



Safety effects of wider edge lines on rural, two-lane highways

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ABSTRACT

Although it is generally expected that wider lines will have a positive effect on vehicle safety, there have not been any convincing evidence based on the crash data analysis, partly because of the lack of relevant data. In this paper, the safety effect of wider edge lines was examined by analyzing crash frequency data for road segments with and without wider edge lines. The data from three states, Kansas, Michigan, and Illinois, have been analyzed. Because of different nature of data from each state, a different statistical analysis approach was employed for each state: an empirical Bayes, before-after analysis of Kansas data, an interrupted time series design and generalized linear segmented regression analysis of Michigan data, and a cross sectional analysis of Illinois data. Although it is well-known that causation is hard to establish based on observational studies, the results from three extensive statistical analyses all point to the same findings. The consistent findings lend support to the positive safety effects of wider edge lines installed on rural, two-lane highways.

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1. Introduction

The Manual on Uniform Traffic Control Devices (MUTCD) establishes standards and guidelines for traffic control devices, including pavement markings (MUTCD, 2009). Longitudinal pavement markings (center lines, lane lines, and edge lines) provide a continuous stream of information to drivers helping them preview the roadway alignment and maintain appropriate lane position. The MUTCD specifies a nominal width of 4 in. for longitudinal pavement markings. Some state agencies have chosen to use wider pavement markings, mostly on freeway type facilities and mostly with edge lines. Wider longitudinal pavement markings may provide a safer environment for drivers by increasing visibility. There is, however, evidence that some safety-related treatments have an adverse safety effect at some locations (Evans, 1985; Bahar et al., 2004). Driver adaptation has been proposed as one reason for the counterintuitive findings: for example, improved visibility leads to increased driver comfort and higher operating speeds. This

adaptive effect has been identified as a focus of future safety research (Transportation Research Board, 2009) and it is becoming clear that safety effects cannot be deduced purely from human factors theory alone. The safety effects of wider lines must be empirically explored before conclusions can be drawn.

Across the United States, the use of 4-in. markings is the default application, with wider markings being used on a selective basis. The existing research does not provide conclusive results on the benefits of wider markings and the results of various studies often conflict. Despite these inconclusive findings, the use of wider markings is on the rise (Obeng-Boampong et al., 2009).

The objective of this paper is to evaluate the safety effects of wider pavement markings, specifically edge lines on rural, two lane roadways. This paper presents enhanced statistical analyses of the potential safety effects of wider edge lines on rural, two-lane highways in Kansas, Michigan, and Illinois. Three different evaluation approaches, an empirical Bayes before-after analysis for Kansas data, an interrupted time series design and generalized linear segmented regression analysis for Michigan data, and a cross-sectional safety comparison for Illinois data, were utilized to account for different characteristics of the data from each state.

2. Previous studies

One of the first safety evaluations of wider edge lines was conducted by Cottrell (1987, 1988) in Virginia. The researcher

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conducted a before–after crash study of run-off-road and opposite-direction crashes using data from three years prior to installing 8-in.-wide edge lines and two years after installation at three test sections. The analysis resulted in a 13.6 percent reduction in both run-off-road and opposite-direction crashes, which was not statistically significant when compared to the comparison sites. Another before–after crash study conducted in New Mexico by Hall (1987) suggested that wider lines have no safety benefit in terms of reducing crashes. Both of these studies were hampered by insufficient data.

In lieu of safety studies, many agencies justify wider pavement markings based on subjective evaluations citing added visibility (Gates and Hawkins, 2002). However, the results of visibility studies based on detection distances of pavement marking widths are inconclusive. On the one hand, a number of research efforts show increased visibility for wider lines (Ward, 1985; Zwahlen and Schnell, 1995; COST 331, 1999), while on the other hand, research findings also show that there are no consistent statistical or practical differences (Ohme, 2001; Carlson et al., 2007). An empirical study has shown that theoretical calculations of marking detection distance as a function of marking width are invalid, and more work is needed to develop mathematical relationships between marking width and detection distances (Gibbons, 2006).

3. Methods and results

In this study, the focus of the safety evaluation is wider edge lines on rural, two-lane highways using observational studies. The results of three analyses are presented. Three separate analyses were required due to unique characteristics of the data, including how, when, and the extent to which states made the transition to wider lines, and how long it took the state to complete the transition. The first analysis is an empirical Bayes before–after analysis of rural, two-lane segments in Kansas for which the edge line width was changed from 4 in. to 6 in. in multiple years. The second is a piecewise regression analysis of interrupted time series design with the change from 4 in. to 6 in. in 2004 being treated as an intervention for Michigan data. The third is a cross-sectional safety comparison of rural two-lane segments with 5 in. center lines and edge lines to segments with 4 in. center lines and edge lines for Illinois.

3.1. Empirical Bayes before–after analysis for Kansas crash data

The Kansas (KS) crash data consist of non-intersection/interchange, non-winter month crash counts obtained from 2801 rural, two-lane road segments (corresponding to 2194.7 miles) in District 2 and District 6 for years 2001–2008. An empirical Bayes (EB) approach was employed to analyze the KS crash data. The EB method can account for the effect of regression-to-the mean along with changes in traffic volume and other changes not due to the treatment in crash frequencies. It has been considered a statistically defensible safety evaluation tool in observational before–after studies for more than two decades (Persaud and Lyon, 2007). In the EB method, Safety Performance Functions (SPFs) are used to estimate the expected crash frequencies at the treated sites had treatments not been applied (see Hauer, 1997 for details). Generalized linear regression models, specifically, negative binomial regression models are often used to derive the SPFs (see Lord and Mannering, 2010 for a detailed review of statistical analysis of crash-frequency data). Although the details on the EB method are available elsewhere (Hauer, 1997; Bahar et al., 2004; Persaud and Lyon, 2007), the steps of the EB procedure used for the KS data analysis are described here for completeness. Note that in this evaluation safety performance functions are calibrated for each year of the before and after periods rather than just for each period.

Step 1. Develop a Safety Performance Function (SPF) and estimate the regression coefficients and a negative binomial dispersion parameter (k) using data from the reference group.

