Safety Analysis of Changed Speed Limits on Rural Highways in British Columbia

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E-1 Introduction

In the fall of 2013, the British Columbia Ministry of Transportation and Infrastructure (MoTI) initiated a safety and speed review on approximately 9,100 km of stretches of provincial rural highways. A technical team conducted over 300 speed surveys with measurement of the 85th percentile operating speed, a measure used by many jurisdictions for establishing speed limits. It was found that the 85th percentile speed on these highways was upwards of 10 km/h higher than corresponding posted speed limits. It was also noticed that serious crashes were trending down significantly since 2003. These observations led to consideration of speed limit increases, and, after a public consultation was conducted, approximately 1,300 km of highway segments were recommended for higher speed limits.

The increased speed limits were implemented in the second-half of 2014. Rural divided highways had a maximum posted speed limit increase to 120 km/h and rural undivided highways to 100 km/h with some 4-lane sections up to 110 km/h.

As speed plays an important role in road safety, and traffic operations is enhanced when appropriate speed limits are set, the main objective of this project was to estimate the safety effects of the changed speed limits on rural highways after the first year of implantation, with particular focus on the most severe crashes (fatal plus injury).

E-2 Overview of Before-After Evaluations

The study design used to estimate the safety effects of the changed speed limits is a time-series analysis, which is often referred to as a before-after (BA) analysis. This approach attempts to measure the change in safety over time due to the implementation of a safety initiative. For BA analyses, Bayesian methods are commonly used within an odds-ratio (OR) analysis for their ability to: a) ensure that a noted change in the safety performance is caused by the safety initiative and not by other "confounding" factors or causes external to the initiative, b) treat unknown parameters such as predicted crash frequency as random variables having their own probability distributions.

Examples of Bayesian evaluation techniques include the empirical Bayes (EB) and full Bayes (FB) method, which are commonly used in traffic safety analyses. The FB approach was employed for this evaluation as it offers several methodological and data advantages. In terms of methodological advantages, the FB approach has the ability to account for most uncertainty in the data, to provide more detailed inference, and to allow inference at more than one level for hierarchical models, among others. In terms of data requirements, the FB approach efficiently integrates the estimation of the crash prediction model (CPM) and treatment effects in a single step thereby negating the need for a reference group data and reducing the data requirements.

A FB technique with advanced CPMs (i.e., non-linear intervention functions) was used for this evaluation.

E-3 Data Evaluation

This task was carried out through the use of crash and traffic records made available by MoTI. The sites (highway segments) with increased speed limits were reviewed in detail to create a subset of homogeneous locations. A total of 60 treatment segments were used for this analysis. Furthermore, the selection of comparison sites was a key step to control for potential confounding factors that may affect the accuracy of the evaluation. The number of available comparison sites was equal to 95 segments.

Crash data was available for all treated and comparison sites for approximately 3.8 years, from January 2012 to October 2015. As the new speed limits were implemented in mid-2014, a time period (time unit) of four months was selected in order to obtain a wider range of post-treatment time frames (i.e., 4 periods of 4 months in total). Therefore, the before period ran from March 2012 to June 2014 (i.e., 7 periods of 4 months) and the after period from July 2014 to October 2015 (i.e., 4 periods of 4 months), with July-October 2014 as a transition period. Fatal-plus-injury (F+I) crash records were used to estimate the effect of increased speed limits. After a thorough review, property-damage-only crash records were found to be incomplete and were not used in the analysis. Finally, traffic volume information was obtained from existing records.

E-4 Results

As mentioned before, a FB technique with advanced non-linear intervention function was applied to estimate the resulting crash frequency change. Overall, the results showed that the sections of roadway where new speed limits were imposed, experienced an increase in the number of severe (fatal and injuries) crashes of 11.1%, following the implementation of speed limit increases (see Table E-4.1). This increase was found statistically significant at the 95% confidence level (CL).

Table E-4.1 Change from the before to the after period for F+I crashes

Odds Ratio	5% CL	95% CL	Change*
1.11±0.070	1.002	1.228	+11.1%

* Positive sign means increase of crashes

It should also be noted that although the FB technique can produce crash change estimations by site, the individual site results were not provided in this report for the following reasons:

- the after study period in this study was relatively short (i.e., approximately 1.3 years only); this caused the individual site results to be less reliable and not statistically significant;
- as the FB technique matches treatment sites with appropriate comparison sites, the results for individual locations will become sensitive to the safety performance of the smaller matched comparison group with short after period.

E-5 Comparison to Similar Studies Worldwide

Many studies conducted worldwide have investigated the relationship between speed and safety showing the important role of speed management. Generally, the results indicate that the higher the travel speed, the greater the probability of crashes and the higher severity of the crashes. Similar to the model form used in this study, a number of meta-analysis studies revealed that the relationship between speed and accidents is best represented by a power model:

$$\textit{Accident Ratio} = (\textit{Mean Speed Ratio})^{\textit{Power}}$$

where the "Accident Ratio" is the ratio between accident frequency after and before the speed change; and the "Mean Speed Ratio" is the ratio between the means of driving speeds (after to before). A study by Elvik in 2009 concluded the power parameter to have values of 4.1, 2.6, 1.1 and 1.5 for fatal, serious injury, slight injury and PDO crashes, respectively, on rural roads. Using an average exponent value from Elvik, the fatal and injury crash increase reported in this study (11.1%) can be obtained from about 3 km/h increase in the mean operating speed for a segment with initial mean speed of 90 km/h.

A case study from Hong Kong evaluated the increase of speed limits that occurred from 1999 to 2002 on major roadways from 50 to 70 km/h and 70km/h to 80 km/h for other highways. Overall, the relaxation of the speed limit from 50 to 70 km/h caused an increase of 15% for fatal-plus-injury crashes. The relaxation of speed limits from 70 to 80 km/h was found to increase fatal-plus-injury crashes by 18% and fatal plus serious-injury only crashes by 36%. It should be noted that although this study was carried out in an urban environment, the comparison may be relevant for the stretches of highways with higher speed limits.

