# Estimating the Safety Effects of Raising Speed Limits on Rural Freeways in Ohio

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## Abstract

The impacts of raising speed limits on traffic safety is an area that has generated much research, although a strong consensus has not emerged on the relationship between speed and safety. The Ohio legislature raised speed limits from 65 mi/h to 70 mi/h on 570 miles of rural freeways in Ohio on July 1, 2013 and an additional 398 miles of rural freeways starting on September 29, 2013. The primary goal of the current study was to investigate the safety impacts of this new speed limit using available crash, roadway, and traffic characteristics data. Statewide crash data from January 1, 2010 to December 31, 2015 were obtained from the Highway Safety Information System (HSIS). The study utilized the empirical Bayes (EB) before-after study in the evaluation of the safety effectiveness of the raised speed limit. The intent of the before-after study was to estimate the performance (in terms of crash frequency and severity levels) following the speed limit increase and what the safety performance would have been if there was no increase in speed limit. Safety performance functions (SPFs) were developed for both total crashes and fatal and injury (FI) crashes combined using the negative binomial regression and the SPFs were used to predict the average crash frequency of each of the segments in the observed period. The EB analysis showed that total crashes went down by 24.6% and FI crashes went down by 8.8% for the two years after the speed limit was changed. Therefore, caution should be taken in drawing conclusion from this study because the after period did not meet the minimum of three years recommended by the HSM since the data available for the after period were only for two years. We have received additional 2 years of data and the updated analysis is ongoing.

Keywords: Speed limit, Empirical Bayes, Before-after study, Negative binomial, Crash frequency, Crash severity.

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## 1. Introduction

Historically, speed limit has been used for several purposes such as to conserve fuel, to reduce noise and to promote road safety [1].The increase in the cost of fuel due to oil embargo in the early 1970s caused many states to adopt a lower speed limit with the goal of saving fuel and resources. On January 2, 1974, President Richard M. Nixon signed the Emergency Highway Energy Conservation Act, setting a new National Maximum Speed Limit (NMSL) of 55 mi/h with the expectation of saving $2 million annually in fuel consumption [2]. Most studies [2,3] reported that the actual savings was way less than the estimated amount, which instead attributed to fewer fatalities.

However, drivers became less compliant of the lowered speed limit, which made the implementation of the NMSL on interstates more difficult. The NMSL law was amended in 1987 and then 1988 to allow speed limits up to 65 mi/h on some limited-access rural highways [4]. Eventually, the Congress repealed the NMSL law in 1995 and returned the speed limit-setting authority to the individual states as it was before the oil crisis that brought up the NMSL law [4]. Following the repeal of the 55-mi/h national speed limit policy, several studies were conducted to examine the relationship between speed limits and the frequency and severity of traffic crashes [5]. For example, Greenstone [6] tracked the fatality rates in all 50 states from 1982 to 1990. He concluded that fatality rose by 30% on rural interstate.

Since the repeal of the NMSL, states and local agencies have been making changes to speed limits without a thorough review and understanding of the impact of the changes on road safety [7]. Studies on the effects of speed limit changes have produced conflicting results. Some studies have found higher speed limits to be associated with more traffic crashes and fatalities while others suggest that the source of crashes is not speeding per se, but the variances in the speeds selected by drivers [8,9]. However, despite these findings, at least 14 states have increased speed limits from 65 mi/h to 70 mi/h or more on rural freeways since early 2012 [5]. Over the same time period, four states have increased speed limits on undivided rural highways while additional states have considered, or are considering, increases on various road types [5].

According to the Federal Highway Administration (FHWA) [10], in 2018, about 72% of traffic-related fatalities in rural areas occurred on roads with speed limits of 55 mi/h or higher compared with 30% of fatalities on urban roads with similar speed limits. Similarly, in 2018, in terms of the rate of fatalities per 100 million miles traveled (VMT), it was estimated to be two times higher in rural areas (1.68) than in urban areas (0.86) [10]. Whenever speed limits are raised, the primary concern is always about safety [11]. Traffic speed plays a significant role in roadway safety. The risk of being involved in a crash, as well as the severity of the outcome, could be increased dramatically by the increasing speed of the moving vehicle [12]. Traveling at higher speeds results in longer stopping distances, as well as less maneuverability, and requires more prompt reaction to a certain incident or change in the roadway [13].

