Statistical Analysis of the Traffic Safety Impacts of On-Premise Digital Signs

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ABSTRACT

For generations, most signs — including traffic and business signs — were static, displaying a message that did not change with time. Advances in information display technologies in recent years have led to an increase in the use of dynamic digital signs, particularly for on-premise business signs (i.e., signs located on the same property as the business it is advertising). From the beginning of the use of on-premise digital signs, there have been concerns related to the traffic safety impact of these types of signs. So far, no studies have actually examined the safety effects of on-premise signs based on the number of crashes. The primary objective of this study sought to fill this important gap. To accomplish the study objective, the researchers conducted a before-after study using the empirical Bayes (EB) method. In the first phase, the researchers identified sites where on-premise digital signs were installed in 2006 or 2007 in California, North Carolina, Ohio, and Washington. A total of 135 sign locations were identified and analyzed in the safety analysis phase. To apply the EB method, reference data were also collected at 1,301 control group sites where no changes were performed and used predictive models available from the literature. The results show that there was no statistically significant change in crash frequency associated with the installation of on-premise digital signs. Thus, there seems to be no evidence the installation of on-premise signs at these locations led to an automatic increase in the number of crashes.

INTRODUCTION

For generations, most signs — including traffic and business signs — were static, displaying a message that did not change with time. Advances in information display technologies in recent years have led to an increase in the use of dynamic digital signs, particularly for on-premise business signs. An on-premise sign is a sign located on the same property as the business it is advertising. These on-premise digital signs represent an advancement in communication technologies because of the ability to deliver various marketing information to potential customers. From the beginning of the use of on-premise digital signs, there have been concerns related to the traffic safety impact of these types of signs. The traffic safety concerns are typically related to issues of potential driver distraction from the roadway due to the dynamic nature of these signs.

The concerns associated with on-premise digital signs has existed for some time, but there has been little research, particularly on a national level, that directly addresses the safety impacts of on-premise digital signs. In part, this is due to the fact that the use of such signs has become more widespread in the last 5–10 years. More roadside businesses, especially for those with multiple users (e.g., shopping centers, auto malls, sports complexes, and entertainment places), now install larger sized on-premise digital signs because of the lower cost and better performance of the LED display. Most of the research related to digital signs has focused on off-premise digital signs because off-premise signs usually have wider visible area and greater viewership than on-premise signs (/). More specifically, off-premise signs are usually located adjacent to interstate highways with higher traffic volume and have higher mounted heights,
while on-premise signs are installed on the private property where the business is located and most are located along urban streets or local highways. With respect to on-premise signs, a few studies (2, 3) have suggested or hypothesized that some on-premise signs affect traffic safety more than some off-premise digital signs, because the locations and elevations of on-premise signs might be closer to the road users. However, there has been little scientific study of the traffic safety impacts of on-premise digital signs. The research described in this paper was conducted to provide a scientifically based, national analysis of the traffic safety impacts of on-premise digital signs through the analysis of crash records. This research is the first study of its kind that analyzed digital signs using a large dataset.

The primary objective of this study was evaluating the traffic safety effects of installing on-premise digital signs. To accomplish this, the researchers conducted a before-after study using the empirical Bayes (EB) method. In the first phase, researchers identified sites where on-premise digital signs were installed in 2006 or 2007 in California, North Carolina, Ohio, and Washington. Of the initial set of over 3,000 possible sites, 135 sign locations were identified and used in the safety analysis phase (referred to hereafter as ‘target group’). The researchers compared crash data before and after installations of signs at each site to assess the safety impacts. To apply the EB method, reference data were also collected at 1,301 control group sites where no changes were performed, about a 10-to-1 ratio between the target and control groups. Predictive models available from the literature were used for the EB method.