In North America, a before-after study accounting for confounding factors was conducted on the increase of the speed limits on several Utah highways (urban, rural and high-speed highway segments). Overall, the results showed a significant increase in both total crash rates on urban interstate segments, and fatal crash rates on high-speed rural non-interstate segments. However, total, fatality, and injury crash rates on rural interstate segments; fatality and injury crash rates on urban interstate segments; and total and injury crash rates on high-speed non-interstate segments were substantially unchanged.

Farmer *et al.* in 1999 investigated the trends in fatalities over 8 years for 24 states that raised interstate speed limits and 7 states that did not. The study revealed an increase of 15% in motor vehicle occupant deaths for the 24 states that raised speed limits. After accounting for changes in vehicle miles of travel, fatality rates were 17% higher following the speed limit increases. Another US study (Shafi and Gentilello, 2007) reported that, after the repeal of the national maximum speed limit law, there was a 13% increase in the risk of traffic fatalities in 29 states that increased speed limits on roadways with speed limits greater than 65 mph compared to states that did not increase speed limits.

E-6 Conclusions and Study Limitations

Overall, the impact of increasing speed limits resulted in an increase of crashes on BC rural highways, where speed limits have been changed. In details, the full Bayes evaluation technique showed a statistically significant increase of crash frequency of 11.1%. The results are consistent with similar studies conducted worldwide in showing an increase in fatal and injury crash frequency after raising the speed limit. However, it should be noted that the post-treatment period for this evaluation was relatively short. As such, although the results are statistically significant at the 95% confidence level, it is recommended that the evaluation is repeated when more crash data becomes available for a longer post-treatment period. It should also be noted that the robustness of the evaluation results highly depends on the quality of the crash data provided.

1 Introduction

1.1 Background

In 2013, the British Columbia (BC) Ministry of Transportation and Infrastructure (MoTI) initiated a review of several potential challenges affecting safety and traffic operations on rural provincial highways. The review included several areas: speed limits, winter tire regulations, passing lanes for slower-moving vehicles and wildlife hazards.

For the speed limits review, throughout the fall of 2013, a technical team conducted over 300 speed surveys on approximately 9,100 km of stretches of highways with measurements of the mean and 85th percentile operating speeds. After these surveys were carried out, it was found that the 85th percentile speed on these highways was 10 km/h higher than corresponding posted speed limits, as shown in Table 1.1. It was also noticed that, overall, serious crashes were trending down significantly since 2003.

These considerations led to the option of increasing speed limits on BC rural highways. Therefore, after a public consultation process was conducted, approximately 1,300 km of rural provincial highway segments were recommended for higher speed limits. The increased speed limits took effect in the second-half of 2014. Rural divided highways had a maximum posted speed limit increase to 120 km/h and rural undivided highways to 100 km/h with some 4-lane sections up to 110 km/h.

Table 1.1 Summary of Speed Surveys Results on Key Corridors (Source: MoTI, 2014)

Highway Segment	Current Speed Limit	85th percentile operating speed
Hwy 1: Abbotsford to Hope	100	116
Hwy 1: Revelstoke to Golden	90	103
Hwy 3: Sunshine Valley to Manning Park	80, 90	103
Hwy 5: Hope to Kamloops	110	127
Hwy 19: Parksville to Campbell River	110	121
Hwy 97C: Aspen Grove to Peachland	110	126
Hwy 99: Horseshoe Bay to Squamish	80	102
Hwy 99: Squamish to Whistler	80, 90	105

1.2 Project Objectives

Driving speed is perhaps the most studied indicator for crash risk. Speed plays an important role in road safety, and traffic operations are enhanced when appropriate speed limits are set. Therefore, it is important to evaluate the safety impact of changing speed limits.

The main objective of this study was to estimate the effect of increased speed limits on crash occurrence and severity during the period of post-implementation (approximately 1.3 years). The methodology used to evaluate the safety impact of increased speed limits utilized state-of-the-art knowledge and experience in field road safety evaluation. In particular, before-after (BA) evaluations were undertaken with the full Bayesian (FB) technique, which is a well-established statistical methodology with considerable literature available to provide guidance for its application for safety evaluations. It has been shown in several studies that the FB analysis has many advantages over other safety evaluation methodologies.

1.3 Report Structure

Chapter 1 of this report has provided a short introduction to the evaluation objective, establishing background information of the main motivation of MOTI for the speed limit change. Chapter 2 describes different safety evaluation methods with particular focus on the full Bayesian (FB) before-after (BA) analysis, which was selected for this evaluation. Chapter 3 presents the data for the selected treatment and comparison sites used in the evaluation including crash and traffic volume data. Chapter 4 discusses the results of the evaluation and changes in the safety level of subject roadways after implementing the speed limit increases. To compare results of this study with similar studies worldwide, Chapter 5 provides a thorough review of BA evaluation studies covering the safety impact of speed limit changes in other jurisdictions. Chapter 6 contains the conclusions of the study along with the study limitations. At the end of the report, a comprehensive reference list and several appendices are also provided.

2 Overview of Before-After Evaluations

2.1 Safety Evaluation Methods

Time-series and cross-sectional studies are two techniques that are frequently used to estimate the effect of specific road safety interventions. The most common method to estimate the effectiveness of safety initiatives is a time-series analysis, which is often referred to as a before-after (BA) analysis as mentioned earlier. This approach attempts to measure the change in safety over time due to the implementation of a safety initiative. A cross-sectional study compares the expected crash frequencies of a group of locations having a specific component of interest (treatment) to the expected crash frequency of a group of similar locations that lack the presence of this specific component. Any differences in crash frequency between the two groups are attributed to the change in conditions, representing the safety effect of the treatment. Cross-sectional studies are generally considered inferior to time-series analysis (before-after studies) since no actual change has taken place. Cross-sectional studies were also shown by many researchers to have several statistical shortcomings (see for instance Hauer, 2010). BA studies are known as observational when countermeasures have been implemented and treatment sites are selected where concerns about crash frequency were raised. Observational studies are much more common in road safety literature than experimental studies, i.e., studies where treatments have been implemented randomly in some locations to specifically estimate their effectiveness. Indeed, random selection in assigning treatments is an impractical and uneconomical solution for traffic agencies to undertake (Highway Safety Manual, 2010). An observational before-and-after study is generally perceived to be an effective way to estimate the safety effect of changes in traffic and roadway characteristics.