After the increase of the speed limit up to 65 mi/h in 1987, the National Highway Traffic Safety Administration (NHTSA) was directed to assess the impact of the increased speed limits on safety. From the yearly fatality data, they concluded that the increase in rural interstate fatalities was 16% higher in 1987 than would have been expected had the speed limits not been increased [14]. Other numerous studies have found significant increases in fatality rates on high-speed roads following the 1987 NMSL relaxation from 55 to 65 mi/h speed limits on rural interstates. By using aggregate data, fatality rate increases in the range of 30% to 57% were reported [7].

Farmer et al. [15] compared the number of fatalities across 12 states that increased the posted speed limit to 70 mi/h in 1996 using data from 1990 to 1995. Rural and urban interstates as well as other freeways were included in this study. States with a higher posted speed limits were associated with a 12% increase in the number of fatalities on interstates and freeways. However, on other types of roadways, this increase was only 3%, while the overall increase on all types of roadways was 6%.

Patterson et al. [16] reported that fatalities in the groups of states that raised their speed limits to 75 mi/h and 70 mi/h were 38% and 35%, respectively, higher than expected compared to fatalities in the states that did not change their speed limits. A study by Kockelman et al. [17] investigated the safety impacts of raising the speed limit from 55 to 65 mi/h. Their study's model predicted that crash rates would increase by 3% and the probability of a vehicle's occupant being fatally injured would increase by 24% when the speed limits were to be increased from 55 to 65 mi/h.

Responding to the nationwide ongoing trend of raising speed limits and the desire of the Ohio Turnpike Commission to raise the speed limit on the Ohio Turnpike to 70 mi/h, the Ohio legislature raised speed limits on rural interstates. That led to the implementation of the 70-mi/h speed limit on 570 miles of rural freeways in Ohio on July 1, 2013 and an additional 398 miles of rural freeways starting on September 29, 2013. Over the years, several research efforts have been conducted attempting to analyze the safety impact of speed limit increases in various states. Due to the availability of data and the time frame since the speed limit increase to Ohio's rural interstates was implemented, it seems natural to investigate the effects of these new speed limits on rural freeways and the long term effect of the increase, which was the motivation behind this study. Table 1 shows the summary of total crash and fatalities in Ohio from 2010-2018. The data reveal that the annual average number of traffic fatalities had increased by 4% between the before (2010-2013) and the after (2014-2018) speed limits increase to rural interstates periods. The growth in the annual average number of total crashes, total fatalities, and vehicle miles traveled (VMT) between the two periods are very comparable. However, the average annual number of speed related fatalities had decreased by 22% over the same periods as shown in Table 2.

**Table 1: Summary of Total Crash and Fatalities in Ohio from 2010-2018**

| Year | Total Crashes | Total Fatalities | VMT |
|---|---|---|---|
| 2010 | 300,164 | 1080 | 185,170,812 |
| 2011 | 297,831 | 1016 | 183,331,993 |
| 2012 | 287,050 | 1122 | 186,002,877 |
| 2013 | 269,079 | 990 | 185,307,544 |
| Average (2010-13) | 288,531 | 1052 | 184,953,307 |
| 2014 | 282,368 | 1008 | 185,874,881 |
| 2015 | 302,307 | 1110 | 186,726,498 |
| 2016 | 305,966 | 1133 | 193,351,904 |
| 2017 | 303,298 | 1179 | 197,124,474 |
| 2018 | 297,826 | 1068 | 197,117,219 |
| Average (2014-18) | 298,353 | 1099.6 | 192,038,995 |
| Growth | 3% | 4% | 4% |

**Table 2: Summary of Speed Related Fatalities in Ohio from 2010-2018**

| Year | Speed-Related Fatalities | Average |
|---|---|---|
| 2010 | 321 | 311.8 |
| 2011 | 299 | |
| 2012 | 354 | |
| 2013 | 273 | |
| 2014 | 274 | 256.2 |
| 2015 | 207 | |
| 2016 | 257 | |
| 2017 | 253 | |
| 2018 | 290 | |
| Growth | | -22% |

