data collection and treatment group identification
- SPF development
- EB analysis of pavement condition effect

Data Collection

The most recent five years of data available were used, from 2007 to 2011. Two data sets were created: one for the reference group and another for the treatment group. The reference group included segments of rural two-lane undivided highways that did not have major construction, alignment changes, or resurfacing during the study period, while the treatment group included rural two-lane undivided segments that had been resurfaced but also did not have major construction or alignment changes in the study period. Also, no safety improvements were included in any treatment group projects examined. Information from the reference group was used to develop the SPFs, and information from the treatment group was used to conduct the before-after studies.

The data were mainly obtained from two separate data systems, both of which are maintained by VDOT. The pavement condition data were from pavement management system, while roadway inventory, AADT, and crash history information were from the VDOT Roadway Network System (RNS). These data elements were collected on all rural two-lane undivided segments in Virginia. Note that crashes reported within 250 ft of an intersection were excluded from this study because of the differing characteristics of intersection crashes and road segment crashes. Also, segments were excluded if they were shorter than 0.1 mile or longer than 10 miles.

The pavement condition index used by VDOT is called the Critical Condition Index (CCI), first derived in 1998 by the US Army Corps of Engineers (12). CCI is represented on a scale of 0 to 100, with 100 representing a pavement with no visible distress. For asphalt pavements, the CCI is calculated based on alligator cracking, longitudinal cracking, transverse cracking, patching, potholes, delaminations, bleeding, and rutting (2). The details of the CCI calculation methodology are provided in a VDOT report published in 2002 (13). VDOT does not collect friction data on a systematic basis at this time, although that capability is under investigation. Friction may or may not be correlated with the CCI. If cracking is driving CCI at a site, then friction factor and CCI may be correlated. If rutting is driving CCI, then friction may not be correlated with CCI. As shown in Table 1, CCI values are grouped into five condition categories: excellent, good, fair, poor and very poor.
TABLE 1 Pavement Condition Category Based on CCI (13)

<table>
<thead>
<tr>
<th>Pavement Condition</th>
<th>CCI Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excellent</td>
<td>90 and above</td>
</tr>
<tr>
<td>Good</td>
<td>70-89</td>
</tr>
<tr>
<td>Fair</td>
<td>60-69</td>
</tr>
<tr>
<td>Poor</td>
<td>50-59</td>
</tr>
<tr>
<td>Very Poor</td>
<td>49 and below</td>
</tr>
</tbody>
</table>

In VDOT’s pavement maintenance practice, pavement sections with a CCI value below 60 (poor and very poor) are considered “deficient” and will be further evaluated for maintenance and rehabilitation actions (12). In other words, it is expected that a pavement section should have a CCI value below 60 before being resurfaced, and a CCI value above 90 immediately after the project. To ensure that the EB approach has sufficient data, only sites with at least two years of before data and two years after data were examined. Since VDOT CCI data are only available between 2007 and 2011 when this research was conducted, the range of the “before” period was limited. As a result, pavement sections that rehabilitated/resurfaced in 2009 were picked as the initial set for examination. The process to select the treatment group sites was as follows:

1. Select pavement sections on rural two-lane undivided roads that were rehabilitated in 2009;
2. Check the CCI of the selected sites and remove sites that have a CCI value higher than 60 in 2007 and 2008 or have a CCI value lower than 70 in 2010 and 2011;
3. To ensure that the selected sites did not experience changes in geometric or traffic control conditions, remove sites where one or more of the following features were changed between 2007 and 2011: shoulder width, lane width, posted speed limit, surface type, number of lanes, and facility type.
4. Remove segments with a length less than 0.1 mile (0.161 km) or greater than 10 miles (16 km).

Once the study sites were selected, their roadway features, AADT, pavement condition, and crash information were matched. In addition, 2009 data were excluded in the treatment group data as it was the year when pavements were resurfaced.

In summary, 5,723 segments with a total centerline mileage of 3,504 miles (5,639 km) were identified as the reference group and 131 segments with a total centerline mileage of 76.12 miles (122.5 km) were selected as the treatment group. The before period is 2007 and 2008, while the after period is 2010 and 2011. Table 2 shows descriptive statistics for the reference group, as well as for the before and after periods for the treatment group.