An observational BA study, where the treatment effect is naively evaluated as the change in observed crash frequency between the before and the after period, is known as a simple BA evaluation. The simple BA evaluation has many shortcomings; the crash frequency observed at a road location during a certain period of time is a biased measure that does not correctly reflect the location level of safety during that time period. The reason is that traffic crashes are events that have a random component. Crash frequency is a stochastic variable and the single number of crashes observed represents only one realization of its true (expected) value. Therefore, determining treatment effect should deal with the difference between the true safety levels, estimated with the use of statistical techniques, rather than the observed safety levels available in crash records.

For these reasons, other study types are preferred over a simple BA evaluation. For BA analyses, Bayesian methods are commonly used within an odds-ratio (OR) analysis for their ability to treat unknown parameters such as predicted crash frequency as random variables having their own probability distributions. Examples of Bayesian evaluation techniques include the Empirical Bayes (EB) (Hauer, 1997) (Sayed *et al.*, 2004) and fully Bayes (FB) (Persaud *et al.*, 2009) (El-Basyouny & Sayed, 2011), which are commonly used in traffic safety analyses. A typical EB before-after study requires the collection of data for three distinct sets of data: i) treatment sites, ii) comparison sites, and iii) reference sites. The comparison group is used to correct time-trend effects and other unrelated effects and includes sites that have not been treated but experience similar traffic and environmental conditions. The reference group is used to correct the regression-to-the-mean (RTM) artifact. Usually, the reference group includes a larger number of sites that are similar to the treatment sites and is used to develop a crash prediction model (CPM). The EB approach is used to refine the estimate of the expected number of crashes at a location by combining the observed number of crashes (at the location) with the predicted number of crashes from the CPM.

Alternatively, the FB approach has been proposed in the road safety literature to conduct before-after studies. The FB approach is appealing for several reasons, which can be categorized into methodological and data advantages. In terms of methodological advantages, the FB approach has the ability to account for all uncertainty in the data, to provide more detailed inference, and to allow inference at more than one level for hierarchical models, among others (El-Basyouny & Sayed, 2011). In terms of data requirements, the FB approach efficiently integrates the estimation of the CPM and treatment effects in a single step, whereas these are separate tasks in the EB method thereby negating the need for a reference group and reducing the data requirement.

To benefit from the additional advantages of the FB approach, several researchers have proposed the use of intervention models in the context of a before-after safety evaluation. Crash prediction models have been proposed to conduct crash intervention analysis by relating the crash occurrence on various road facilities as a function of time, treatment, and interaction effects. These intervention models acknowledge that safety treatment (intervention) effects do not occur instantaneously but are spread over future time periods and are used to capture the effectiveness of safety interventions.

2.2 Confounding Factors

As mentioned earlier, the evaluation process should ensure that a noted change in the safety performance measured is caused by the safety initiative and not by other "confounding" factors or causes. If other factors are allowed to contribute to the noted change, then sound conclusions about the effect of the countermeasure cannot be made. This report will focus on the main factors that are most relevant to road safety evaluations.

The regression-to-the-mean (RTM) artifact is considered one of the most important confounding factors since a countermeasure is not typically assigned randomly to sites but to locations with high-crash frequency. This high-crash frequency may regress toward the mean value in the post-treatment period regardless of the effect of the treatment. This condition will lead to an overestimation of the treatment effect in terms of the crash reduction. Usually, a group of reference sites are used to correct the RTM phenomenon by developing CPMs, i.e., a calibrated relationship between crash frequency and annual average daily traffic (AADT) volumes. The reference group includes an adequate number of sites that are similar to the treatment sites but have not undergone any improvements from the before to the after periods. Full Bayes techniques have been shown to account for the regression to the mean-using comparison groups (Persaud *et al.*, 2009) (El-Basyouny & Sayed, 2012).

Other confounding factors, theorized to have an effect on the frequency of crashes attributed to a road safety measure, are: the exposure effect, unrelated effect, and trend effects (maturation).

- **Exposure effect:** the most common measure of exposure is traffic volume, which can be represented in a number of ways (such as the total volume entering the location in a set period, or be separated into major or minor entering traffic volumes, or even be separated down to the particular movement). Traffic volume can vary over time because of various reasons such as increased demand of travel, population growth, or a change in the capacity of the intersection. It is important that the applied methodology accounts for exposure.

- **Unrelated effect:** refers to the possibility that factors other than the treatment being investigated caused all or part of the observed change in crashes. For example, traffic and driver composition, enforcement level, weather conditions, etc. can be changed from the before period to the after period.

- **Maturation:** refers to changes in long-term crash trends. Comparing crashes before and after implementing a specific countermeasure may indicate a reduction attributed to the countermeasure. However, it is possible that the crash reduction could be attributed to a continuing decreasing trend (e.g., caused by improvements to vehicle performance).

To account for unrelated effects and maturation, a group of comparison sites, which are similar facilities for geographic proximity and comparability (mainly traffic and geometry) to the treatment sites, are normally used. This is done with the assumption that the unknown factors should affect the comparison group in the same manner that they influence the treatment group. By comparing the change in crashes in the comparison group to the change in crashes in the treated sites, the treatment effect can be calculated.