The primary objective of the current study was to analyze the safety impact of raising the speed limit from 65 mi/h to 70 mi/h on rural freeways in Ohio. This research attempts to understand if there is a significant relationship between the increased posted speed limits and crash frequency on those rural freeways whose speed limits were increased in 2013. The impacts of raising speed limits on traffic safety is an area that has generated much research, although a strong consensus has not emerged on the relationship between posted speed limit and safety.

The simplest element of the speed/safety relationship that can be isolated is the concept of dissipation of kinetic energy resulting from a crash [18]. Energy is calculated using the vehicle mass, a constant and the speed of the vehicle, a variable under the control of the driver [19]. Crash severity increases with increasing vehicle speed, because in a collision, the amount of kinetic energy dissipated is proportional to the square of the velocity, therefore, speed is directly related to injury severity in a crash [20]. From the aspect of road safety theories, higher speed increases the drivers overall required stopping distance, which in turn may increase the probability of a crash occurrence. On the other hand, drivers at a higher speed may be more cautious and a crash risk on highways where speeds are higher is lower due to various reasons such as higher construction standards and better traffic information provided [21].

Many studies have related high speed to the increasing number of crashes. Nilsson [22] developed a power model with the aim of modeling the relationship between the number of people injured in a crash and speed as well as the number of people fatally injured in a crash and speed. This model incorporated the concept of kinetic energy because an increase in the amount of kinetic energy has an association with an increased risk of being in a crash, as well as a change in the outcomes of such crashes. Similarly, Elvik et al. [23] also using the power model undertook an extensive evaluation of the effect of speed on crashes. They concluded that there is a causal relationship between changes in speed and changes in traffic crashes, i.e., the number of crashes will go down if speed goes down and vice versa. It seems intuitively obvious that the higher the average speed, the more likely a crash is to occur and the more severe the consequences are likely to be when it does occur.

A study by Pei et al. [24] evaluated the relationship between speed and crash severity using a full Bayesian method and they concluded that speed is positively associated with the injury severity. According to the research conducted by Nouvier and France [25] showed that a reduction in driving speed of 5% leads to a reduction in fatalities of approximately 20%.. Aarts et al. [13] provided a thorough list of studies that were conducted to investigate the relationship between crash risks and speed. They concluded that crash rates increased exponentially for individual vehicles that increased their speeds.

Some other studies after careful examination of the role of speed on crashes they reveal a dfferent picture. A study by Lave [8] found that the fatality rate was strongly associated with speed variance rather than the average speed, thus it was argued that speed variance caused safety problems instead of speed itself. Likewise, a study by Zlatoper [9] concluded that it is the dispersion of vehicle speeds (i.e. speed variance rather than speed itself) that affects the crash frequency. A study by Garber and Gadiraju [26] also showed that roads with larger speed variance (that is, larger speed differentials between drivers) exhibited higher crash rates than roads with lower variance. Lee et al. [27] using real time traffic data also concluded that as the variation of speed along the section and the variation of speed difference across lanes increase, crashes are more likely to occur. These results reflect the fact that as the variation of speed increases, drivers have to adjust their speeds more frequently and they are more likely to make a misjudgment in keeping a safe separating distance from other vehicles after controlling for road geometry, weather, and time of day.

However, a very illustrative analysis was undertaken by Snyder [28], he differentiated the variation in driving speed (slow drivers and fast drivers) to indicate whether the faster vehicles, the slower vehicles, or both accounted for the increase in fatalities The results obtained were consistent with conventional wisdom that average traffic speed is an important determinant of highway fatalities. His study further suggested that speed variance is important for the fastest vehicles only: slow vehicles do not have a statistically detectable influence on fatality rates. The whole situation might be summed up as follows: the faster you drive relatively or absolutely, the more likely you are to get involved in a crash or get injured/killed. It seems reasonably safe to assume that the average speed of vehicles would significantly increase fatality rates. This conforms to the other findings observed by others, e.g. [29,30].