BACKGROUND

Although most of the work on studying the safety effects of signs focused on off-premise locations or traditional static display, to the knowledge of the authors, only two studies have investigated the relationship between safety and on-premise digital signs. It should be pointed out that the safety relationships identified in these two research documents were not based on crash data but more centered on opinions and hypotheses, which limits their value as a direct measure of on-premise sign safety. The first study performed a literature review and listed two hypotheses about how on-premise signs can influence crash risk (2). The first hypothesis states that on-premise business signs distract drivers’ attention from their primary driving tasks, resulting in higher crash risks. The second hypothesis asserts that on-premise business signs may mask the visibility of regulatory and warning road signs, which also can negatively influence crash risk.

That study also noted positive effects associated with commercial signs (2). It reported that commercial signs could reduce unnecessary traffic exposure by providing adequate navigation information for drivers, such as providing restaurant information for drivers who are looking for a meal. However, only measuring the frequency and duration of drivers’ distraction may not represent the safety impacts of on-premise signs because a study published earlier showed that half of the objects that drivers see are not related to driving tasks (4). In other words, besides on-premise signs, other roadside features may also distract drivers. The possible solution to minimize the negative effects of an on-premise sign, but still keep its positive effects, is to separate the sign’s content to primary (navigation) and secondary (commercial) information.
The second study mentioned that more roadside businesses, especially those with multiple users (e.g., shopping centers, auto malls, sports complexes, and entertainment places), now install larger-sized on-premise digital signs because of the lower cost and better performance of the LED display (3). That study also suggested that some on-premise signs affect traffic safety more than some off-premise digital signs because the locations and elevations of on-premise signs might be closer to the road users. In addition, the angles of on-premise signs may be out of the cone of vision and require extreme head movements to read.

In summary, these two studies showed more research is needed for understanding the relationship between on-premise digital signs and crash risk, on that relies on crash data.

STUDY DATA

The key to this safety analysis was collecting site data for a large number of on-premise digital signs in selected states and also crash data for roadways in the vicinity of those sign sites. Potential study sites were limited to specific states for which extensive crash data were available. Once the states with crash data were identified, the research team collected information related to the installation of on-premise digital signs in those states. Once collected, these two datasets were combined and then analyzed as described in the Methodology section of this paper.

Crash Data

The analysis locations were limited to the states of California, North Carolina, Ohio, and Washington, as these states are part of the Federal Highway Administration’ (FHWA) Highway Safety Information System (HSIS). The HSIS crash data provided the only readily available and comprehensive crash database that could be used to analyze crashes at locations identified through the sign database. The researchers requested HSIS crash data for the years 2003-2009 inclusively. In order to apply the EB method, reference crash data were also collected at ten adjusted sites where no changes occurred during the study period. The sites for the control group were located along the same route where an on-site digital sign was installed, usually within one mile of a study site.

Sign Data

As described above, the researchers worked with two electronic sign-manufacturing companies to get a list of on-premise digital signs installed in any of the four study states during 2006 or 2007. This period was selected to provide adequate numbers of crashes in both the before and after periods. Each of the two manufacturer lists was converted into datasets for use in the research effort. The first dataset (dataset #1) contained 2,953 sign sites and 27 variables, which included the characteristics of signs and roads, such as sign order date, sign address (road, county, and state), the nearest cross street and its distance from the sign, the nearby cross street with the highest volume and its distance from the subject intersection, and traffic volume on the subject road. The researchers did not use the road information from dataset #1, relying instead upon the road data in the HSIS crash dataset. This ensured consistency in the approach with the different sign datasets. Also, the sign installation date was considered to be the sign order date plus two weeks. This assumption was based on input from the sign-manufacturing company.
Since the entire year that the sign was installed was excluded from the analysis, this was considered not to be a critical issue. The second dataset (dataset #2) had 63 site addresses and 10 variables. Unlike the first dataset, most variables in dataset #2 were related to product information, such as installation data, sales representative, product name, matrix, color, customer ID (address), and status of signs.