As shown in Table 2, in total of 17,074 crashes, including 7,183 FI crashes, were recorded on segments in the reference group from 2007 to 2011. Based on the crash history, the after period experienced 3 fewer total crashes and 15 fewer FI crashes than the before period. This indicates that there was an increase of 15-3 =12 in PDO crash frequency in the after period. It was also found that the proportion of total crashes constituted by the FI crashes changed from 0.39 in the before period to 0.29 in the after period. Among the treatment group segments, the average pavement conditions of the selected segments improved from very poor to excellent. The average AADT trend was found to be consistent with economic trends, dropping from 4,303 vehicles per day in the before period to 4,115 vehicles per day in the after period. The reference group sites had wider range of AADT but a smaller average AADT than the treatment sites.
### Table 2: Descriptive Statistics of Continuous Variables for Segments in the Reference and Treatment Groups

<table>
<thead>
<tr>
<th>Groups</th>
<th>Variable</th>
<th>Mean</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Std. Deviation</th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Reference Group (2007-2011)</strong></td>
<td><strong>Total crashes</strong></td>
<td>0.60</td>
<td>0</td>
<td>18</td>
<td>1.10</td>
<td>17,074</td>
</tr>
<tr>
<td></td>
<td><strong>FI crashes</strong></td>
<td>0.25</td>
<td>0</td>
<td>8</td>
<td>0.61</td>
<td>7,183</td>
</tr>
<tr>
<td></td>
<td><strong>Length (miles)</strong></td>
<td>0.61</td>
<td>0.1</td>
<td>10</td>
<td>0.60</td>
<td>3,504</td>
</tr>
<tr>
<td></td>
<td><strong>AADT</strong></td>
<td>3.529</td>
<td>76</td>
<td>29,142</td>
<td>2.773</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td><strong>Lane width (ft)</strong></td>
<td>10.54</td>
<td>9</td>
<td>15</td>
<td>0.91</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td><strong>Shoulder size (ft)</strong></td>
<td>4.66</td>
<td>0</td>
<td>10</td>
<td>1.86</td>
<td>--</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Groups</th>
<th>Variable</th>
<th>Mean</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Std. Deviation</th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Treatment Group -Before (2007-2008)</strong></td>
<td><strong>Total crashes</strong></td>
<td>0.56</td>
<td>0</td>
<td>9</td>
<td>1.70</td>
<td>146</td>
</tr>
<tr>
<td></td>
<td><strong>FI crashes</strong></td>
<td>0.22</td>
<td>0</td>
<td>7</td>
<td>1.03</td>
<td>57</td>
</tr>
<tr>
<td></td>
<td><strong>Length (miles)</strong></td>
<td>0.58</td>
<td>0.1</td>
<td>2.58</td>
<td>0.51</td>
<td>76.12</td>
</tr>
<tr>
<td></td>
<td><strong>AADT</strong></td>
<td>4.303</td>
<td>410</td>
<td>25,739</td>
<td>3.757</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td><strong>Lane width (ft)</strong></td>
<td>10.34</td>
<td>10</td>
<td>12</td>
<td>0.64</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td><strong>Shoulder size (ft)</strong></td>
<td>4.45</td>
<td>2</td>
<td>8</td>
<td>1.26</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td><strong>CCI</strong></td>
<td>44.79</td>
<td>13</td>
<td>59</td>
<td>--</td>
<td>9.81</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Groups</th>
<th>Variable</th>
<th>Mean</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Std. Deviation</th>
<th>Sum</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Treatment Group -After (2010-2011)</strong></td>
<td><strong>Total crashes</strong></td>
<td>0.55</td>
<td>0</td>
<td>10</td>
<td>1.62</td>
<td>143</td>
</tr>
<tr>
<td></td>
<td><strong>FI crashes</strong></td>
<td>0.16</td>
<td>0</td>
<td>4</td>
<td>0.68</td>
<td>42</td>
</tr>
<tr>
<td></td>
<td><strong>Length (miles)</strong></td>
<td>0.58</td>
<td>0.1</td>
<td>2.58</td>
<td>0.51</td>
<td>76.12</td>
</tr>
<tr>
<td></td>
<td><strong>AADT</strong></td>
<td>4.115</td>
<td>430</td>
<td>26,943</td>
<td>3.578</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td><strong>Lane width (ft)</strong></td>
<td>10.34</td>
<td>10</td>
<td>12</td>
<td>0.64</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td><strong>Shoulder size (ft)</strong></td>
<td>4.45</td>
<td>2</td>
<td>8</td>
<td>1.26</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td><strong>CCI</strong></td>
<td>95.75</td>
<td>85</td>
<td>100</td>
<td>4.69</td>
<td>--</td>
</tr>
</tbody>
</table>

^ Sum of segment length in one year.