2.3 Full Bayes Approach

Researchers have recently introduced the use of the full Bayesian (FB) approach to evaluate the effect of road safety countermeasures (Li *et al.*, 2008)(Persaud *et al.*, 2009) (El-Basyouny & Sayed, 2010, 2012). As discussed earlier, the FB method has several advantages including the ability to:

a) Conduct multivariate analysis. Crashes of different severity and types can be strongly correlated, thus, multivariate modeling can lead to more accurate and precise estimations.

b) Allow inference at more than one level for hierarchical (multi-level) models. It has been proposed that aside from being correlated across different severities and types, crash data exhibit a multi-level structure.

c) Treat each time period as an individual data point; that is, if the time period selected for the analysis is by month, then each month of the year represents a separate data point in the FB analysis, while the EB method typically deals with the entire study period as a single data point (either total or calculated as per year). This has two advantages: the ability to account for seasonal changes throughout the year and to look for changes in treatment effects with respect to time.

d) Integrate the estimation of the CPM and treatment effects in a single step. The FB method differs in that the model parameters have prior distributions and, therefore, the posterior distribution integrates and includes both prior information and all available data. Then, the expected crash frequency is a distribution of likely values rather than a point estimate.

Therefore, if we consider a BA study where crash data are available for a reasonable period of time before and after the intervention and, in addition, we also consider the availability of a comparison/reference group for the before and after period of the intervention at treatment sites, it is possible to write the foundational model for FB analysis of crash data in the form of a Poisson-lognormal (PLN) model. Different forms for the PLN model can be adopted. The full model form used in this evaluation can be found in appendix A.1.

By implementing the models in statistical software, the FB method provides the output of the odds ratio (OR) and regression coefficients in a seamless integration. This is done by computing B_i and D_i which are the predicted crash counts for the i^{th} treated site averaged over appropriate years during the before and after periods, respectively, and A and C the corresponding quantities for the specific site comparison group where the predicted crash counts are averaged over all sites in the matching comparison group and years. Then, the OR can be computed as:

$$OR_i = \frac{A/C}{B_i/D_i}$$

or

$$\ln(OR_i) = \ln(\mu_{TAi}) + \ln(\mu_{CB}) - \ln(\mu_{TBi}) - \ln(\mu_{CA})$$

where μ_{TB} and μ_{TAi} are the predicted crash counts for the i^{th} treated site averaged over appropriate years during the before and after periods, respectively, and μ_{CB} and μ_{CA} are the corresponding quantities for the comparison group where the predicted crash counts are averaged over all sites in the matching comparison group and years. Finally, the overall index can be calculated from the following equation where NT is the number of traded sites:

$$\ln(OR) = \frac{1}{NT} \sum_{i=1}^{NT} \ln(OR_i).$$

The statistical software WinBUGS (Spiegelhalter *et al.*, 2005) was selected as the modeling platform to obtain FB estimates. The final part of the project consisted of calculating the treatment effectiveness indexes for the different points outlined above. After the results were obtained, it was possible to discuss and draw conclusions regarding the speed limit change intervention as a whole.

3 Evaluation Data

3.1 Treatment Sites

The sites (i.e., segments of highways) with increased speed limits were reviewed in detail to create a subset of treatment locations needed for the time-series (BA) analysis. A total of 60 treatment segments were selected along the stretches of highways with changed speed limits (see Table 3.1).

Table 3.1 Available Highways with Changed Speed Limits

Highway #	City/Town
1	Abbotsford to Hope
5	Hope to Kamloops
19	Nanaimo to Campbell River
97C	Merritt to Peachland
1	Hope to Cache Creek
3	Hope to Princeton
7	Mission to Hope
99	North Vancouver to Cache Creek
1	Victoria to Nanaimo
19	Campbell River to Port Hardy
1	Tobiano to Savona
1	Salmon Arm to Golden
3	Sunday Summit to Princeton
5	Heffley to Little Fort
6	New Denver to Nakusp
33	Black Mountain to Big White
33	Rock Creek to Westbridge
97	Swan Lake to Monte Creek
97A	Armstrong to Enderby
97A	Grindrod to Sicamous

3.2 Comparison Sites Selection

The selection of comparison sites is a key step to control confounding factors, such as maturation and unrelated effects, to ensure they do not influence the number of crashes attributed to change of speed limits. Therefore, a lack of proper control groups may be considered a flaw in the analysis and could affect the accuracy of the final results.

In this regard, some specific criteria were developed in order to ensure a systematic process for the selection of control group sites, which include the following:

- The potential control group sites must be a rural highway segment;

- The potential control group site must be in relatively close proximity to the treatment site;

- The potential control group site must have reliable crash data and traffic volume data available to support the evaluation;

- The potential control group site should be reasonably similar in design and operation, and stable over the evaluation timeframe to the treatment site: for example, there should be no major changes to the potential control group site such as significant construction.

With regard to the group size, the number of control sites should be large enough to avoid being subject to large random fluctuations which will consequently lead to a large standard error. For this study, the number of available comparison sites was equal to 95 segments which belonged to 35 matched-pair groups.

3.3 Crash and Traffic Data

Crash data was available for all treated and comparison sites for approximately 3.8 years, from January 2012 to October 2015. As the new speed limits were implemented in mid-2014, a study period of four months was selected in order to obtain a wider range of post-treatment time frames (i.e., 4 periods of 4 months in total).

Specifically, the three 4 month time periods used were:

- March to June;
- July to October;

- November to February.

Therefore, the before period ran from March 2012 to June 2014 (i.e., 7 periods of 4 months) and the after period from July 2014 to October 2015, with July-October 2014 as a transition period. Fatal-plus-injury (F+I) crash records were used to estimate the effect of increased speed limits. After a thorough review, property-damage-only crash records were found to be incomplete and were not employed for the analysis. Finally, traffic volume information, in the form of annual average daily traffic (AADT), was obtained both for treatment and comparison sites from existing MoTI records.