For the analysis, these two datasets were combined as one for use in analyzing the crashes by individual state. The combined dataset was further refined by removing all sign locations that were not installed in either 2006 or 2007. The calendar year that a sign was installed was treated as the construction year, and the crashes that occurred in that year were removed from the analysis. The entire calendar year was removed from the analysis due to uncertainty over the exact installation date of the sign since the data provided only the order date for the sign. Removing the entire calendar year associated with installation also eliminated the novelty effect associated with implementing a new sign. The second variable, the sign installation address, was used to select related crashes by the sign’s location and default sign-effective areas. For example, the researchers defined the crashes located within 0.1 miles from the target signs as related crashes. In reality, the effective area could be larger or smaller depending upon the size of the sign. The procedure used for this analysis did not adjust the effective area based on sign size or other factors. Overall, significant effort was put into ensuring the accuracy of the sign datasets because the quality of the data had a huge impact on the precision and accuracy of the analysis. In total, 1,301 sites for the control group were selected. The information extracted included detailed information about the roadway and crashes, including such factors as the number of lanes, the speed limit, crash severity among others.

Data-Merging Procedure

Several steps were involved in merging the crash and sign location datasets into a single dataset that could be used for the statistical analysis. They are briefly described below, but a more detailed description is provided in the research report (5). The early steps focused on confirming that the digital sign was still in place and near the road that it is related to. This was needed because a site could have an address on one road but have the sign facing traffic on another road bordering the site property. The later steps focused upon converting the street address of the sign location to a route and milepost value that could be used with the crash dataset. This complex effort was necessary due to the fact that the sign and crash datasets used different location methods. The sign dataset was based on the site address, while the HSIS crash database was based on route number and milepost. In order to define the related crashes that were adjusted to the target signs, the researchers needed to transfer sign locations into the HSIS location system. The signs in the database also had to be located on a road that was included in the HSIS database for a given state. The HSIS crash data for most states were applicable only to major roads. The basic steps involved in merging the two datasets are described below.

1. For each record in the sign dataset (3,016 total records), the researchers evaluated the location information (typically a street address) and the sign order date. Records with missing or incomplete location information or with sign installation dates that were not in 2006 or 2007 were deleted from the dataset.
2. Research team members then verified the location of the sign using the site address in the sign dataset using Google Street View in Google Maps and Google Earth (6).

3. The sign location was entered into Google Earth to determine the county in which the sign was located and the mileage from the county border. This included identifying the county identification code in the appropriate HSIS manual for a given state. This provided the milepost location information needed to relate the sign location to the location information in the crash dataset.

**Summary Statistics**

As illustrated in Table 1, the final sample size of the database used in the analysis was a small percentage of the original sign database provided by the manufacturers. For example, the original sign dataset for Washington included 413 site addresses that might have an on-premise digital sign. In order to ensure there was an adequate before-after crash data period for further analysis, the researchers had to filter these site addresses. The first filter excluded sites where the sign was not installed in 2006 or 2007, which was needed so that there was adequate time before and after the sign was installed to perform the safety analysis. About 40 percent of the Washington sites (159 sites) met this criterion. Then, the researchers used the Street View function in Google Maps to double-check whether a digital sign was present at the given addresses and whether the sign was on a major road since the HSIS crash dataset only included crashes on major roads. Only 33 sites fit this criterion. The result was that in Washington, the researchers were able to use about 33 of the 400 original sites, giving an 8.0 percent yield on the raw data. The researchers had similar outcomes in the other states, resulting in an overall yield rate of 12.1 percent. The main advantage of this study is the large sample size of data and advanced statistical methods that provide more accurate results than in similar studies. This study has 135 sites from four states, a number much higher than the sample size of other similar studies.

