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Original Research Paper

Evaluating the safety benefit of retrofitting motorways section with barriers meeting a new EU standard: Comparison of observational before–after methodologies

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HIGHLIGHTS

- The paper investigates how the wrong methodology can negatively influence the decision making process.
- The implementation on motorways of a new class of EU safety barrier was tested from a safety point of view.
- Three different approaches were used, such as the empirical Bayes before–after, the before–after with comparison group and the naive before–after.
- The reliability of the two "simple" approaches was compared with the empirical Bayes before–after analysis.
- A benefit-cost analysis was performed considering the three approaches.

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ABSTRACT

The road safety barriers are today designed and installed in compliance with the European standards for Road Restraint Systems (EN 1317), which lays down common requirements for the testing and certification in all EU countries. The introduction of the European Union (EU) regulation for safety barriers, which is based on performance, has encouraged European road agencies to perform an upgrade of the old barriers installed before 2000, with the expectation that there will be safety benefits at the retrofitted sites. Due to the high cost of such treatments, a benefit-cost analysis (BCA) is often used for site selection and ranking and to justify the investment. To this aim a crash modification factor (CMF) has to be applied and errors in the estimation of benefits are directly reflected in the reliability of BCA. Despite the benefits of empirical Bayes before–after (EB–BA) analysis or similar rigorous methods are well-known in the scientific world, these approaches are not always the standard for estimating the effectiveness of safety treatments. To this aim, the differences between the EB–BA and a naive comparison of observed crashes before and after the treatment are presented in the paper. Crash modification factors for total and target crashes are estimated by performing an EB–BA based on data from a motorway in Italy. As expected the results suggest a strong safety benefit for the ran-off-road crashes by reducing the number of severe crashes (fatal and injury). The statistical significance of results obtained by the EB–BA approach show that the retrofits are still cost-effective. The

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comparison pointed out as selection bias effects can overestimate the safety benefit of the retrofits when a naive approach is used to estimate the CMF and how those can significantly affect a benefit-cost analysis.

1. Introduction

Agencies are required to evaluate the safety effects of a specific improvement to compare its net benefit to other improvement options as well as to justify its implementation at subsequent locations. The typical method of evaluating the safety improvements of a treatment is comparing the crash prevalence associated with the transportation facility before and after the treatment implementation (a before–after study). A challenge inherent in these studies is that crashes change from year to year with a random variation known as regression to the mean, unlike laboratory experiments in which the analyst can control many extraneous conditions. Other parameters that affect the safety of a facility, such as traffic volume and weather conditions, change over time. Consequently, specific evaluation techniques are required to account for changes in order to estimate the true effects of safety improvements (ITE, 2009) avoiding naive methodologies which are not able to take into account possible bias due to the random nature of crashes and the other confounding factors described earlier. Because of that, since Hauer (1997) formalized the use of empirical Bayes before–after analysis as one of the way to account for regression to the mean effects.

This paper, particularly focuses on the safety improvements that can be achieved by replacing old guardrails with new ones to improve protection against roadside hazards on motorways. Retrofitting old guardrails with new ones complying with modern EU standards is one of the main retrofitting policies for infrastructure safety adopted by Italian motorway agencies, with the expectation that there will be a reduction in serious and fatal crashes. The high construction costs for updating the barriers are estimated to be about €300,000/km and €200,000/km for bridges and embankments respectively, so it is important to assess whether the safety benefits would offset these costs. The present study aims to assist in this assessment by estimating the change in the frequency of crashes following barrier retrofits by using an empirical Bayes before–after methodology (Hauer, 1997; Persaud and Lyon, 2007). The comparison with the naive approach is useful to assess how an agency can make mistake in the evaluation of the safety benefit of a treatment when methodologies not able to account for regression to the mean effects are applied. Crashes are random effects and crash frequency in a "short" period of time is not always able to estimate the long term mean of the expected number of crashes in a site with that characteristics and in that context. The phenomena for which a different number of crashes are registered in a site year by year, and the probability to have few (or zero) crashes the year following one that registered a high number of crashes is very high and due the regression to the mean (RTM) effect. In this context, and using just crash frequency which is not able to account for RTM bias, the chance of making mistake, evaluating the effects of a treatment is very high. The new class of EU barriers are designed and installed in compliance with the European Norm (EN) 1317 standards. The EN 1317 for Road Restraint Systems was created in 1998 and lays down common requirements for the testing and certification of road restraint systems in all countries of the European Committee for Standardization (CEN), i.e., the 27 member states of the European Union as well as Croatia, Iceland, Norway, Switzerland and Turkey.