Step 2. Estimate the expected number of crashes $E(\kappa_{iy})$ for each year in the before period at each treatment site using the SPF developed in Step 1.

Step 3. Compute the sum of the annual SPF predictions during the before period at each treatment site by:

$$P_i = \sum_{y=1}^{y_{0i}-1} \hat{E}(\kappa_{iy})$$

where y_{0i} denotes the year during which the countermeasure was installed at site i .

Step 4. Obtain an estimate of the expected number of crashes (M_i) before implementation of the countermeasure at each treatment site and an estimate of variance of M_i . The estimate M_i is given by combining the sum of the annual SPF predictions during the before period (P_i) with the total count of crashes during the before period as follows:

$$M_i = w_i P_i + (1 - w_i) K_i$$

where K_i is the total crash counts during the before period at site i and the weight w_i is given by

$$w_i = \frac{1}{1 + k P_i}$$

where k is the estimated dispersion parameter of the negative binomial regression model developed in Step 1. An estimated variance of M_i is given by:

$$\hat{V}ar(M_i) = (1 - w_i) M_i$$

Step 5. Determine SPF predictions $\hat{E}(\kappa_{iy})$ for each year in the after period at each treatment site, and compute C_i , the ratio of the sum of the annual SPF predictions for the after period (Q_i) and the sum of the annual SPF predictions for the before period (P_i).

$$C_i = \frac{\sum_{y=y_{0i}+1}^Y \hat{E}(\kappa_{iy})}{\sum_{y=1}^{y_{0i}-1} \hat{E}(\kappa_{iy})} = \frac{Q_i}{P_i}$$

Step 6. Obtain the predicted crashes ($\hat{\pi}_i$) and its estimated variance during the after period that would have occurred without implementing the countermeasure. The predicted crashes ($\hat{\pi}_i$) are given by:

$$\hat{\pi}_i = C_i M_i$$

The estimated variance of $\hat{\pi}_i$ is given by:

$$\hat{V}ar(\hat{\pi}_i) = C_i^2 \hat{V}ar(M_i) = C_i^2 (1 - w_i) M_i$$

Step 7. Compute the sum of the predicted crashes over all sites in a treatment group of interest and its estimated variance by:

$$\hat{\pi} = \sum_{i=1}^I \hat{\pi}_i$$

$$\hat{V}ar(\hat{\pi}) = \sum_{i=1}^I \hat{V}ar(\hat{\pi}_i)$$

Table 1

Number of segments and miles for each implementation year of wider edge lines in Kansas.

Implementation year	# of segments	Miles
Unknown	734	746.6
2005	1222	815.9
2006	404	362.1
2007	178	112.0
2008	173	116.0
Not implemented until after 2008	90	42.1
Total	2801	2194.7

where I is the total number of sites in a treatment group of interest. Step 8. Compute the sum of the observed crashes over all sites in a treatment group of interest by:

$$L = \sum_{i=1}^I L_i$$

where L_i is the total crash counts during the after period at site i . Step 9. The index of effectiveness of the countermeasure is estimated by:

$$\hat{\theta} = \frac{L}{\hat{\pi}(1 + \text{var}(\hat{\pi})/\hat{\pi}^2)}$$

The percent change in the number of crashes at site i is given by $100(1 - \hat{\theta})$. If $\hat{\theta}$ is less than 1 then the countermeasure has a positive effect on safety.

Step 10. Compute the estimated variance and standard error of the index of effectiveness and the approximate 95% confidence interval for θ . The estimated variance and standard error of the index of effectiveness are given by

$$\text{Var}(\hat{\theta}) = \hat{\theta}^2 \frac{(1/L + \text{Var}(\hat{\pi})/\hat{\pi}^2)}{(1 + \text{Var}(\hat{\pi})/\hat{\pi}^2)^2}$$

$$\text{s.e.}(\hat{\theta}) = \sqrt{\text{Var}(\hat{\theta})}$$

The approximate 95% confidence interval for θ is given by adding and subtracting $1.96 \text{ s.e.}(\hat{\theta})$ from $\hat{\theta}$. If the confidence interval contains the value 1, then no statistically significant effect has been observed. This does not mean that a safety effect does not exist, so

all indices that were estimated are reported in this paper to show a complete picture of safety effects. A confidence interval placed below 1 (i.e., the upper limit of the interval is less than 1) implies that the countermeasure has a significant positive effect (i.e., a reduction in crashes) on safety. The confidence interval placed above 1 (i.e., the lower limit of the interval is greater than 1) implies that the countermeasure has a significant negative effect (i.e., an increase in crashes) on safety.

While the success of an empirical Bayes approach largely depends on reliable estimation of SPFs, it is oftentimes hard to identify a reference group that is similar enough to the treatment group. Originally, the researchers considered sites untreated during the eight years of the study period, 2001–2008, for Kansas. In Kansas, the wider lines were installed in years 2005, 2006, 2007, and 2008. Table 1 summarizes the number of segments and the corresponding mileage for each implementation year. There were only 42.1 miles of roadways (90 segments) in the database that can be used as a reference group (without wider edge lines installed until the end of 2008). The limited length of comparable roadway made it difficult to develop reliable SPFs. Researchers decided to use the segments for which wider edge lines were installed in 2008 as additional sites for a reference group, and restricted the study period to seven years (from 2001 to 2007) instead. The number of segments and mileage for the resulting reference group are 263 and 158.1 miles, respectively. Because the segments with 2007 as an implementation year (178 segments corresponding to 112 miles) do not have any after period data, these 178 segments were excluded from the EB before–after evaluation, which left two treatment groups, Group 1 consisting of 1222 segments (815.9 miles) with 2005 as the implementation year and Group 2 consisting of 404 segments (362.1 miles) with 2006 as the implementation year, in the evaluation. Note also from Table 1 that there are 734 segments (totaling 746.6 miles) for which the implementation year is unknown. Those 734 segments were also excluded from the evaluation reported in this paper.