Speed and safety issues are so interconnected that sometimes it is difficult to distinguish whether a specific factor affects safety or speed. Most often, it influences both. These factors include environmental conditions, driver behaviors, and posted speed limits [31]. There are numerous strategies for managing speeds however, most of them are focused primarily on regulating speed through speed limits [25]. They are established on the basis for the enforcement of legislation against unreasonably high travel speeds [32]. A maximum speed limit is posted or set by statute on a highway to inform motorists of the highest speed considered to be safe and reasonable under favorable road, traffic, and weather conditions [20]. Since the introduction of maximum speed limits, there has been significant debate as to how speed limits are most appropriately determined for specific locations [5]. The most common approach sets the limit on the basis of an engineering study, which takes into consideration such factors as operating speeds of free-flowing vehicles, traffic crash history, traffic volume, number and types of intersecting roads, streets and other access points, roadside development and roadway geometry to make a judgment about the speed at which the limit should be set [33].

The American Association of State Highway and Transportation Officials (AASHTO) noted that driving speeds are affected by the speed limit, the physical characteristics of the road, weather, and the presence of other vehicles [34]. This suggests that the choice of speed by drivers are not only always based on the posted speed limits of the roadways. Similar conclusion by Garber and Gadiraju [26] in their findings tell us that drivers tend to drive at increasing speeds as the roadway geometric characteristics improve, regardless of the posted speed limit. Kockelman et al. [17] also make it clear that the average speed and the speed variability are more influenced by roadway geometry and cross-sectional characteristics as compared to posted speed limits. However, road users generally favor higher posted speed limits due to the resulting increases in travel speeds and associated reductions in travel times [5].

NHTSA [35] examined the changes in fatalities that occurred on rural Interstates on which the posted speed limit was increased to 65 mph. Of the 44,529 fatalities in 1990, slightly more than 5% occurred on rural Interstates with a speed limit of 65 mph. Compared with 1989, nationwide rural Interstate fatalities in 1990 declined about 2%, an amount equal to the change experienced in total motor vehicle crash fatalities. A similar study was carried out by Wagenaar et al. [36] in the state of Michigan to assess the safety impact of the speed limit that was raised to 65 mi/h on rural limited access highways. Results revealed a significant increase in casualties on roads where the speed limit was raised, including a 19.2% increase in fatalities, a 39.8% increase in serious injuries, and a 25.4% increase in moderate injuries. Another study found that the fatal crash rate on rural interstates in the state of Washington rose 110% more than would have been expected had the 55-mi/h speed limit had been maintained. Although the fatal crash rate did increase, it was noted that the total crash rate showed a negative change, indicating that only fatal crashes were on the rise [37].

An additional argument against higher maximum speed limits is the "speed spillover" hypothesis that contends that higher speed limits on rural interstates pose additional hazards for other roadway types [38,39]. In contrast to other studies in the literature, a before and after analysis was conducted in Ohio using 36 months of data before and after the implementation of the 65 mph speed limit in the state [40].Their study found that fatal crash rates on rural Interstate highways posted at 65 mph or rural non-Interstate highways posted at 55 mph did not significantly change after the implementation of the 65-mph speed limit although there were some increases in injury and property damage only (PDO) crash rates on rural Interstate highways posted at 65 mph. Similar findings from Smith [41] and Brown et al. [42] also support this above claim. However, Lave and Elias [43] argued that higher speed limits had saved lives and determined that the raised speed limits on interstates reduced overall statewide fatality rates by 3.4%. A significant amount of other studies have contributed to this debate of traffic safety not been compromised by raised speed limit [44]. Between April 2011 and January 2014, at least 14 states had either increased maximum speed limits or were proposing to do so, with most of these increases involving rural freeways [45].

## 2. Methodology

### 2.1 Data Collection

Ohio road data files from 2010 to 2015 and crash data from the same years were obtained from the Highway Safety Information System (HSIS). The 3 years of data prior to the speed limit increase and 2 years after the change were available. We would have wanted to have at least 3 years for the after period, but currently as this study was in progress, HSIS did not yet have 2016 or newer data. The datasets contained references (mileposts), which helped to identify specific crashes to the exact road locations.