Table 3 summarizes the distribution of lane/shoulder width of the reference and treatment groups. Overall, the treatment group has a similar trend in the distribution, although there are some magnitude differences. For example, in both groups the most common lane width is 10 ft (3.0 m), followed by 11 ft (3.3 m) and 12 ft (3.6 m) and the most common shoulder widths are 4 ft (1.2 m) and 6 ft (1.8 m), followed by 3 ft (0.9 m) and 5 ft (1.5 m). The large size of the reference group allows the diversity of lane/shoulder width combinations to be incorporated into the SPF development, thereby permitting an evaluation of the interactions of lane/shoulder width with pavement condition.

### Table 3: Distribution of Lane/Shoulder Width of the Reference and Treatment Groups

<table>
<thead>
<tr>
<th>Lane Width</th>
<th>Site Numbers (Percentages)</th>
<th>Shoulder Width</th>
<th>Site Numbers (Percentages)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Reference Group</strong></td>
<td><strong>Treatment Group</strong></td>
<td><strong>Reference Group</strong></td>
</tr>
<tr>
<td>10 ft</td>
<td>3,211 (56.1%)</td>
<td>96 (73.3%)</td>
<td>2 ft</td>
</tr>
<tr>
<td>10.5 ft</td>
<td>269 (4.7%)</td>
<td>5 (3.8%)</td>
<td>3 ft</td>
</tr>
<tr>
<td>11 ft</td>
<td>1,133 (19.8%)</td>
<td>17 (13.0%)</td>
<td>4 ft</td>
</tr>
<tr>
<td>11.5 ft</td>
<td>97 (1.7%)</td>
<td>1 (0.7%)</td>
<td>5 ft</td>
</tr>
<tr>
<td>12 ft</td>
<td>692 (12.1%)</td>
<td>12 (9.2%)</td>
<td>6 ft</td>
</tr>
<tr>
<td>Other</td>
<td>320 (5.6%)</td>
<td>0 (0.0%)</td>
<td>Other</td>
</tr>
<tr>
<td>Sum</td>
<td>5,723 (100%)</td>
<td>131 (100%)</td>
<td>Sum</td>
</tr>
</tbody>
</table>

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Safety Performance Functions

The general EB procedure has been studied or described by many authors, and is summarized in the HSM (10). One key step for the EB procedure is to develop or select a SPF. A well-developed SPF will properly account for traffic volume and other changes. In addition, developing SPFs based on crash types and severities is necessary since most treatments affect various crash and severity types differently. In 2010, VDOT developed a set of SPFs for two-lane roads in Virginia based on data from 2003 to 2007 (14). Considering that the 2007-2011 period saw systematic reductions in crashes across Virginia due in part to the economic downturn, the existing SPFs may not represent our study period well. As a result, the authors developed two new Virginia-specific SPFs for total and fatal and injury (FI) crashes for rural two-lane undivided highways. The traffic, geometric, and crash data from 2007 to 2011 collected for the reference group discussed earlier were used to develop these new SPFs.

Many SPF forms were studied by other authors. The most commonly used is a negative binomial regression model with the form as follows:

\[ n = \alpha (\text{SegmentLength})^{\beta_1} (\text{AADT})^{\beta_2} e^{(\beta_3 x_1 + \beta_4 x_2 + \ldots)} \]

Or \[ \ln(n) = \alpha + \beta_1 \ln(\text{SegmentLength}) + \beta_2 \ln(\text{AADT}) + \beta_3 x_1 + \beta_4 x_2 + \ldots \]

Where:

- \( n \) = the predicted annual crash number,
- \( \alpha \) and \( \beta_i \) = coefficients, and
- \( x_i \) = explanatory variables other than segment length and AADT.