Types of crashes analyzed were: Total, Fatal plus injury, PDO, Day, Night, Daytime fatal plus injury, Nighttime fatal plus injury, Wet, Wet night, Single vehicle, Single vehicle fatal plus injury, Single vehicle night, Single vehicle night fatal plus injury, and Fixed object crashes. The negative binomial regression models with Indicator variables for District (2, 6) and year (2001–2007) to control for general trends, shoulder width, log(AADT), and log(segment length) as independent variables were employed to develop SPFs. Although some other roadway characteristic variables such as lane width and speed limit were also available in the database, there was not much variation in those variables, so they were not included in the model. Due to the small sample size, the coefficients for SPFs

Table 2

Estimates of coefficients for safety performance functions (SPFs) developed based on a reference group consisting of 263 segments (158.1 miles) in rural 2 lane roadways in Kansas.

Variable		Total	PDO	Night	Single vehicle	Fixed object
District	2	−3.6379	−3.2113	−3.4905	−5.9374	−5.8490
	6	−4.3876	−4.2954	−4.5546	−5.6381	−6.1533
Year	2001	−0.2675	−0.3677	−0.4718	−0.0019	0.2471
	2002	−0.4691	−0.4751	−0.5295	−0.5750	−1.2428
	2003	−0.3074	−0.3017	−0.2076	−0.2756	−0.5567
	2004	−0.2422	−0.1518	−0.2021	−0.1410	−0.1162
	2005	−0.4321	−0.5192	−0.3898	−0.2484	−0.5252
	2006	−0.2557	−0.3070	−0.5006	0.0516	0.0219
	2007	0.0000	0.0000	0.0000	0.0000	0.0000
Shoulder width		−0.0464	−0.0126	−0.0534	−0.1531	−0.0790
Log (AADT)		0.5384	0.4334	0.4348	0.7110	0.5979
Log (length)		0.9365	0.9401	0.8686	1.0221	1.0496
Dispersion		0.2779	0.2913	0.4742	0.9161	0.2670
Pearson chi-square/DF		1.0642	1.1156	1.0707	1.1330	1.0596

Table 3

Ratio of the number of crashes of a specific type and the total number of crashes for the reference group.

Crash type	α_f
Total	1.000
Fatal plus injury	0.226
PDO	0.774
Day	0.375
Night	0.493
Daytime fatal plus injury	0.127
Nighttime fatal plus injury	0.071
Wet	0.064
Wet night	0.033
Single vehicle	0.358
Single vehicle fatal plus injury	0.167
Single vehicle night	0.108
Single vehicle night fatal plus injury	0.052
Fixed object	0.182

could be directly estimated only for Total, PDO, Night, Single vehicle, and Fixed object crashes. (Note again that these crash types are all restricted to non-intersection/interchange, non-winter month crashes.) SPFs for other crash types were obtained by applying a multiplier α_f (computed as the number of crashes of a specific type divided by the total number of crashes for the reference group) to the SPF for total crashes as in Bahar et al. (2004). The estimated coefficients for SPFs for Total, PDO, Night, Single vehicle, and Fixed object crashes, and the multipliers (α_f) for the crash types considered in this study are presented in Tables 2 and 3, respectively.

Table 4 includes the results of an EB before-after evaluation based on the Kansas crash data. It can be observed from the table that almost all crash types considered resulted in statistically significant (at the 95% confidence level) crash reduction estimates with an exception of Night, Nighttime fatal plus injury, Wet night, and Single vehicle night fatal plus injury crashes. It needs to be noted that single vehicle road departure crashes are especially relevant target crashes for assessing the safety effects of wider edge lines. The results of Table 4 support consistent safety effects of wider edge lines for single vehicle and associated disaggregate crash types (e.g., Single vehicle night, Single vehicle fatal plus injury). A sensitivity analysis was conducted that used the SPF for total crashes combined with the corresponding crash type ratio (α_f) in Table 3 to predict the expected number of PDO, Night, Single vehicle, and Fixed object crashes. This is one alternative to using the disaggregated SPFs, estimated for each individual crash type, and reported in Table 2. The results from the analysis using the total crash SPF combined with the crash type ratios for PDO, Night, Single vehicle, and Fixed object crashes are also presented in Table 4 and noted by the * symbol. The results from this sensitivity analysis were not materially different from those obtained by using the individual SPF model coefficients from Table 2.

3.2. Generalized linear segmented regression analysis for Michigan crash data

The Michigan crash data consist of non-intersection/interchange non-winter month crash counts obtained from 253 rural, two-lane road segments (corresponding to 851.5 miles) for years 2001–2007. In Michigan, the change from 4-in. edge lines to 6-in. edge lines were made on almost all of the state-owned systems during 2004. Originally, researchers attempted to conduct an EB before-after analysis on the Michigan data. However, the widespread switch from 4-in. to 6-in. edge lines on almost all of the state-owned roads (i.e., all facility types) in 2004 left almost no sites within Michigan available for a reference group/comparison group in the before-after safety evaluation. Although the SPFs could be developed based on the before period data, the general

time trends in crash frequencies from 'before' to 'after' periods not due to wider lines could not be easily estimated. The researchers attempted to use the Illinois fatal plus injury data to estimate the change in underlying trends. Michigan intersection crashes were also tested as an alternative, but the trends of these crashes in the before period were opposite to those on Michigan rural, two-lane highways. The lack of an appropriate reference group (within the same state) remained one of the main limitations of conducting an EB analysis of the Michigan data.