Traffic crash data from January 1, 2010 to December 31, 2015 was obtained from the Highway Safety Information System (HSIS). The dataset is composed of 36 months before and 24 months after speed limit changes were implemented and were used to assess the impact of the increased speed limits. The road data had several variables but only a few of them were needed for the current study, this includes the segment location and length, median width, median type, number of lanes, and traffic volumes. The crash data needed include crash year and crash severity. Table 3 shows the summary statistics of the variables used in the models.

**Table 3 Summary Statistics for the Variables Used in the Models**

| Variables | N | Levels | Min | Max | Mean | Standard Deviation |
|---|---|---|---|---|---|---|
| Number of lanes | 2,395 | 2 | | | | |
| Segment length (mi) | 2,395 | N/A | 0.010 | 10.040 | 1.4036 | 1.6034 |
| FI Crashes | 2,394 | N/A | 0 | 48 | 2.4327 | 3.374 |
| Total Crashes | 2,395 | N/A | 0 | 153 | 12.316 | 15.12 |
| AADT | 2,395 | N/A | 4,870 | 75,040 | 35,884 | 10,830 |
| Median Type | 2,395 | 2 | | | | |
| Median Width (ft) | 2,395 | N/A | 3.0 | 99.0 | 50.8 | 25.14 |

## 2.2 Statistical Method

### 2.2.1 Development of Safety Performance Functions (SPFs)

In this study, SPFs were developed using the data available for the before speed limit increase period to estimate the average annual frequency of crashes that occurred on the roadways. SPFs are regression models for estimating the predictive average crash frequency of individual roadway segments. The regression equations relate average crash frequency for the selected year at a segment with one or more traffic and/or geometric related independent variables. According to the Highway Safety Manual (HSM), they are developed through statistical multiple regression techniques using historical data collected over several years at a given site [46].

Count data are properly modelled with a number of methods, the most popular regression methods used for the development of SPFs are the negative binomial (NB) and Poisson distributions, however, the mean and the variance of the Poisson distribution are expected to be equal, which is not often the case for crash frequencies where the variance typically exceeds the mean [47]. To this end, the negative binomial distribution presents a more appropriate modeling framework because it incorporates an additional statistical parameter, the overdispersion parameter, which is estimated along with the parameters of the regression equation. The overdispersion parameter has positive values [46]. The greater the overdispersion parameter the more that crash data vary. The overdispersion parameter is used to determine a weighted adjustment factor for the use in empirical Bayes (EB) method, which is discussed later in this section.

The HSM [46] outlines at least three different ways in which SPFs can be used by jurisdictions to make better safety decisions. One application is to use SPFs to determine the safety impacts of design changes at the project level. The second application is to use SPFs as part of network screening to identify sections that may have the best potential for improvements. The third application is the use of SPFs as part of an EB before-after study to evaluate the safety effectiveness of engineering treatments (such as speed change), which was the method used in this current study.

JMP Pro 14.1 software was used to explore the data and perform the statistical analyses. ArcGIS was used to to determine the exact locations where crashes occurred on selected freeways. The Generalized Regression Personality in JMP Pro is useful for many modeling situations. This personality enables you to specify a variety of distributions for your response variable, it is used when your response is continuous, binomial, a count, or zero-inflated. The distributions fit includes normal, Cauchy, exponential, gamma, Weibull, lognormal, etc. This flexibility enables you to fit categorical and count responses, as well as continuous responses, which our data had.

Akaike's Information Criterion (AIC) was used to determine the best fit model. AIC is a single number score that can be used to determine which of multiple models is most likely to be the best model for a given dataset. It estimates models relatively, meaning that AIC scores are only useful in comparison with other AIC scores for the same dataset. AIC works by evaluating the model's fit on the training data and adding a penalty term for the complexity of the model. The desired result is to find the lowest possible AIC, which indicates the best balance of model fit with generalizability. A lower AIC score is better.