4 Results

4.1 Treatment Effectiveness Estimates

The resulting output of the model, i.e., the Odds Ratios (OR), which represents an average index of treatment effectiveness across the treated locations, is showed in Table 4.1. The full set of estimated model parameters was found in line with the ones obtained in similar studies (see for instance Sacchi *et al.,* 2014). The estimated effectiveness of the treatment in reducing crashes "C.R." can easily be estimated from the following equation:

$$C.R. = 100\times(1 - OR)$$

Overall, the resulting CR showed that the sections of roadway where new speed limits were changed, experienced an increase in the number of severe (fatal and injuries) crashes equal to 11.1% following the implementation of speed limit increases (see Table 4.1). This increase was found statistically significant at the 95% confidence level (CL).

Table 4.1 Change From the Before to the After Period for F+I Crashes

Odds-Ratio ± Standard Deviation	5% CL	95% CL	Estimated Crash Change (C.R.)*
1. 111±0.070	1.002	1.228	+11.1%

* Positive sign means increase of crashes

It should also be noted that although the FB technique can produce crash change estimations by site, the individual site results were not provided in this report for the following reasons:

- the after study period in this study was relatively short (i.e., approximately 1.3 years only); this caused the individual site results to be less reliable and not statistically significant;
- as the FB technique matches treatment sites with appropriate comparison sites, the results for individual locations will become sensitive to the safety performance of the smaller matched comparison group with short after period.

4.2 Time-Varying Crash Modification Function

The FB technique also allowed for the estimation of a crash modification function that varies over time (El-Basyouny and Sayed, 2012) (Sacchi *et al.*, 2014). In fact, the OR provided in Table 4.1 describe the effect of the speed limit change as point estimate. However, the intervention (i.e., speed limit change) effects do not always occur instantaneously but are spread over future time periods. Therefore, a crash modification function can be more adequate to explain how an intervention affects crash frequency over time. Within the FB context of technique, a crash modification function was developed as shown in Figure 4.1. The model form to obtain this curve is described in the Appendix A.1.6.

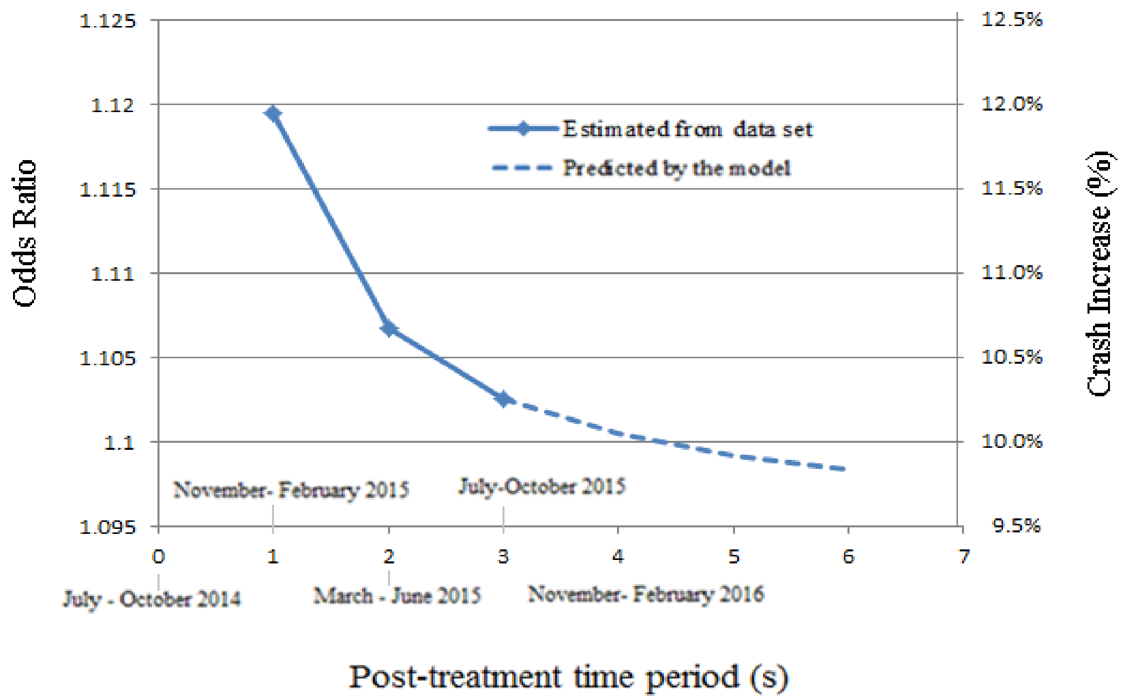

Figure 4.1 Crash Frequency Change over Time

Overall, it appears that the initial increase may be further reduced over time, as predicted by the model (dashed line in Figure 4.1).

5 Comparison to Similar Studies Worldwide

To test the results of the current study, a review of the available peer-reviewed published literature was made on the subject of speed limit changes and the safety effects that have resulted from their implementation. The review focused on information that would be considered the most reliable, including studies that deployed a robust methodology that accounted for some confounding factors, as well as studies that were supported with the availability of good quality data.

5.1 Safety Evaluations of Speed Limit Change

Many studies conducted worldwide have investigated the relationship between speed and safety showing the important role of speed management. Generally, the results indicate that the higher the travel speed, the greater the probability of crashes and the higher severity of the crashes.