Besides segment length and AADT, lane and shoulder width are factors that have been shown to be significantly correlated with crash frequency in previous research [e.g., Zegeer et al. (15), Gross et al. (16), and Zeng and Schrock (17)]. As a result, lane and shoulder width were also included in the SPF models. In addition, year and district were treated as two categorical variables in the model to account for yearly variation and differences in topography and driver behavior in different parts of the state. The variable of year also acts as a surrogate for declining CCI if no paving occurs since the reference group should theoretically have had declining pavement conditions throughout the after period. VDOT has 9 construction districts: Bristol, Culpeper, Fredericksburg, Hampton Roads, Lynchburg, Northern Virginia, Richmond, Salem, and Staunton Districts. Including district information will at least partially account for the differing characteristics across Virginia. For example, rural two-lane highways in the Bristol, Salem, and Staunton Districts tend to occur in mountainous regions of the state with significant horizontal and vertical curvature, while the Hampton Roads and Northern Virginia areas tend to have a more aggressive driving population.

The SPSS statistical software was used to develop SPFs by regressing collected data to negative binomial models. Table 4 shows the result of the developed SPFs, as well as their goodness of fit information. Both SPFs have the expected positive or negative coefficients. \( \ln \text{AADT} \) and \( \ln \text{Length} \) have positive coefficients, indicating that the crash frequency increases with traffic volume and segment length, while negative coefficients for shoulder size and lane width show that crash frequency decreases as the width of the lane and shoulder increases. According to the results, most variables have coefficients that are significant at the 0.01 level. The coefficients of \( \text{Years} \) address that year 2007 and 2008 experienced significantly higher (at the 0.01 level) crashes than year 2011, which is representative of the general downturn in crash frequency observed in Virginia and in many other states during this period. The coefficients of Districts show that rural two-lane undivided roads in mountainous districts (Bristol and Salem) tend to experience significantly higher crashes than other districts, given the same conditions in terms of AADT, lane and shoulder width, year, and segment length. Ideally, horizontal and vertical...
curvature would have been included in this model as well, but VDOT lacks a systematic inventory of that information.

It is necessary to discuss the transferability of these SPFs. The models developed are applicable to two-lane undivided roads in Virginia, and calibration procedures from the HSM are recommended to gain a more accurate estimation if they are used in other states due to differences in crash reporting and roadway characteristics.

<table>
<thead>
<tr>
<th>Variable</th>
<th>SPF for Total Crashes</th>
<th>SPF for FI Crashes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient (Std. Error)</td>
<td>Wald Chi-Square</td>
</tr>
<tr>
<td>Intercept</td>
<td>-3.770 (0.159)</td>
<td>563.2***</td>
</tr>
<tr>
<td>Ln AADT</td>
<td>0.620 (0.013)</td>
<td>2,133.8***</td>
</tr>
<tr>
<td>Ln Length</td>
<td>0.952 (0.012)</td>
<td>6,764.5***</td>
</tr>
<tr>
<td>Shoulder size</td>
<td>-0.026 (0.006)</td>
<td>21.7***</td>
</tr>
<tr>
<td>Lane width</td>
<td>-0.104 (0.012)</td>
<td>72.2***</td>
</tr>
<tr>
<td>Year 2007</td>
<td>0.213 (0.028)</td>
<td>60.1***</td>
</tr>
<tr>
<td>Year 2008</td>
<td>0.093 (0.028)</td>
<td>10.8***</td>
</tr>
<tr>
<td>Year 2009</td>
<td>-0.020 (0.029)</td>
<td>0.5</td>
</tr>
<tr>
<td>Year 2010</td>
<td>-0.090 (0.029)</td>
<td>9.5***</td>
</tr>
<tr>
<td>Year 2011</td>
<td>0.000</td>
<td>--</td>
</tr>
<tr>
<td>Bristol</td>
<td>0.253 (0.056)</td>
<td>20.1***</td>
</tr>
<tr>
<td>Salem</td>
<td>0.229 (0.055)</td>
<td>17.3***</td>
</tr>
<tr>
<td>Lynchburg</td>
<td>-0.137 (0.058)</td>
<td>5.7**</td>
</tr>
<tr>
<td>Richmond</td>
<td>-0.217 (0.058)</td>
<td>14.0***</td>
</tr>
<tr>
<td>Hampton Roads</td>
<td>-0.111 (0.065)</td>
<td>3.0*</td>
</tr>
<tr>
<td>Fredericksburg</td>
<td>-0.134 (0.058)</td>
<td>5.4**</td>
</tr>
<tr>
<td>Culpeper</td>
<td>-0.035 (0.055)</td>
<td>0.4</td>
</tr>
<tr>
<td>Staunton</td>
<td>-0.107 (0.057)</td>
<td>3.5*</td>
</tr>
<tr>
<td>Northern VA</td>
<td>0.000</td>
<td>--</td>
</tr>
<tr>
<td>k</td>
<td>0.358 (0.018)</td>
<td>--</td>
</tr>
<tr>
<td>Log-likelihood ratio Chi-Square</td>
<td>7,848.3***</td>
<td>4,129.6***</td>
</tr>
<tr>
<td>AIC</td>
<td>52,358</td>
<td>31,650</td>
</tr>
<tr>
<td>Pseudo R Square</td>
<td>0.75</td>
<td>0.75</td>
</tr>
</tbody>
</table>