**Table 1 Sign site sample size yield.**

<table>
<thead>
<tr>
<th>Number of Sites</th>
<th>California</th>
<th>North Carolina</th>
<th>Ohio</th>
<th>Washington</th>
<th>All States</th>
</tr>
</thead>
<tbody>
<tr>
<td>Included in original list from sign manufacturers (with complete location information)</td>
<td>86</td>
<td>249</td>
<td>372</td>
<td>413</td>
<td>1,120†</td>
</tr>
<tr>
<td>Sign installation time between 2006–2007</td>
<td>27</td>
<td>94</td>
<td>178</td>
<td>159</td>
<td>458</td>
</tr>
<tr>
<td>Digital signs &amp; located on major roads</td>
<td>6</td>
<td>40</td>
<td>73</td>
<td>34</td>
<td>153</td>
</tr>
<tr>
<td>With HSIS crash data (all crashes)</td>
<td>6</td>
<td>33</td>
<td>63</td>
<td>33</td>
<td>135</td>
</tr>
<tr>
<td>Data yield rate</td>
<td>7.0%</td>
<td>13.3%</td>
<td>16.9%</td>
<td>8.0%</td>
<td>12.1%</td>
</tr>
<tr>
<td>With HSIS crash data (multiple-vehicle crashes)</td>
<td>6</td>
<td>31</td>
<td>61</td>
<td>33</td>
<td>131</td>
</tr>
<tr>
<td>With HSIS crash data (single-vehicle crashes)</td>
<td>6</td>
<td>32</td>
<td>63</td>
<td>33</td>
<td>134</td>
</tr>
</tbody>
</table>

Table 2 shows the number of crashes in the before and after periods for all crashes for each state. Those values represent the raw counts and sites may have different before and after time periods even within the same state.
Table 2 Observed crashes for each state.

| State | Installation year | Target group | | | | Control group | | | |
|-------|-------------------|--------------|----------------|----------------|----------------|----------------|----------------|----------------|
|       | Before period (years) | After period (years) | Number of sites | Observed crashes Before | Observed crashes After | Number of sites Before | Observed crashes After |
| CA    | 2006 | 2 | 2 | 1 | 4 | 3 | 9 | 16 | 17 |
|       | 2007 | 3 | 1 | 5 | 40 | 12 | 50 | 347 | 64 |
| NC    | 2006 | 2 | 2 | 18 | 107 | 141 | 175 | 1583 | 1637 |
|       | 2007 | 3 | 1 | 15 | 91 | 156 | 156 | 711 | 229 |
| OH    | 2006 | 2 | 3 | 31 | 344 | 564 | 306 | 2805 | 3993 |
|       | 2007 | 3 | 2 | 32 | 395 | 255 | 301 | 4375 | 2602 |
| WA    | 2006 | 2 | 3 | 17 | 226 | 311 | 162 | 2123 | 3055 |
|       | 2007 | 3 | 2 | 16 | 325 | 191 | 142 | 2642 | 1500 |

METHODOLOGY

As mentioned above, the objective of this study was to evaluate the safety impacts of installing on-premise digital signs using crash frequencies. These impacts were evaluated with a before-after study using EB method. Among all before-after study methods, the EB method is the most popular procedures for conducting safety analyses of highway safety improvements, because it can provide a more accurate estimation of long-term crash mean by combining short-term observed crash numbers with crash prediction model data (7). It is the method recommended in the Highway Safety Manual (HSM) (8). As recently discussed in the literature, this is conditional on the fact that site selection effect is adequately handled in the analysis (9, 10).

The change in safety may be determined through the index of safety effectiveness, (illustrated in Equation 1) (11). An index greater than 1.00 indicates that there was an increase in crash frequency in the after condition, while a value less than 1.00 indicates a decrease in crash frequency. With the EB method, the analyst first estimates or recalibrates a regression model or safety performance function (SPF) using the data collected with the control group. Then, the model is applied to the sites where an intervention was implemented to get a preliminary predicted value for the after period. The EB method is then used to refine the estimate to account for the regression-to-the-mean (RTM) bias and the external factors. Although it is possible for the EB method to be biased if the characteristics of the treatment and control groups are not the same (9), the researchers assumed that the characteristics were the same, since there is currently no approach that exists to determine if this is true.