In the US, for instance, several authors studied the effect on road safety of relaxing speed limits after the repeal of the national maximum speed limit law. Farmer *et al.* (1999) investigated the trends in fatalities over 8 years for 24 states that raised interstate speed limits and 7 states that did not. The study revealed an increase of 15% in motor vehicle occupant deaths for the 24 states that raised speed limits. After accounting for changes in vehicle miles of travel, fatality rates were 17% higher following the speed limit increases. Vernon *et al.* (2004) focused their attention on Utah highways (urban, rural and high-speed highway segments). The methodology used for the evaluation was an autoregressive integrative moving average (ARIMA) intervention time series analysis. The study only indicated statistically significant increase/decrease in collisions but did not provide the magnitude of the increase/decrease. Overall, the results showed a significant increase in both total crash rates on urban interstate segments, and fatal crash rates on high-speed rural non-interstate segments. However, 1) total, fatality, and injury crash rates on rural interstate segments, 2) fatality and injury crash rates on urban interstate segments and 3) total and injury crash rates on high-speed non-interstate segments were substantially unchanged. Finally, Shafi and Gentilello (2007) reported that, after the repeal of the national maximum speed limit law, there was a 13% increase in the risk of traffic fatalities in 29 states that increased speed limits on roadways with speed limits greater than 65 mph compared to states that did not increase speed limits. The researcher estimated that approximately 2,985 lives may be saved per year with a nationwide speed limit of 65 mph or less.

Another major study from Hong Kong evaluated the increase of speed limits that occurred from 1999 to 2002 on different highways. Nineteen sections were major roadways with increases in speed limits from an initial 50 km/h limit to a higher 70 km/h limit (Wong et al., 2005). Overall, the relaxation of the speed limit from 50 to 70 km/h caused an increase of 15% for fatal-plus-injury crashes. The relaxation of speed limits from 70 to 80 km/h was found to increase fatal-plus-injury crashes by 18% and fatal plus serious-injury only crashes by 36%. It should be noted that although this study was carried out in an urban environment, the comparison may be relevant for the stretches of highways with higher speed limits.

5.2 The Power Model of the Relationship between Speed and Safety

A number of meta-analysis studies (e.g., Elvik, 2009) revealed that the relationship between speed and safety (accident frequency) is best represented by a power model which was first introduced by Nilsson (1984):

$$\text{Accidents}_{\text{after}} = \text{accidents}_{\text{before}} \left(\frac{\text{speed}_{\text{after}}}{\text{speed}_{\text{before}}}\right)^{\text{Power}}$$

These meta-analysis have suggested that the estimates of the exponents ("Power") are generally higher for fatal and major injuries than minor injuries and property-damage-only (PDO) crashes. Moreover, the coefficient has been found higher for inter-urban highways than urban roads. For example, the power parameters were calibrated by Elvik (2009) as illustrated in Table 5.1.

Table 5.1 Summary Estimates of Exponents by Traffic Environment (Source: Elvik, 2009)

Rural roads/Freeways		
	Best Estimate ("Power")	**95% Confidence Interval**
Fatal crashes	4.1	(2.9, 5.3)
Serious injury crashes	2.6	(-2.7, 7.9)
Slight injury crashes	1.1	(0.0, 2.2)
Injury crashes - all	1.6	(0.9, 2.3)
Property-damage-only crashes	1.5	(0.1, 2.9)

Using average exponent values from Table 5.1, the fatal and injury crash increase reported in this study can be obtained from about 3 km/h increase in the mean operating speed for a segment with initial mean speed of 90 km/h.

6 Conclusions

Overall, the impact of increasing speed limits caused a statistically significant increase of crashes on rural highways in BC where the speed limits have been changed. The full Bayes evaluation technique adopted for this evaluation showed an increase 11.1% that was statistically significant at the 95% confidence level. The results are consistent with similar studies conducted worldwide in showing an increase in fatal and injury crash frequency after raising the speed limit

However, it should be noted that the post-treatment period for this evaluation was relatively short. As such, although the results are statistically significant, it is recommended that the evaluation is repeated when more crash data becomes available for a longer post-treatment period. It should also be noted that the robustness of the evaluation results highly depend on the quality of the crash data provided.

7 References

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Appendix

A.1 Theoretical Background for Full Bayes Models

The methodology employed to evaluate the effects on safety of the speed limit change was a full-Bayes BA study with advanced non-linear intervention functions.

Let Y_{it} denote the collision count recorded at site i (i = 1, 2, …, n) during time-period t (t = 1,2, …, m) (e.g., year, month, etc.). It is assumed that accidents at the n sites are independent and that

$$Y_i \mid \lambda_i \sim Poisson(\lambda_i) \quad (1)$$

To address over-dispersion for unobserved or unmeasured heterogeneity, it is assumed that

$$\lambda_i = \mu_i \exp(\varepsilon_i) \,, \quad (2)$$

where, μ_i is determined by a set of covariates representing site-specific attributes and a corresponding set of unknown regression parameters; whereas, the term $\exp(\varepsilon_i)$ represents a multiplicative random effect. The Poisson-lognormal (PLN) regression model is obtained by the assumption:

$$\exp(\varepsilon_i) \mid \sigma_\varepsilon^2 \sim Lognormal(0, \sigma_\varepsilon^2) \text{ or } \varepsilon_i \mid \sigma_\varepsilon^2 \sim Normal(0, \sigma_\varepsilon^2) \,. \quad (3a,b)$$

A.1.2 Non-Linear Intervention (Koyck) Model

A way to define μ_{it} is using the so-called “intervention” model, which has been available in the literature for some time (Li et al., 2008) (El-Basyouny and Sayed, 2011). An intervention model is a piecewise linear or non-linear function of the covariates designed to accommodate a possible change in the slope of crash frequency on time at treatment sites, which might be attributable to the intervention. El-Basyouny & Sayed (2012a, 2012b) advocated the use of the nonlinear “Koyck” intervention model (Koyck, 1954) to represent the lagged treatment effects that are distributed over time. The Koyck model is an alternative dynamic regression form involving a first-order autoregressive (AR1) CPM that is based on distributed lags. The model affords a rich family of forms (over the parameter space) that can accommodate various profiles for the treatment effects. Therefore, the Koyck model is used as an alternative nonlinear intervention model to estimate the effectiveness of safety treatments in BA designs. Recently, a comparison of several Bayesian evaluation techniques has shown the advantages of using the nonlinear intervention model for BA studies (Sacchi & Sayed, 2015).