The researchers employed an alternative approach to perform safety evaluation of Michigan rural 2-lane roadway crash data. The new approach adapted was an interrupted time series design (see e.g., Campbell and Ross, 1968; Gillings et al., 1981; Wagner et al., 2002; Friedman et al., 2009; Grundy et al., 2009). An interrupted time series design is a quasi-experimental method used to determine the impact of an intervention. Quoting from Campbell and Ross (1968), "In the interrupted time-series, the 'causal' variable is examined as an event or change occurring at a single time, specified independently of inspection of the data." Here the causal variable (intervention) is the installation of wider lines that took place in 2004 statewide. A generalized linear segmented regression analysis was used as a statistical method for analyzing the data from the interrupted time series design. Specifically, a negative binomial regression model that introduces Time as a variable to control for overall trend and Intervention (installation of wider lines) as a variable to estimate the effect of the wider lines was utilized. For Time, the years prior to the installation of wider lines were coded as negative integers starting at -1 in descending order, and the years after the installation of wider lines were coded as positive integers starting at 1 in ascending order. For Intervention, the years corresponding to the after period are coded 1 , and the years in the before period are coded as 0 . An additional variable 'time after Intervention', coded 0 before the intervention and $(\text{time} - t_0)$ where t_0 is the year of the intervention, can also be included in the model to estimate a possible change in the trend (not just in the level) in the expected number of crashes. Then, at road segment i , the log of expected number of annual crashes in year t (μ_{it}) can be expressed as follows:

$$\log \mu_{it} = \beta_0 + \beta_1 * \text{time}_t + \beta_2 * \text{intervention}_t + \beta_3 * \text{time after intervention}_t + \beta_4 X_{i,4t} \cdots + \beta_k X_{i,kt}$$

where $X_{i,kt}$ is the value of the k th predictor variable measured at road segment i in time t . The underlying assumption for the above model is that the relationship between the log mean annual crash count and time is linear within each segment of time period (i.e., for the time period before the intervention and independently for the time period after the intervention). The intercept β_0 represents the baseline level of the log mean annual crash count, and β_1 represents the baseline trend that corresponds to the change in the log mean annual crash count that occurs with each year before the intervention. The coefficients β_2 and β_3 represent the level change (i.e., the change in the intercept) in the log mean annual crash count immediately after the intervention and the change in the trend (i.e., the change in the slope) in the log mean annual crash count after the intervention, respectively. The key parameters of interest are β_2 and β_3 , which can measure the effects of intervention, while β_0 and β_1 play the role of controlling for baseline level and trend.

In addition to time, intervention, and time after intervention, lane width, terrain, log(AADT), log(segment length), and log(number of rainy days) were included as predictors in the negative binomial regression model for Michigan crash data. The Generalized Estimating Equations (GEE) was employed as an estimation method to account for correlation in crash counts obtained for multiple years from the same segment. Table 5 contains the

Table 4

Results of empirical Bayes before–after evaluations based on the KS crash data without intersection/interchange crashes obtained from 1626 segments (1178 miles) of rural two-lane roadways.

Crash type	Crashes in the after period		$\hat{\theta}$ (S.E.)	95% Confidence interval for θ	Percent crash reduction
	Observed	EB estimate			
Total	1034	1253.47	0.825 (0.028)	(0.770, 0.879)	17.5
Fatal plus injury	156	245.64	0.635 (0.052)	(0.533, 0.737)	36.5
PDO	878	1000.37	0.877 (0.032)	(0.814, 0.941)	12.3
PDO*	878	984.65	0.892 (0.033)	(0.828, 0.955)	10.9
Day	294	411.40	0.714 (0.043)	(0.629, 0.799)	28.6
Night	600	623.20	0.962 (0.043)	(0.879, 1.046)	3.7
Night*	600	629.19	0.953 (0.042)	(0.872, 1.035)	4.7
Daytime fatal plus injury	80	136.72	0.585 (0.066)	(0.455, 0.715)	41.5
Nighttime fatal plus injury	68	77.84	0.873 (0.107)	(0.663, 1.083)	12.7
Wet	54	70.05	0.771 (0.106)	(0.563, 0.978)	22.9
Wet night	27	36.63	0.757 (0.147)	(0.470, 1.045)	24.3
Single vehicle	274	374.92	0.730 (0.048)	(0.637, 0.824)	27.0
Single vehicle*	274	392.48	0.698 (0.044)	(0.612, 0.784)	30.2
Single vehicle fatal plus injury	113	178.83	0.632 (0.061)	(0.513, 0.750)	36.8
Single vehicle night	98	120.08	0.816 (0.084)	(0.651, 0.980)	18.4
Single vehicle night fatal plus injury	46	56.57	0.813 (0.121)	(0.576, 1.050)	18.7
Fixed object	160	197.42	0.810 (0.066)	(0.681, 0.939)	19.0
Fixed object*	160	196.33	0.815 (0.066)	(0.685, 0.944)	18.5

Notes: (1) EB estimate is the predicted number of crashes during after period had wider lines not been installed; (2) $\hat{\theta}$, estimated index of effectiveness; (3) percent crash reduction = $100(1 - \hat{\theta})$; (4) SE, standard error; (5) statistically significant percent crash reductions at 95% confidence level are shown in bold.

* The results from the sensitivity analysis using the coefficients from the total crash SPF for prediction.

estimated coefficients for negative binomial regression models considered and the corresponding percent crash reduction estimates. Originally, an additional variable ‘time after intervention’ had also been included in the negative binomial regression models to estimate a possible change in the trend (not just in the level) in the expected number of crashes. However, time after intervention was not statistically significant for any of the crash types considered in the study, and was consequently dropped from the models, to facilitate the interpretation of the results. It can be observed from Table 5 that, for Total, PDO, Night, Wet, Wet night, Single vehicle, Single vehicle wet, and Single vehicle night crashes, statistically significant (at the 95% confidence level) crash reductions were found.

In addition to the crash types reported in Table 5, opposite direction crashes and additional disaggregated fatal plus injury crashes such as Wet fatal plus injury, Wet night fatal plus injury, and Single vehicle wet fatal plus injury were also analyzed. Due to insufficient data (there were very few crashes of those types in the MI non-intersection/interchange non-winter month crash data from 253 segments during the study period), however, model coefficients could not be estimated reliably and reliable crash reduction estimates could not be obtained.

The researchers obtained crash data for rural two-lane roadways in Michigan for two additional years 2008 and 2009. Because of the changes on some road segments after 2007, the number of segments of which roadway characteristics stayed the same for the entire study period (2001–2009) was reduced to 238 segments (corresponding to 787.8 miles). The researchers performed another interrupted time series analysis with 9 years of the data as a sensitivity analysis. The number of rainy days could not be included in the models for the extended time period because the data for that variable were not available after 2007. Table 6 contains the results for the crash data obtained from 238 segments for 2001–2009. It can be observed from the table that the results did not materially change from those of Table 5 although the magnitude of crash reduction moderately decreased compared to the results based on 2001–2007 data (except for fatal plus injury, daytime fatal plus injury and wet night crashes).