* indicates statistically significant at the 0.1 level;
** indicates statistically significant at the 0.05 level; and
*** indicates statistically significant at the 0.01 level;
B Set to zero as it is the basic condition of this category valuable;
C Given by SPSS, it compares the fitted model against the intercept-only model;
D Pseudo R² = 1-k/k_max, where k_max is the estimated overdispersion parameter in the intercept-only model (18) (19);
E Wald Chi-Square is the default test statistic for coefficients in negative binomial regression models in SPSS.

Empirical Bayes Analysis and Results

For every individual treated segment, the next step was to combine the sum of initial predictions (N_i) with the sum of observed count of crashes (O_i) through the use of an overdispersion parameter (k) to generate an acceptable estimate (E_i) for the expected number of crashes in the before period. The related variance (Var(E_i)) was also estimated. The calculation process is indicated by the equations below (10):

\[ N_{i,\text{total}} = SPF_{i,\text{total}} \]
\[ N_{i,FI} = SPF_{i,FI} \]
\[ N_B = \sum N_i \]
\[ E_B = wN_B + (1 - w)O_B, \quad w = \frac{1}{1 + kN_B} \]
\[ Var(E_B) = (1 - w)E_B \]

Where:

- \( N_{i,\text{total}}, N_{i,FI} \) = predicted total crash or FI crash frequency for the segment in year \( i \) of the before period;
- \( N_B \) = sum of predicted crash frequency of the segment in the before period;
- \( w \) = weight factor;
- \( E_B \) = expected crash frequency for the before period;
- \( k \) = overdispersion parameter;
- \( O_B \) = sum of observed crash number for the study segment.

With the above results and the predicted sum of number of crashes \( (N_i) \) for the same segment, the expected number of crashes in the after period \( (E_A) \) without upgrading the pavement condition could be estimated by the following equation:

\[ E_A = E_B \frac{N_A}{N_B} \]

To estimate the index of safety effectiveness, or CMF, one needs to sum \( E_A \) over all road segments in the treatment group \( (E_{Asum}) \) and then compare with the total observed crash number \( (O_{Asum}) \) during the after period in the same group. The standard deviation \( (\sigma) \) of CMF is determined by another equation.

\[ CMF = \frac{O_{Asum}/E_{Asum}}{1 + Var(E_{Asum})/E_{Asum}^2} \]
\[ \sigma = \sqrt{CMF^2(Var(E_{Asum})/E_{Asum}^2 + Var(O_{Asum})/E_{Asum}^2)/(1 + Var(E_{Asum})/E_{Asum}^2)^2} \]

The EB analysis was conducted using several different scenarios to investigate whether the safety effect of pavement condition varied with different lane and shoulder width combinations. First, the aggregated CMFs were calculated based on all 131 sites’ data. Then the sites were divided into two groups based on lane width and CMFs were produced for 10-ft-lane segments and for segments with a lane width from 11 ft to 12 ft. Since a majority of the segments had 10-ft lanes, further evaluation was conducted for these segments based on shoulder width. Two additional CMFs were developed for segments with 10 ft lanes: one for segments with 3 or 4 ft shoulders, and a second one for segments with 5 or 6 ft shoulders.

Table 5 summarizes these CMF results and their standard deviations, as well as sample size of each scenario.
According to the aggregated results, improving pavement condition from poor or very poor to excellent or good for rural two-lane highways does not have statistically significant effect on reducing total crashes. However, the improvement is able to reduce FI crashes by an average of 26 percent. The disaggregated analysis has similar results across different lane width and shoulder size. Because of the lack of sites, not all CMFs are significant at the 0.05 level.