Apart from the logarithm of the total circulating AADT and the length of the stretch of highway analyzed, $V_{,it}$ and L_i respectively, there are other covariates for crash frequency that can be included in the model: an indicator of whether the site was an intervention site or a comparison site (a treatment indicator T_i equal to 1 for treated sites, 0 for comparison sites), a time indicator for a sudden drop in crash frequency at the time of the intervention (I_{it} equal to 1 in the after period, 0 in the before period), and a two-way interaction to allow a different intervention slope across the treated and comparison sites. Moreover, the treatment effects can be modeled using distributed lags along with the AR1 model as a proxy for the time effects (Judge et al., 1988) (Pankratz, 1991). The regression equation for the rational distributed lag model is given by (El-Basyouny & Sayed, 2012a):

$$\ln(\mu_{it}) = \alpha_0 + \alpha_1 T_i + [\omega/(1-\delta B)] I_{it} + [\omega^*/(1-\delta B)] T_i I_{it} + \beta_1 \ln(V_{it}) + \beta_2 \ln(L_i) + \nu_t, \tag{6}$$

where B denotes the backshift operator $(B Z_t = Z_{t-1})$, $|\delta| < 1$ and ν_t satisfies the following stationary AR1 equation

$$\nu_t = \phi \nu_{t-1} + e_t, \qquad |\phi| < 1, \qquad e_t \sim N(0, \sigma_\nu^2), \qquad t = 2, 3, \ldots, m. \tag{7}$$

Consider the expansion $(1-\delta B)^{-1} I_{it} = I_{it} + \delta I_{i,t-1} + \delta^2 I_{i,t-2} + \ldots$, and note that the rational distributed lag model depicts an everlasting treatment effect as $\ln(\mu_{it})$ is tacitly assumed to be a function of the infinite distributed lags $(I_{it}, I_{i,t-1}, I_{i,t-2}, \ldots)$. The parsimonious model (6) is known as the Koyck model (Koyck, 1954) in which the lag weights $\omega \delta^k$ and $\omega^* \delta^k$ decline geometrically for $k = 0, 1, 2, \ldots$. Consequently, the earlier time frames following the intervention are more heavily weighted than distant years. It should also be noted that although the weights never reach zero, they will eventually become negligible. The two parameters ω (the intervention effect) and ω^* (intervention effects across treated and comparison sites) are impact multipliers, whereas δ is a decay parameter controlling the rate at which the weights decline.

A.1.3 Index of Treatment Effectiveness

To estimate the index of effectiveness of the countermeasure, let μ_{TBi} and μ_{TAi} denote the predicted collision counts for the i[th] treated site averaged over appropriate years during the before and after periods, respectively, and let μ_{CBi} and μ_{CAi} denote the corresponding quantities for the matching comparison group where the predicted collision counts are averaged over appropriate sites (all sites in the matching comparison group) and time periods. The ratio μ_{CAi} / μ_{CBi} can be used to adjust the prediction for general trends between the before and after periods at the i[th] treated site. Thus, the predicted crashes in the after period for the i[th] treated site had the countermeasures not been applied is given by $\pi_{TAi} = \mu_{TBi} (\mu_{CAi} / \mu_{CBi})$. The index of effectiveness of the countermeasures at the i[th] treated site is given by the ratio μ_{TAi} / π_{TAi}, which reduces to

$$\theta_i = \mu_{TAi}\, \mu_{CB} / \mu_{TBi}\, \mu_{CA} \tag{8}$$

or

$$\ln(\theta_i) = \ln(\mu_{TAi}) + \ln(\mu_{CB}) - \ln(\mu_{TBi}) - \ln(\mu_{CA}) \tag{9}$$

The overall index can be computed from

$$\ln(\theta) = \frac{1}{NT} \sum_{i=1}^{NT} \ln(\theta_i). \tag{10}$$

where NT is the total number of treatment sites. The overall treatment effect is calculated from $(\theta - 1)$, while the overall percentage of reduction in predicted collision counts is given by $(1 - \theta) \times 100$.

A.1.4 Parameters used for posterior estimates

The statistical software WinBUGS (Spiegelhalter *et al.*, 2005) was selected as the modeling platform to obtain full Bayes estimates of the unknown parameters (e.g., α_j and β_j). First, it is required to specify prior distributions for the parameters. To do so, prior distributions for all parameters are assumed and then the posterior distributions are sampled using Markov Chain Monte Carlo (MCMC) techniques available in WinBUGS. The most commonly used priors are diffused normal distributions (with zero mean and large variance) for the regression parameters and Gamma(ε, ε) or Gamma(1, ε) for the precision (inverse variance) parameters, where ε is a small number (e.g., 0.01 or 0.001).

Second, the whole set of parameters were assumed as non-informative with normal distribution with zero mean and large variance, i.e., normal (0, 10^3), to reflect the lack of precise knowledge of their value (prior distribution). Moreover, since comparison sites were selected to be as similar to treatment sites as possible, this may generate a correlation in collisions between sites within comparison-treatment pairs; hence, the variation due to comparison-treatment pairing was represented by allowing the model coefficients to vary randomly from one pairs to another, such that:

$\alpha_{p(i),j} \sim N(\alpha_j, \sigma^2_j)$,

$\beta_{p(i),j} \sim N(\beta_j, \sigma^2_j)$,

where the only difference in the PLNI model is the additional subscript $p(i)=1,2,\ldots, NC$ which denotes which treatment group the regression coefficient belongs to (with NC equal to the number of comparison groups) (El-Basyouny & Sayed, 2012).

Finally, to implement the Koyck model in WinBUGS, Equation 6 was rewritten and decomposed in three different equations (for t=1, t=2, and t≥3). The regression models obtained are showed in the next section (A.1.5).