The pruned forward selection algorithm in JMP Pro, which is a systematic method of selecting regressors was used in this study for the negative binomial regression model by computing parameter estimates using a mixture of forward and backward steps. The algorithm starts with an intercept-only model. At the first step, the effect with the most significant score test is added to the model. After the first step, the algorithm considers the following two possibilities at each step:

1. From the effects not in the model, add the effect that has the most significant score test.
2. From the effects in the model, remove the effect that has the least significant Wald test.

To choose the action taken at each step, the algorithm uses the specified validation method. For example, if the validation method is AIC, the algorithm chooses the action that results in the smallest AIC value. When there are interactions and the effect heredity option is enabled, compound effects are considered for adding effects, but they are not considered for removing effects. When the model becomes saturated, the algorithm attempts a backward step to check if that improves the model. The maximum number of steps in the algorithm is 5 times the number of parameters. The model chosen is the one that provides the best solution relative to the selected validation method.

### 2.2.2 Empirical Bayes (EB) Before-After Study

The intent of the EB method was to estimate the expected number of crashes that would have occurred had there been no speed limit change and then compare that with the number of observed crashes after posted speed limit change occurred. The EB before-after study is a reliable method because it accounts for the potential bias due to regression-to-the-mean (RTM). The treatment safety effectiveness was computed for each crash severity level, which is the final step used to determine how the posted speed limit change has affected the safety performance.

Thus, the empirical Bayes method combines the estimates of the predictive model (SPF) and the observed crash frequencies to obtain a more reliable estimate of expected average crash frequency [46]. Detailed procedure of EB before-after study is outlined in the Highway Safety Manual (HSM) [46].

## 3. Analysis and Results

### 3.1 Results of the Development of the Safety Performance Functions (SPFs)

In this study, five independent variables were selected based on the requirements laid down by the HSM for the development of an SPF. These explanatory variables including their interactions were investigated to identify their impact on crash frequency and significant variables were selected statistically by using the pruned forward algorithm in JMP Pro software package. Two separate models were developed: (i) total crashes, (ii) fatal and all injuries combined (FI).

Table 4 shows only variables that were either significant or their interaction terms were significant at $\alpha = 0.05$. Non-significant variables were removed and thus do not show up in Table 4. For the total crash model, there was a significant interaction between the segment length and AADT, which indicates that the relationship between segment length and total crashes depends on the value of AADT and vice versa. Also, the interaction between the median width and number of lanes was significant. Although median width was not significant, it was left in the model due to its significant interaction with the number of lanes.

**Table 4 Results of Parameter Estimates for Total Crashes Model**

| Parameter | Estimate | Standard Error | P value |
|---|---|---|---|
| Intercept | -3.3078 | 0.6156 | <.0001 |
| Ln (AADT) | 0.46 | 0.0575 | <.0001 |
| Number of lanes | -0.2671 | 0.0798 | <.0001 |
| Segment length | 0.51075 | 0.0136 | <.0001 |
| Median width | 0.0029 | 0.002 | 0.1485 |
| Number of lanes* Median width | -00079 | 0.0023 | 0.0006 |
| Segment length* Ln (AADT) | 0.2001 | 0.0345 | <.0001 |
| -Loglikehood | 4412.42 | | |
| AIC | 8840 | | |
| Generalized $R^2$ | 0.655 | | |

The results from the FI crash model are shown in Table 5. The AADT, segment length, and median width were significant at $\alpha = 0.05$. Number of lanes and median type were not significant in the models. The segment length and natural log of AADT had a significant interaction, which means we cannot know the effect of one variable on the FI crashes without knowing the value of the other variable. The final model results for both (total and FI crashes) indicate that variables with positive coefficients will bring about an increase in crashes when these variables are increased and on the other hand variables with negative coefficients means that the crashes are fewer as these variables are increased.