One important question is whether there are significant differences in the safety effect of pavement conditions among different lane and shoulder width combinations. A t-test for two samples with unequal variances, indicated by the equation below, was conducted (20). The null hypothesis was that the CMFs for segments with different lane width or shoulder width were the same.

\[
t = \frac{|CMF_1 - CMF_2|}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}}\\
DF = \frac{(\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2})^2}{(\frac{\sigma_1^2}{n_1})^2/(n_1 - 1) + (\frac{\sigma_2^2}{n_2})^2/(n_2 - 1)}
\]

Where:
- \( t \) = t test statistic;
- \( CMF_1, CMF_2 = \) CMF values for the two compared groups;
- \( \sigma_1, \sigma_2 = \) related standard deviations of the tested CMFs;
- \( n_1, n_2 = \) number of sites in the two compared groups; and
- \( DF = \) degree of freedom.

Table 6 shows the test results, with the number in bold indicating that the t statistic is large enough to reject the null hypothesis.

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Sample Size</th>
<th>Total Crash (Std Dev.)</th>
<th>FI Crash (Std. Dev.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggregated results</td>
<td>131</td>
<td>1.03 (0.100)</td>
<td>0.74 (0.123)**A</td>
</tr>
<tr>
<td>Segments with 10 ft lanes</td>
<td>96</td>
<td>1.03 (0.112)</td>
<td>0.74 (0.138)**</td>
</tr>
<tr>
<td>Segments with 11 ft, 11.5 ft, or 12 ft lanes</td>
<td>35</td>
<td>0.98 (0.218)</td>
<td>0.74 (0.279)</td>
</tr>
<tr>
<td>Segments with 10 ft lanes and 3 ft or 4 ft shoulders</td>
<td>69</td>
<td>1.04 (0.134)</td>
<td>0.77 (0.161)*</td>
</tr>
<tr>
<td>Segments with 10 ft lanes and 5 ft or 6 ft shoulders</td>
<td>27</td>
<td>1.26 (0.259)</td>
<td>0.78 (0.321)</td>
</tr>
</tbody>
</table>

A ** indicates significance at the 0.05 level; * indicates significant at the 0.1 level.
The results indicated that the safety benefits of repaving pavement are not expected to change statistically significantly as the lane width increase from 10 ft to 11, 11.5, or 12 ft. However, disaggregated analysis for the 10-ft lane segments shows that segments with wider shoulders is expected to have statistically higher overall crash frequency than segments with narrow shoulders after repaving, although no significant difference is expected regarding FI crash frequency. Considering that the sample size is only 27 sites for segments with 10 ft lanes and 3 ft or 4 ft shoulders, the t-test may not truly represent the real situation. Since only sites that were resurfaced in 2009 were examined, sample sizes could not be increased further. Also, it should be noted that the CMFs for both of these scenarios were not significant different from 1.0. As a result, this analysis indicates that there may be a differential impact of pavement condition by shoulder width when lane widths are 10 ft, but the impact on CMF was not statistically significant with this data set. Future study that includes more sample size for this segment type should be able to draw a more robust conclusion.

DISCUSSION

Generally speaking, two direct outcomes are created by a pavement resurfacing project: improved pavement conditions and new pavement markings. According to previous research, better pavement condition may impact highway safety in two ways. On one hand, it can create faster vehicle operating speeds, which is linked to higher crash severity; on the other hand, it provides better roadway friction and decreases the risk of skidding crashes. Many previous research studies have also shown a positive safety impact of new markings [e.g., Smadi et al. (21), Carlson et al. (22)]. New markings are usually tied to reduction in nighttime, run of the road, or sideswipe crashes.

The EB results show that the FI crashes were reduced by 26 percent and the overall crash frequency did not change significantly after pavement resurfacing. To better interpret this result, a breakdown of crash types was conducted for the before and after periods. Table 7 summarizes observed crash types, the number of nighttime crashes, and the number of wet pavement crashes during the before and after period for the treatment group.