The estimation approaches for the EB method is described in Equation 1:

\[
\hat{\theta}_{EB} = \frac{\hat{\lambda}}{\hat{\pi}} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{t} N_{ij}^{T}}{\sum_{i=1}^{n} \sum_{j=1}^{t} M_{ij}^{T}}
\] (1)
Where, 

\( \hat{\theta}_{EB} \) = the estimate of safety effectiveness based on the EB method; 

\( \hat{\pi} \) = the predicted number of crashes for the target group in the after period; 

\( \hat{\lambda} \) = the estimated number of crashes for the target group in the after period; 

\( N_{ij1}^T \) = the observed response for site i (T = target group) and year j (in the before period), 

\( N_{ij2}^T \) = the observed response for site i (T = target group) and year j (in the after period). 

\( M_{ij} \) = the expected responses for site i for the EB method, 

\[
M_{ij} = W_i \times (\hat{\Lambda}_{ij} + (1 - W_i) \times (\sum_{j=1}^{1} N_{ij1}^T));
\]

\( W_i \) = the weight for sites for the EB method, 

\[
W_i = \frac{1}{1 + \hat{\Lambda}_{ij} \times \hat{\alpha}};
\]

\( \hat{\Lambda}_{ij} \) = the estimate for the average number of crashes of site i in the before period; and 

\( \hat{\alpha} \) = the estimate of the dispersion parameter.

\( \hat{\Lambda}_{ij} \) and \( \hat{\alpha} \) can be estimated using two different approaches (7). They can be estimated based on a regression model, as was done in this project, or the method of moment.

For this research, the average number of crashes and dispersion parameter were estimated using a regression model selected from the HSM (8), which includes road types from two to five lanes. Although these models are referred to as base models in the HSM, they were applied without adjusting the values using Crash Modification Factors (CMFs), in large part because the researchers did not have access to all the geometric design characteristics for all the sites investigated, including intersection flows for the minor approaches at intersections or driveways. The large effort of this project was devoted to spending most of the limited resources to increase the sample size. Furthermore, the re-calibration procedure using sites located nearby those where on-premise digital sign is located will minimize the effects of associated with the CMFs (same characteristics between both groups). Finally, given the uncertainty associated with the predictive value and the CMFs, it is expected that this will not have an impact on the final analysis (12).

As for sites located on wider roads (six lanes and eight lanes, which are not yet covered in the HSM), the researchers used the Safety Performance Functions (SPFs) developed by in recent research (13). The number of crashes in each year during the before period (\( \hat{\Lambda}_{ij} \)) was estimated using the regression model shown in Equation 2. Table 3 shows the regression coefficients (a, b) used in Equation 3 for multi- and single-vehicle crashes.

\[
\Lambda_{ij} = \exp(a + b \ln(AADT_{ij}) + Ln(L_i))
\]  

Where

\( \Lambda_{ij} \) = the estimator for the average number of crashes for site i and year j,

\( a, b \) = the coefficients in the regression model,
\( AADT_{ij} \) = the average daily traffic volume for site i and year j,

\( L_i \) = the road length for site i, and

\( Ln \) = natural logarithm.

### Table 3 Coefficients for multi and single-vehicle crash regression model.

<table>
<thead>
<tr>
<th>Crash Type</th>
<th>Road Type*</th>
<th>Regression Coefficients</th>
<th>Dispersion Parameter (( \alpha ))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Intercept (a)</td>
<td>AADT (b)</td>
</tr>
<tr>
<td>Multi-vehicle</td>
<td>2U</td>
<td>-15.22</td>
<td>1.68</td>
</tr>
<tr>
<td></td>
<td>3T</td>
<td>-12.4</td>
<td>1.41</td>
</tr>
<tr>
<td></td>
<td>4U</td>
<td>-11.63</td>
<td>1.33</td>
</tr>
<tr>
<td></td>
<td>4D</td>
<td>-12.34</td>
<td>1.36</td>
</tr>
<tr>
<td></td>
<td>5T</td>
<td>-9.7</td>
<td>1.17</td>
</tr>
<tr>
<td>Single-vehicle</td>
<td>2U</td>
<td>-5.47</td>
<td>0.56</td>
</tr>
<tr>
<td></td>
<td>3T</td>
<td>-5.74</td>
<td>0.54</td>
</tr>
<tr>
<td></td>
<td>4U</td>
<td>-7.99</td>
<td>0.81</td>
</tr>
<tr>
<td></td>
<td>4D</td>
<td>-5.05</td>
<td>0.47</td>
</tr>
<tr>
<td></td>
<td>5T</td>
<td>-4.82</td>
<td>0.54</td>
</tr>
</tbody>
</table>

Note: *U = undivided road, T = road with two-way left turn lane, D = divided road.