In addition to the crash types reported in Table 6, opposite direction crashes and additional disaggregated fatal plus injury crashes such as Single vehicle night fatal plus injury, Wet fatal plus injury,

Wet night fatal plus injury, and Single vehicle wet fatal plus injury crashes were also analyzed. Due to the insufficient data, however, model coefficients could not be estimated reliably and reliable crash reduction estimates could not be obtained.

3.3. Cross-sectional analysis for Illinois crash data

Illinois crash data for years 2001 through 2006, obtained from 6531 segments, roughly corresponding to 1733 miles of rural, two-lane highways, were analyzed. Only the non-intersection/interchange crashes were considered. Crashes occurred during the winter months (November, December, January, February, and March) were excluded from the analysis to avoid any potential confounding by snow crashes. Animal collisions were removed from the data before the analysis because they were deemed to be irrelevant for assessing safety effects of wider edge lines while they constitute a large proportion of the rural, two-lane crashes in Illinois. Out of the 6531 segments in two-lane highways in Illinois, 5343 (corresponding to 1446 miles) have 4 in. edge lines and 4 in. centerlines and 1188 (corresponding to 287 miles) have 5 in. edge lines and 5 in. centerlines. The negative binomial regression models (or Poisson regression models when negative binomial regression models could not be fitted) were applied to these cross-sectional data. Types of crashes analyzed were: Total, Fatal plus injury, PDO, Day, Night, Daytime fatal plus injury, Nighttime fatal plus injury, Wet, Wet night, Single vehicle, Single vehicle wet, Older Driver (≥ 55 years old), Opposite direction (head on and sideswipe opposite direction), and Fixed object crashes. After exploring various negative binomial regression model forms with different predictors and interaction terms, the model including wider edge line (coded as 1 when edge line width = 5 and 0 when edge line width = 4), lane width, shoulder width, log of AADT, presence of horizontal curve (coded as 1 when a curve is present in the segment and 0 when no curve is present in the segment), and log of segment length as predictors seemed to be most appropriate for these data. The cross-sectional data analysis assumes that segments are identical or similar except for the variables included in the model, which may not always be true. It needs to be emphasized that it is possible that the remaining site-to-site variability may be confounded with the effect of edge line width.

Table 5

Results of generalized linear segmented regression analysis applied to the MI non-intersection/interchange non-winter month yearly crash data from 253 segments (851.5 miles) of rural two-lane roadways with 3 years (2001–2003) of pre-intervention and 3 years (2005–2007) of post-intervention data.

Crash type	Intercept	Time	Intervention	Lane width	Terrain	Log(AADT)	Log(length)	Log(# of rainy days)	Percent crash reduction	95% C.I. for percent crash reduction
Total	−3.4846	0.0782	−0.3204	−0.0977	0.1721	0.5205	1.0980	0.0769	27.4	(15.4, 37.7)
Fatal plus injury	−8.6073	0.0050	−0.1668	−0.0379	0.1945	0.8216	1.0277	0.0056	15.4	(−21.5, 41.0)
PDO	−3.3755	0.0953	−0.3633	−0.1140	0.1700	0.4981	1.1149	0.1026	30.5	(18.1, 40.9)
Day	−3.9724	0.0512	−0.2271	−0.1008	0.2735	0.5638	1.0141	−0.0968	20.3	(0.2, 36.4)
Night	−5.4095	0.0984	−0.3666	−0.0474	0.1008	0.5666	1.1596	0.1228	30.7	(15.0, 43.5)
Daytime fatal plus injury	−8.6123	0.0031	−0.0860	−0.0801	0.2077	0.9254	0.9238	−0.1079	8.2	(−43.3, 41.2)
Nighttime fatal plus injury	−10.7416	0.0348	−0.2564	0.0780	0.1336	0.6430	1.2491	0.2353	22.6	(−50.3, 60.2)
Wet	−11.2267	0.1715	−1.1140	−0.0626	0.2183	0.4813	0.9848	1.2745	67.2	(45.2, 80.3)
Wet night	−11.8302	0.2715	−1.4633	−0.0321	0.1819	0.4009	1.0133	1.3551	76.9	(57.2, 87.5)
Single vehicle	−2.9988	0.1004	−0.3566	−0.1117	0.1917	0.4313	1.1665	1.1046	30.0	(17.7, 40.5)
Single vehicle wet	−9.9483	0.2313	−1.3394	−0.1147	0.2328	0.3202	1.0439	1.3670	73.8	(55.8, 84.5)
Single vehicle night	−5.2232	0.0987	−0.3476	−0.0519	0.1062	0.5438	1.1694	0.1174	29.4	(13.4, 42.4)
Single vehicle fatal plus injury	−6.0126	0.0062	−0.1056	−0.0671	0.1209	0.5717	1.2009	−0.1233	10.0	(−40.8, 42.5)
Single vehicle night fatal plus injury	−8.1645	−0.0016	−0.1023	−0.0382	0.1039	0.5420	1.2847	0.0835	9.7	(−85.7, 56.1)

Notes: (1) Generalized Estimating Equations (GEE) approach was used as an estimation method; (2) percent crash reduction estimates are obtained by $\{1 - \exp(\beta_I)\} \times 100$ where β_I represents the estimated coefficient of the intervention variable; (3) statistically significant results at 95% confidence level are shown in bold; (4) C.I. stands for confidence intervals.

Table 6

Results of generalized linear segmented regression analysis applied to the MI non-intersection/interchange non-winter month yearly crash data from 238 segments (787.8 miles) of rural two-lane roadways with 3 years (2001–2003) of pre-intervention and 5 years (2005–2009) of post-intervention data.