<table>
<thead>
<tr>
<th>Crash Type</th>
<th>Total Crash Before</th>
<th>Total Crash After</th>
<th>FI Crash Before</th>
<th>FI Crash After</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rear End</td>
<td>26 (17.8%)</td>
<td>31 (21.7%)</td>
<td>10 (17.5%)</td>
<td>9 (21.4%)</td>
</tr>
<tr>
<td>Angle</td>
<td>6 (4.1%)</td>
<td>12 (8.4%)</td>
<td>4 (7.0%)</td>
<td>3 (7.1%)</td>
</tr>
<tr>
<td>Sideswipe (same direction)</td>
<td>4 (2.7%)</td>
<td>1 (0.7%)</td>
<td>3 (5.3%)</td>
<td>0 (0.0%)</td>
</tr>
<tr>
<td>Sideswipe (opposite direction)</td>
<td>6 (4.1%)</td>
<td>0 (0.0%)</td>
<td>3 (5.3%)</td>
<td>0 (0.0%)</td>
</tr>
<tr>
<td>Non-collision</td>
<td>9 (6.2%)</td>
<td>6 (4.2%)</td>
<td>5 (8.8%)</td>
<td>1 (2.4%)</td>
</tr>
<tr>
<td>Run off the road</td>
<td>51 (34.9%)</td>
<td>56 (39.2%)</td>
<td>25 (43.9%)</td>
<td>25 (59.5%)</td>
</tr>
<tr>
<td>Animal</td>
<td>37 (25.3%)</td>
<td>32 (22.4%)</td>
<td>5 (8.8%)</td>
<td>1 (2.4%)</td>
</tr>
<tr>
<td>Other</td>
<td>7 (4.8%)</td>
<td>5 (3.5%)</td>
<td>2 (3.5%)</td>
<td>3 (7.1%)</td>
</tr>
<tr>
<td>Sum</td>
<td>146 (100.0%)</td>
<td>143 (100.0%)</td>
<td>57 (100.0%)</td>
<td>42 (100.0%)</td>
</tr>
</tbody>
</table>

According to the summary, the most common crash type was run off the road (ROR), and it accounted for 35 percent (51 out of 146) and 39 percent (56 out of 143) of overall crashes in before and after periods, respectively. Both the before and after periods had 25 ROR FI crashes. The number of...
sideswipe crashes was reduced significantly (overall: from 10 to 1; FI: from 6 to 0). Animal related
crashes were also reduced. For other crash types, there were increases in rear end and angle crashes,
although the FI crashes of the two types did not change much. The frequency of total night time crashes
increased by 14 percent in the after period. However, the night time FI crashes decreased by 37.5 percent.
The after period had a similar number of wet pavement crashes and wet pavement ROR crashes with the
before period, but had five, or 41.7 percent, less wet pavement FI crashes. In general, diverse changes
were found between overall and FI crashes for most crash types except sideswipe crashes.

Although resurfacing projects had diverse safety impacts on overall crash frequency by type, they
had positive impacts on most types of FI crashes, with sideswipe FI crashes and animal FI crashes, night
time FI crashes or wet pavement FI crashes receiving the largest safety benefits. To conclude, improving
pavement condition from deficient to good appears to have a neutral impact on frequency of overall
crashes. However, it can offer significant safety benefit in reducing crash severity. Specifically, the new
pavement markings associated with the repaving likely help reduce nighttime and sideswipe FI crashes,
while the new pavement surface likely creates positive impacts on wet weather crashes and helps reduce
severity across all crash types.

CONCLUSIONS AND FUTURE RESEARCH

Given the historical pavement condition data, as well as roadway and crash information, this study was
able to quantitatively evaluate the safety effectiveness of good pavement conditions versus deficient
pavement conditions. According to the Empirical Bayes analysis, it was found that compared with
deficient pavements, good pavements are able to reduce the fatal and injury crashes by 26 percent but do
not have a statistically significant impact on overall crash frequency. Further analysis indicated that the
safety benefit of pavement improvement does not statistically significantly change as the lane or shoulder
width increases. The results of this study could be used for a variety of applications, including prioritizing
sites for the agency’s annual paving program or quantifying the benefits of preventative maintenance
treatments.

One limitation of this study is a lack of before and after data. Since the pavement condition data
has only been available since 2007 and crash data have only been updated through 2011 so far, the
research could only use segments that were resurfaced in 2009 as the study sites. As a result, the selected
sites only had two years before and after data available.

Also, this study focuses specifically on rural two-lane undivided roads. Future research could
expand this analysis to other facility types such as freeways or urban/rural multi-lane roads. This would
give DOTs an idea whether these findings are transferable to other locations. Another direction could be
to research the safety effect of pavement treatments other than resurfacing after which pavement
condition could be improved from fair to good or from deficient to fair/good. With these information,
DOTs could quantify the safety benefit of most pavement treatments across the entire network. However,
it may be hard to find adequate before-after data to conduct the EB study, so a cross-sectional study
design could be used to investigate these trends.

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REFERENCES