It should be pointed out that the models were re-calibrated using the data collected in the control group. The procedure documented in the HSM (8) was used for the calibrating process. The models were re-calibrated for each studied site using data collected at sites located within one mile from that site. This approach meant that every model was specifically tailored for the conditions located within the area where the on-premise sign was installed, as suggested by the HSM.

### RESULTS

This section presents the results of the before-after analysis. The first part documents the results of the before-after study for each state and all the states combined. The second part provides more details about how digital on-premise signs impact traffic safety for multi-vehicle and single-vehicle crashes.

#### Results for Individual and Combined States

Table 4 shows the predicted and estimated number of crashes for the after period for all crashes, single- and multi-vehicle crashes for each state and all the states combined. The estimated number of crashes represent the actual number of crashes in the after period (hence the integer values) while the predicted number of crashes in the after period is calculated (resulting in a decimal value). This table shows that the index of safety effectiveness (\( \theta \)) vary from 0.57 to 1.28. As discussed in greater detail further below, these values are not statistically significantly different than 1.0 at the 5 percent level.
### Table 4 Predicted and estimated number of crashes for each state.

<table>
<thead>
<tr>
<th>State</th>
<th>All Crashes</th>
<th>Multiple-Vehicle Crashes</th>
<th>Single-Vehicle Crashes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\hat{n}$</td>
<td>$\hat{\lambda}$</td>
<td>$\theta$</td>
</tr>
<tr>
<td>California</td>
<td>11.7</td>
<td>15</td>
<td>1.28</td>
</tr>
<tr>
<td>North Carolina</td>
<td>135.9</td>
<td>156</td>
<td>1.15</td>
</tr>
<tr>
<td>Ohio</td>
<td>843.1</td>
<td>819</td>
<td>0.97</td>
</tr>
<tr>
<td>Washington</td>
<td>494.0</td>
<td>502</td>
<td>1.02</td>
</tr>
<tr>
<td>All states*</td>
<td>1484.7</td>
<td>1492</td>
<td>1.00</td>
</tr>
</tbody>
</table>

1 $\hat{n}$ = the predicted number of crashes for the target group in the after period

2 $\hat{\lambda}$ = the estimated number of crashes for the target group in the after period (round numbers)

Figure 1 presents the before-after results for all crashes. The upper and lower bounds indicate the limits of statistical significance. If the upper and lower bounds include 1.00, then the change in crashes is not statistically significant at a 95 percent confidence level. A larger sample size usually leads to a smaller difference between the upper and lower bounds, but this may not always be the case since it is also governed by the variability observed in the data.

The overall results show that there is no statistically significant increase in crash frequency after the installation of the on-premise digital sign because $\theta$ for the entire dataset (all states) is equal to 1.00, and the 95 percent confidence interval is 0.93–1.07 (which includes the index value of 1.00). The results for individual states are similar: no statistically significant safety impacts were observed after the installation of digital signs. In addition, one can see the width of the 95 percent confidence interval is largest for the California data. This is due to the variability of the California data and the small size of the sample set (only 6 sites). Comparing the width of the confidence intervals, from the widest to narrowest, the order is California > North Carolina > Washington > Ohio > all states.