Crash type	Intercept	Time	Intervention	Lane width	Terrain	Log(AADT)	Log(length)	Percent crash reduction	95% C.I. for percent crash reduction
Total	−3.0916	0.0451	−0.2151	−0.1302	0.1737	0.5542	1.1074	19.4	(10.1, 27.6)
Fatal plus injury	−8.0168	0.0132	−0.1754	−0.0118	0.1088	0.7572	1.0270	16.1	(−11.1, 36.6)
PDO	−2.9525	0.0490	−0.2186	−0.1399	0.1806	0.5310	1.1199	19.6	(9.8, 28.4)
Day	−4.0554	0.0264	−0.1277	−0.1296	0.2397	0.5589	1.0106	12.0	(−3.5, 25.2)
Night	−4.7448	0.0489	−0.2081	−0.0734	0.1138	0.5801	1.1665	18.8	(6.3, 29.6)
Daytime fatal plus injury	−8.5857	0.0560	−0.2617	−0.0150	0.1331	0.7860	0.9419	23.0	(−6.6, 44.4)
Nighttime fatal plus injury	−9.1065	−0.0490	0.0560	0.0072	0.0614	0.6744	1.2300	−5.8	(−86.8, 39.5)
Wet	−5.2136	0.1185	−0.9847	−0.0808	0.1628	0.5140	0.9940	62.6	(45.6, 74.4)
Wet night	−12.1894	0.2982	−1.5695	0.0253	0.1669	0.3807	1.0200	79.2	(60.2, 89.1)
Single vehicle	−2.4692	0.0540	−0.2066	−0.1425	0.1984	0.4615	1.1610	18.7	(8.9, 27.4)
Single vehicle wet	−3.4974	0.1386	−1.0768	−0.1574	0.1754	0.3824	1.0386	65.9	(48.6, 77.4)
Single vehicle night	−4.5967	0.0511	−0.1983	−0.0807	0.1234	0.5624	1.1767	18.0	(5.2, 29.0)
Single vehicle fatal plus injury	−5.8489	−0.0190	0.0191	−0.0339	0.0916	0.4476	1.1011	−1.9	(−44.8, 28.3)

Notes: (1) Generalized Estimating Equations (GEE) approach was used as an estimation method; (2) percent crash reduction estimates are obtained by $\{1 - \exp(\beta_I)\} \times 100$ where β_I represents the estimated coefficient of the intervention variable; (3) statistically significant results at 95% confidence level are shown in bold; (4) C.I. stands for confidence intervals.

Temporal correlations in the crash counts obtained from the same road segment over six years were handled by employing two different approaches; (1) negative binomial regression analysis on the crash frequencies aggregated over six years, (2) analysis on yearly crash frequencies using the negative binomial regression models with yearly trend and accounting for temporal correlations in the parameter estimation using Generalized Estimating Equations procedure. Similar conclusions were reached from both approaches. Only the results from the first approach (analyzing the aggregated crash counts over 6 years) are presented in this paper.

The results in Table 7 show that the effect of edge line width is statistically significant for almost all crash types considered in the analysis: Total, Fatal plus injury, PDO, Day, Night, Daytime fatal plus injury, Nighttime fatal plus injury, Wet, Single vehicle, Single vehicle wet, Single vehicle Night, Single vehicle fatal plus injury, Single vehicle night fatal plus injury, Older driver, and Fixed object. The coefficients of the edge line width for all of these crashes are negative, which suggests a positive safety effect of wider lines. For Illinois, RPMs are used statewide and rumble strips are used on Interstates statewide. It needs to be noted, however, that the information on additional delineation and guidance measures (other than RPMs and rumble strips) were not available, and could not be incorporated into the analysis. Therefore, the above observations are based on the assumption that the effects of the variables not in the database such as those additional delineation/guidance measures are the same (or averaged out) for the segments with and without wider edge lines. Percent crash reduction estimates were computed by $\{1 - \exp(\beta_{\text{edge}})\} \times 100$ where β_{edge} represents the estimated coefficient of Edge line width. It also needs to be noted that the removal of animal collisions from the IL crash data made a significant difference in the crash reduction estimates for some crash types such as Total, PDO, Night, Single vehicle, Single vehicle night crashes. The crash reduction estimates (in percent) for those crash types before the removal of animal collisions were, −0.8 (Total), −11.9 (PDO, significant), −9.8 (Night), −4.0 (Single vehicle), and −12.5 (Single vehicle night, significant), respectively. For IL, about 50% of Total crashes (about 60% of PDO crashes and 60% of Single vehicle Crashes) are animal collisions. As can be expected, inclusion of irrelevant crashes in the safety evaluation of wider lines can lead to erroneous results when the proportion of such irrelevant crashes in the data is non-negligible. The safety analysis results for fatal plus injury crashes were not affected significantly whether or not to exclude animal collisions because only 10% of fatal plus injury crashes are animal collisions.

3.4. Consolidated results

Table 8 presents consolidated results for estimations in the percent crash reductions from the four separate analyses. Note that only non-intersection/interchange non-winter crashes were considered for all three states. Animal collisions were also removed from the IL data because about 50% of Total crashes (about 60% of PDO crashes and 60% of Single vehicle Crashes) in IL data are animal collisions. It should also be noted that the animal collisions were excluded from the Kansas single vehicle crash categories by default, since the Kansas crash types were coded so that single vehicle animal collisions were separated from other single vehicle crash types in the raw data. Single vehicle animal collisions were not removed from the crash categories in the Michigan dataset or from other-than-single-vehicle crash categories in the Kansas dataset. The overall effect of these crashes on the safety effectiveness estimates for Kansas and Michigan is deemed to be minimal given the before-after observational study design for these two states (as opposed to the cross sectional study design for Illinois, where different numbers of animal collisions at different locations across the state could mask the wider lines effect on other crash types.

Table 7
Estimates of regression coefficients of negative binomial regression models applied to Illinois crash data without animal collisions and percent crash reduction estimates.