The BUGS code produced draws from the posterior distribution of the parameters and, given those draws, MCMC techniques was used to approximate the posterior mean and standard deviation of the parameters. Hence, the posterior summaries in this study were computed by running two independent Markov chains for each of the parameters in the models for 40,000 iterations. Chains were thinned using a factor of 100 and the first 10,000 iterations in each chain were discarded as burn-in runs. The convergence was monitored by reaching ratios of the Monte Carlo errors relative to the standard deviations for each parameter less than 5% using the BGR statistics of WinBUGS and also using visual approaches such as observing trace plots.

A.1.5 Derivations of the Koyck model for WinBUGS

Rewriting Equation 6 as $\ln(\mu_{it}) = C_{it} + \nu_t$, the AR1 Equation 7 implies that $\nu_t = \phi[\ln(\mu_{i,t-1}) - C_{i,t-1}] + e_t$. Substituting this last expression in (6) leads to

$$\ln(\mu_{it}) = (1-\phi)\alpha_0 + (1-\phi)\alpha_1 T_i + [\omega/(1-\delta B)] I^*_{it} + [\omega^*/(1-\delta B)] T_i I^*_{it}$$
$$+ \beta_1 X_{1it} + (1-\phi)\beta_2 X_{2i} + \phi \ln(\mu_{i,t-1}) + e_t, \qquad (11)$$

where $I^*_{it} = I_{it} - \phi I_{i,t-1}$, $X_{1it} = \ln(V_{it}) - \phi \ln(V_{i,t-1})$, and $X_{2i} = ln(L_i)$.

Applying the operator $(1-\delta B)$ to both sides of (11) yields

$$\ln(\mu_{it}) = (1-\phi)(1-\delta)\alpha_0 + (1-\phi)(1-\delta)\alpha_1 T_i + \omega I^*_{it} + \omega^* T_i I^*_{it}$$
$$+ \beta_1 X^*_{1it} + (1-\phi)(1-\delta)\beta_2 X_{2i} + (\phi+\delta)\ln(\mu_{i,t-1}) - \phi\delta \ln(\mu_{i,t-2}) + e_t, \qquad (12)$$

where $X^*_{1it} = X_{1it} - \delta X_{1i,t-1}$.

Equation 12 holds for $t = 3, 4, ..., m$. The regression model for t=1 (with no lags) is obtained from Equation 11 as follows

$$ln(\mu_{i1}) = \alpha_0 + \alpha_1 T_i + \beta_1 ln(V_{i1}) + \beta_2 ln(L_i) + \nu_1,\ \nu_1 \sim N(0, \sigma^2_\nu/(1-\phi^2)),$$

whereas the regression model for t=2 (with one lag) is obtained from Equation 11 as follows

$$ln(\mu_{i2}) = (1-\phi)\alpha_0 + (1-\phi)\alpha_1 T_i + \beta_1 [ln(V_{i2}) - \phi ln(V_{i1})] + (1-\phi)\beta_2 X_{2i} + \phi \ln(\mu_{i1}) + e_2$$

To derive the variance of ν_1, the AR1 Equation 7 implies that $\mathrm{var}(\nu_t) = \phi^2 \mathrm{var}(\nu_{t-1}) + \sigma^2_\nu$. For $|\phi| < 1$ (stationary AR1), $\mathrm{var}(\nu_t) = \sigma^2_\nu/(1-\phi^2)$, for all t.

It is important to check the appropriateness of such models for a given dataset by monitoring in WinBUGS the posterior probabilities of the stationary conditions $(|\hat{\delta}| \le 1)$ and

$(|\hat{\phi}| \leq 1)$. For posterior probability of non-stationarity $(|\phi| \geq 1)$, a $N(0, \tau)$ prior can be used (stationarity is not imposed) where τ is small, e.g., 1 or 0.5 (Congdon, 2006).

A.1.6 Time-Varying Crash Modification Function under the Koyck Model

The components of a time-varying crash modification function under the Koyck model (estimated in section 5.2) can be obtained from the following equation as shown in (El-Basyouny & Sayed, 2012):

$$\theta_{is} = K_1(i,s)K_2(i,s)K_3(i,s)\ , \tag{13}$$

where

$$K_1(i,s) = [\theta_{i,s-1}]^{\phi} = [\theta_{i1}]^{\phi^{s-1}}, \tag{14a}$$

$$K_2(i,s) = \exp\{c + d(1-\delta^s)/s\},\quad c = \omega^*(1-\phi)/(1-\delta),\quad d = \omega^*(\phi-\delta)/(1-\delta)^2, \tag{14b}$$

$$K_3(i,s) = [\theta(V_{1is})]^{\beta_1} / [\theta(V_{1i,s-1})]^{\phi\beta_1}, \tag{14c}$$

The component $K_1(i,s)$ corresponds to the time (novelty) effects. After the first time period of intervention (s=1), the subsequent novelty component would either grow or decline exponentially at a rate of ϕ according to whether $\theta_{i1}<1$ or $\theta_{i1}>1$. In both cases, $K_1(i,s)$ converges to 1 (since $|\phi|<1$).

The treatment component of the crash modification function (14b) describes a non-linear relation of s involving the impact multiplier ω^* along with the AR1 parameter ϕ and the decay parameter δ. In the long-run $K_2(i,s)$ converges to $\exp\{c\}$, which corresponds to the everlasting (permanent) treatment (ELT) impact.

The component $K_3(i,s)$ represents the effects of the total circulating traffic volume. The numerator is the current traffic volume index raised to a fractional power (β_1) and thereby would be close to 1. Yet, the denominator would be even closer to 1 as the power of the previous year's index is much smaller ($\phi\beta_1 < \beta_1$). Thus, unless the traffic volume is subject to significant annual fluctuations, this component is expected to be near 1. $K_3(i,s)$ is inversely related to the indirect (through traffic volumes) local impact under the Koyck model.