**Table 5 Results of Parameter Estimates for FI Crashes Model**

| Parameter | Estimate | Standard Error | P value |
|---|---|---|---|
| Intercept | -6.5910 | 0.8911 | <.0001 |
| Ln (AADT) | 0.639 | 0.0836 | <.0001 |
| Segment length | 0.4458 | 0.4458 | <.0001 |
| Median width | -0.0037 | -0.0009 | <.0001 |
| Segment length* Ln (AADT) | 0.1638 | 0.0378 | <.0001 |
| -Loglikehood | 2536.8 | | |
| AIC | 5085.7 | | |
| Generalized $R^2$ | 0.446 | | |

Thus, the SPF models generated were used to predict the number of crashes (or crash frequency) that would have occurred if the speed limits were not raised in the after period. These SPFs were utilized in the EB method of before-after study to come up with a conclusion on the effect of posted speed limit changes on rural freeways in Ohio that was applied in 2013.

## 3.2 Results of the Empirical Bayes Before-After Safety Effectiveness Evaluation Analysis

The EB calculation procedure was carried out in an Excel spreadsheet, which consisted of 14 steps of the HSM procedure. Two Excel spreadsheets were developed to implement EB before-after analyses for (1) total crashes and (2) fatal and injury (FI) crashes. Each site/segment was included with their appropriate segment lengths, AADTs and observed crashes for each year (before period: 2010-2012 and after period: 2014-2015). The SPF formula developed from the analysis discussed above was used to compute the predicted average crash frequency for each segment and year (this gave us the predicted number of crashes that would have occurred on each of these segments if the posted speed limit was not raised). Table 6 summrizes the EB before-after safety effectiveness evaluation analysis.

**Table 6 The Before and After Empirical Bayes Estimation Results**

| Parameters | Total Crashes | FI Crashes |
|---|---|---|
| Overall Unbiased Estimate of Treatment (OR) | 0.754 | 0. 912 |
| Safety Effectiveness | 24.6% | 8.8% |
| Variance of Overall Unbiased Effectiveness Var (OR) | 0.000 | 0.001 |
| Standard Error of the Variance SE(OR) | 0.015 | 0.031 |
| SE (Safety Effectiveness) | 1.5% | 3.1% |
| Abs [Safety Effectiveness/SE (Safety Effectiveness)] | 15.93 | 2.85 |
| Statistical Significance Confidence Level | 95% | 95% |
| CMF | 0.754 | 0.921 |
| SE(CMF) | 0.015 | 0.031 |

## 4. Discussion

The evaluation results in Table 6 show that raising posted speed limits on the segments analyzed in this study, the safety effectiveness of total crashes was 24.6%, while the safety effectiveness of speed change for fatal and injury crashes was 8.8 These results show evidence that the increase of posted speed limit from 65 mi/h to 70 mi/h in July and September of 2013 reduced the crash frequency on the rural freeways in Ohio. These results are statistically significant at the 95% confidence level. The reduction seems to be more effective to property damage only (PDO) crashes, which generally make the largest portion of total crashes as the reduction in fatal and injury crashes was lower.

Specifically, the EB analysis resukts show that generally total crashes went down by 24.6% in the period after posted speed limits were raised compared to the period before posted speed limits were raised and injury and fatal crashes went down by 8.8% during the two years (2014-2015) after the posted speed limits change was implemented. However, these results should be interpreted with caution because the after period did not meet the minimum of 3 years recommended by the HSM. In the current study, only 2 years of the after period were available. However, we recently received additional 2 years of data (2016 and 2017) and thus we are currently updating our dataset and efforts are underway to obtain additional data from HSIS and ODOT that are more recent for updating the analysis.

## 5. Conclusions

The findings in this study were based on data collected from reported traffic crashes that occurred on selected rural freeways from January 2010 to December 2015. The impacts of the raised posted speed limits on rural freeways in Ohio are based on the safety effectiveness percentages computed by the empirical Bayes (EB) before-after study method using the Highway Safety Manual (HSM) procedures. The empirical Bayes before-after study was used to analyze the safety impact associated with the anticipated increase of speeds on rural freeways due to raised posted speed limits in Ohio. The following are the findings from the Ohio safety effectiveness results: (1) Safety effectiveness for total crashes is 24.6%, which translates into a CMF of 0.754, and (2) safety effectiveness for fatal and injury crashes combined is 8.8%, which leads into a CMF of 0.912.

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