Crash type	Intercept	Wider edge line	Lane width	Shoulder width	Log(AADT)	Presence of curve	Log(length)	Dispersion	Person chi-square/DF	Percent crash reduction	95% C.I. for percent crash reduction
Total	−7.9368	−0.3587	−0.0651	−0.0579	0.9801	0.3460	0.7714	0.4334	1.0907	30.1	(20.5, 38.6)
Fatal plus injury	−7.4089	−0.4727	−0.0861	−0.0566	0.8471	0.6968	0.8505	0.4701	1.0944	37.7	(24.5, 48.5)
PDO	−9.6705	−0.2728	−0.0500	−0.0599	1.0996	0.0703	0.7241	0.4688	1.0821	23.9	(10.6, 35.2)
Day	−9.0662	−0.3438	−0.0809	−0.0595	1.0878	0.1721	0.7487	0.4135	1.0893	29.1	(17.2, 39.3)
Night	−8.0035	−0.3559	−0.0371	−0.0614	0.8108	0.7443	0.8567	0.6157	1.0611	29.9	(13.0, 43.6)
Daytime fatal plus injury	−7.9157	−0.4468	−0.1350	−0.0670	0.9324	0.4647	0.8332	0.4403	1.1022	36.0	(19.2, 49.4)
Nighttime fatal plus injury	−8.8646	−0.4186	0.0185	−0.0389	0.7231	1.1627	0.9291	1.4959	1.0926	34.2	(10.3, 51.7)
Wet	−9.4281	−0.4260	−0.0453	−0.0884	0.9129	0.5833	0.7836	1.0229	1.0229	34.7	(8.8, 53.3)
Wet night	−8.6417	−0.4419	−0.0800	−0.1039	0.7494	1.0403	0.8765	0.5598	1.0695	35.7	(−8.9, 62.1)
Single vehicle	−5.8930	−0.4616	−0.0241	−0.0739	0.6185	0.8615	0.8286	0.5598	1.1010	37.0	(25.8, 46.5)
Single vehicle wet	−7.7587	−0.3968	−0.0037	−0.1279	0.6380	0.8635	0.8695	0.6547	1.1688	32.8	(4.2, 52.8)
Single vehicle night	−7.7545	−0.3492	−0.0055	−0.0681	0.6964	0.9782	0.8996	0.7124	1.0685	29.5	(10.6, 44.3)
Single vehicle fatal plus injury	−5.3920	−0.5479	−0.0394	−0.0776	0.4844	0.9654	0.8644	0.7124	1.0939	42.2	(26.8, 54.3)
Single vehicle night fatal plus injury	−8.2466	−0.4504	−0.0455	−0.0524	0.5873	1.3439	0.9432	0.7124	1.0879	36.3	(9.9, 54.9)
Older driver	−10.7785	−0.2764	−0.0699	−0.0404	1.1225	0.1637	0.7074	0.6207	1.0552	24.1	(3.1, 40.7)
Fixed object	−6.4892	−0.3495	−0.0307	−0.0889	0.6433	0.4572	0.7786	0.6207	1.1105	29.5	(14.1, 42.1)

Notes: (1) Percent crash reduction estimates are obtained by $\{1 - \exp(\beta_{\text{edge}})\} \times 100$ where β_{edge} represents the estimated coefficient of the edge line width variable; (2) Statistically significant results at 95% confidence level are shown in bold; (3) C.I. stands for confidence intervals; (4) Nighttime fatal plus injury, Wet night, Single vehicle wet, Single vehicle night fatal plus injury, and Older driver were fitted by Poisson regression models because negative binomial regression models could not be fitted to those crashes due to insufficient data.

Table 8

Percent crash reduction estimates for wider edge lines on rural, two-lane highways based on the crash data from three states.

Crash type	Percent crash reduction			
	KS	MI (analysis 1)	MI (analysis 2)	IL (without animal collisions)
Total	17.5	27.4	19.4	30.1
Fatal plus injury	36.5	15.4	16.1	37.7
PDO	12.3	30.5	19.6	23.9
Day	28.6	20.3	12.0	29.1
Night	3.7	30.7	18.8	29.9
Daytime fatal plus injury	41.5	8.2	23.0	36.0
Nighttime fatal plus injury	12.7	22.6	−5.8	34.2
Wet	22.9	67.2	62.6	34.7
Wet night	24.3	76.9	79.2	35.7
Single vehicle	27.0	30.0	18.7	37.0
Single vehicle wet		73.8	65.9	32.8
Single vehicle night	18.4	29.4	18.0	29.5
Single vehicle fatal plus injury	36.8	10.0	−1.9	42.2
Single vehicle night fatal plus injury	18.7	9.7		36.3
Older driver				24.1
Fixed object	19.0			29.5

Note: Estimates in bold are significant at 95% confidence level.

Overall, the results in Table 8 support consistent safety effects of wider edge lines on the (relevant) crashes considered.

4. Discussion

This study provides detailed evidence to suggest that wider edge lines are effective in reducing crashes on rural, two lane highways, especially with regard to relevant target crashes such as single vehicle crashes and related disaggregate crashes (e.g., Single vehicle night, Single vehicle fatal plus injury). The safety effects of wider edge lines were consistently positive and statistically significant using data from three states. To the best of the authors' knowledge, this is the first study that utilizes extensive crash data from multiple states and advanced statistical methods to assess the safety effects of wider lines.

A possibility of confounding effects from other extraneous variables always exists in observational studies and can never be completely excluded. Although researchers tried to account for the effects of important measured variables such as AADT and other roadway characteristics in the data as well as general trends in crash counts to the extent possible, there are some limitations to the analysis. For example, AADT was used as a surrogate for nighttime traffic volumes because of the lack of such measurements. It would be more ideal to include nighttime traffic volumes for nighttime crash models. Also, as noted earlier, the Illinois crash data analysis are subject to the assumption that the effects of additional delineation/guidance measures and other fixed effects not in the data (other than RPMs and rumble strips) are the same (or averaged out) for the segments with and without wider edge lines.