Results for Single- and Multi-Vehicle Crashes

The additional analysis separated crashes into two subgroups: single- and multi-vehicle crashes. All calculations and notations were the same as used previously. Based on the EB method, the researchers determined that the safety effectiveness index is equal to 1.00 for all states, and the 95 percent confidence interval varies between 0.96 and 1.21. Because the confidence interval of the safety effectiveness includes 1.00, there is no statistically significant change in crash frequency after installing the on-premise digital sign. Figure 2 graphically illustrates the results for multi-vehicle crashes. The 95 percent confidence intervals are slightly larger in this figure than in Figure 1.
Figure 1 The safety effectiveness index based on the EB method and the 95 percent confidence interval for each state (all crash types).

Figure 2 The safety effectiveness index based on the EB method and the 95 percent confidence interval for each state (multi-vehicle crashes).
The results for single-vehicle crashes are presented in Figure 3. The overall results are similar: there are no statistically significant safety impacts from digital signs, except for California. The California results for single-vehicle crashes indicate a statistically significant decrease in crash frequency in the after period, because the 95 percent confidence interval does not include 1.0. Although the before-after results of California show a decrease in the after period, it does not affect the overall result because the low sample size (6 sites) makes it more difficult to establish statistical significance in the analysis results. It is also worth noting that the North Carolina data has the largest confidence interval, due to the variability in the North Carolina single-vehicle crash data.

In summary, the overall results show that EB estimates are not significantly different than the value equal to one. Although not shown here, the Naïve estimates provided similar values as for the EB method (see 5). Because both estimates are very close to each other, this implies that site selections effects did not influence the before-after analysis. This is expected since the entry criterion for the study includes the value 0 for the before period (9, 10.). Although the study did not observe a statistically significant increase in the number of crashes, this does not mean that an actual increase did or could not occur (14). However, given the sample size collected in this study, the overall risk appears to be minimal.
SUMMARY AND CONCLUSIONS

While there have been significant amounts of research devoted to the safety impacts of geometric design features and other aspects of the publicly owned transportation infrastructure, the same cannot be said about the research conducted on the safety impacts of privately owned signs that are directed to users of public roads. This research effort focused on addressing the safety impacts of on-premise digital signs. Previous research performed by others has documented the safety effects of on- and off-premise digital signs and their potential influence on crash risk to some extent. However, the results of these recent crash studies are not consistent, and most studies were plagued by important weaknesses, including neglecting biases related to the RTM effects, low statistical power (small sample), and analysis results based on erroneous assumptions.

The research effort described in this study examined the safety impacts of on-premise digital signs using a large sample size of data and statistical methods that provide more robust results than previous studies. With the help of sign data provided by sign-manufacturing companies and crash data obtained from the FHWA’s HSIS, the researchers obtained extensive datasets for signs and crashes in four states. The study began with 1,120 potential sites, but about 135 sites were used given the criteria for selecting the sites. Although the yield of usable data was only 11.3 percent, the number of sites used was much higher than samples previously analyzed (on- and off-premise signs).

The results show that there was no statistically significant change in crash frequency associated with the installation of on-premise digital signs: the safety effectiveness index ($\theta$) was equaled to 1.00, with the 95 percent confidence interval lying between 0.93 and 1.07. The researchers also conducted further analyses for each of the four states and obtained similar results. Finally, the research team analyzed the safety impacts related to both single- and multi-vehicle crashes and also found no statistically significant increase in the number of crashes.

Based on the analysis performed for this research effort, the researchers can claim that there is no evidence the installation of on-premise signs at the locations led to an automatic increase in the number of crashes. It should be pointed out that recent studies, which examined other types of signs or roadside features also did not find increases in the number of crashes ($15, 16, 17$). However, this does not mean that increases could be observed on certain sites or do not exist ($14$).

Although the research showed no statistically significant increase, further research is needed. For example, the impacts for various settings (e.g. target sites in busy urban area or rural area, commuter drivers or new drivers, etc.) should be examined. Finally, it may be interest to examine whether or not the index varies as a function of sign characteristics, such as color, size, content, and type of business, or the characteristics of the crash, such as the collision type, severity, and age of the driver (especially older drivers) among others.
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REFERENCES