Researchers made significant efforts in selecting relevant crashes for wider line safety evaluation, e.g., by selecting only non-intersection/interchange crashes and non-winter month crashes and excluding animal collisions (for the Illinois data). These efforts significantly reduced the data available for the analyses. The researchers also worked with data experts from the state agencies to develop protocols for making sure the same segment was being observed over the multiple years of the observation period. One strategy was to only include segments defined by the exact same linear referencing variables (e.g., beginning and ending milepost) and with no changes in any roadway features during the study period. This meant that the number of segments included in the analysis decreased as the number of data years increased. Although the amount of final data retained for this safety evaluation is still considerably larger than those used for previous studies assessing the effects of wider lines, there remains an issue of insufficient data

for analyzing some of disaggregate crash types, which led to statistically insignificant results for those crash types. Recall also that animal collisions were handled differently across the three datasets due to differences in crash coding as well as differences in the nature of the study designs (i.e., cross sectional versus before-after). A detailed discussion is provided in Section 3.4 of the paper.

Researchers conducted sensitivity analyses such as trying an alternative way (using the SPF for total crashes combined with the corresponding crash type ratio) of deriving SPFs for disaggregated crash types (KS), changing the study period from 2001–2007 to 2001–2009 (MI), or trying alternative methods of accounting for temporal correlations in the crash counts obtained from the same road segment (IL). The results stayed materially the same.

In conclusion, this study lends scientific support to the positive safety effects of wider edge lines installed on rural two-lane highways. Although the magnitudes of crash reductions were somewhat different from state to state, the results point in the same direction.

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References

- Bahar, G., Mollett, C., Persaud, B., Lyon, C., Smiley, A., Smahel, T., McGee, H. 2004. Safety Evaluation of Permanent Raised Pavement Markers. NCHRP Report 518, National Cooperative Highway Research Program, Transportation Research Board, Washington, D.C.
- Campbell, D.T., Ross, H.L., 1968. The connecticut crackdown on speeding: time-series data in quasi-experimental analysis. *Law and Society Review* 3, 33–54.
- Carlson, P.J., Miles, J. D., Pike, A.M., Park, E.S. Evaluation of Wet-Weather and Contrast Pavement Marking Applications: Final Report. Publication FHWA/TX-05/0-5008-2. Texas Transportation Institute, College Station, Texas, March 2007.
- COST 331, Requirements for Road Marking: State of the Art, 1999. European Cooperation in the Field of Scientific and Technical Research. European Commission Directorate-General for Transport, May.
- Cottrell, B.H., 1987. Evaluation of wide edge lines on two-lane rural roads. Publication FHWA-VA-85-37. Virginia Highway and Transportation Research Council. Virginia Department of Transportation, Richmond, Virginia.

- Cottrell, B.H., 1988. Evaluation of wide edge lines on two-lane rural roads. *Transportation Research Record* 1160, 35–44.
- Evans, L., 1985. Human Behavior feedback and traffic safety, human factors. *The Journal of the Human Factors and Ergonomics Society* 27 (October (5)), 555–576.
- Friedman, L.S., Hedeker, D., Richter, E.D., 2009. Long-term effects of repealing the national maximum speed limit in the United States. *American Journal of Public Health* 99, 1626–1631.
- Gates, T.J., Hawkins, H.G., 2002. The Use of Wider Longitudinal Pavement Markings. Texas Transportation Institute Report 0024-1. College Station, TX.
- Gibbons, R.B., 2006. Pavement Marking Visibility Requirements during Wet Night Conditions. Report VTRC-07-CR7. Virginia Transportation Research Council, Charlottesville, Virginia, November.
- Gillings, D., Makuc, D., Siegel, E., 1981. Analysis of interrupted time series mortality trends: an example to evaluate regionalized perinatal care. *American Journal of Public Health* 71, 38–46.
- Grundy, C., Steinbach, R., Edwards, P., Green, J., Armstrong, B., Wilkinson, P., 2009. Effects of 20 mph traffic speed zones on road injuries in London, 1986–2006: controlled interrupted time series analysis. *BMJ* 339 (December (10)), b4469.
- Hall, J.W., 1987. Evaluation of wide edge lines. in transportation research record. *Journal of the Transportation Research Board* (1114), 21–27.
- Hauer, E., 1997. *Observational Before-After Studies in Road Safety: Estimating the Effect of Highway and Traffic Engineering Measures on Road Safety*. Pergamon Press, Elsevier Science, Ltd., Oxford, United Kingdom.
- Lord, D., Mannering, F., 2010. The statistical analysis of crash-frequency data: a review and assessment of methodological alternatives. *Accident Analysis and Prevention* 44, 291–305.
2009. Manual on Uniform Traffic Control Devices. US, DOT, FHWA, Washington, DC.
- Obeng-Boampong, K., Miles, J., Pike, A., Carlson, P. Use of wider pavement markings – survey of state transportation agencies. Paper No. 09-1113, Submitted to TRB's 88th Annual Meeting, Washington, D.C., January 2009.
- Ohme, P.J., 2001. Enhancing nighttime pavement marking visibility for older drivers. Master's Thesis. Department of Industrial Engineering, University of Iowa, Iowa City, Iowa.
- Transportation Research Board, 2009. Theory, explanation and prediction in road safety: identification of promising directions and a plan for advancement. Workshop Circular. Task Force for the Development of a Highway Safety Manual, Transportation Research Board, Washington DC. <http://tcd.tamu.edu/FDsub/Safety_Workshop_Circular_3_.pdf> (accessed 20.06.11).
- Persaud, B., Lyon, C., 2007. Empirical Bayes before-after safety studies: lessons learned from two decades of experience and future directions. *Accident Analysis and Prevention* 39, 546–555.
- Wagner, A.K., Soumerai, S.B., Zhang, F., Ross-Degnan, D., 2002. Segmented regression analysis of interrupted time series studies in medication use research. *Journal of Clinical Pharmacy and Therapeutics* 27, 299–309.
- Ward, A.M., 1985. *Sighting Safety* In Proceedings of the conference Effectiveness of Highway Safety Improvements, American Society of Civil Engineers, New York, NY.
- Zwahlen, H.T., Schnell, T., 1995. Visibility of new pavement markings at night under low-beam illumination. In: *Transportation Research Record: Journal of the Transportation Research Board*, No. 1495. Transportation Research Board of the National Academies, Washington, DC, pp. 117–127.