Since 1998, EN 1317 standards have been continuously reviewed and subjected to change. This study pertains to road safety barriers placed in 2005 complying with the EN 1317-2 in force from 2004, which is not substantially different from the present 2010 version. Old barriers that were replaced in 2005 were not classified by any standard because they were placed during the A18 motorway construction in the years 1965–1971. Fig. 1 provides examples of old and new barriers on embankments (Fig. 1(a) and (c)) and on bridges (Fig. 1(b) and (d)).

The two barrier types can be compared only basing on the maximum containment level (CL_{max}) because there are not other common indices in the two standards related to the old and to the new one.

$$CL = \frac{1}{2}M[V\sin(\Theta)]^2 \tag{1}$$

where M is vehicle weight (kg), Θ is impact angle (rad), V is impact speed (m/s).

The containment level establishes the strength of the system, essentially specifying the maximum capacity for redirecting a vehicle. Higher containment levels produce stronger restraint systems. In Table 1 CL_{max} for old (before) and new (after) barriers are reported highlighting the notable increase in the containment capacity of the new barriers placed in 2005.

2. Literature review

An investigation of the relationship between crash and median barrier was carried out by Fitzpatrick et al. (2008) who developed a CMF from the coefficient of a regression model for Texas freeways that related crashes to the presence of a barrier and its offset from the edge of the carriageway. The results suggested a safety benefit for ran-off-road crashes, while, for the total number of crashes the impact on safety was negligible; for small offsets, the results actually suggested an increase in the total number of crashes.

Fig. 1 – Pictures of barriers installed on a motorway in Italy. (a) Old barriers on the embankment. (b) Old barriers on the bridge. (c) New barriers on the embankment. (d) New barriers on the bridge.

Elvik et al. (2009) in the Handbook of Road Safety Measures summarized the results of different studies on the effect on ran-off-road accidents of setting up guardrails along the roadside. This meta-analysis indicated strong reductions of 44% and 47% for fatal and injury crashes, respectively.

Cafiso et al. (2017), using an enlarged dataset reported in this paper evaluated the effects of the new EU class of safety barrier and found a strong reduction of severe ran-off-road crashes (CMF = 0.28) and a small reduction of total crashes (CMF = 0.62).

Based on several studies, the CMF proposed in the HSM (AASHTO, 2010) suggests a reduction in the number of injury ran-off-road crashes for changing the type of roadside barrier along an embankment to a less rigid type. Conversely, more rigid barriers (e.g., concrete or steel versus wire or cable) produce an increase in ran-off-road crashes of up to 40%, according to the HSM.

A study by Scully et al. (2006) in Australia indicated a 42.2% reduction in all casualty crashes, but, based on a literature review, Turner et al. (2010) suggested that the installation of safety barriers resulted in an average reduction of 40% but only for ran-off-road crashes.

Table 1 – Values of the maximum containment level for old and new barriers for embankment and bridge sections.

	CL_{max} (before) (kJ)	CL_{max} (after) (kJ)	Typology (after)*
Embankment	80	460	H3 (H4 median)
Bridge	150	570	H4a

Note: “*” means typology is according to UNI EN 1317-2-2000 (EN 1317-2-1998).

Zegeer et al. (1987) studied the effect of the distance of safety barriers from the edge of the traveled way (defined as clear zone) for two lane undivided rural roads. The results show reductions in ran-off-road crashes ranging from 13% for 1.5 m of clear zone to 44% for 6 m of clear zone.

In the Crash Modification Factors Clearinghouse managed by FHWA (2013), which contains over 3000 CMF estimates for a wide range of safety countermeasures under a variety of conditions, 25 CMFs for “countermeasure: improve guardrail” are reported, with an average CMF value of 0.82 (min = 0.50, max = 0.95) for all crash types and 0.75 for ran-off-road and fixed object crash types (min = 0.68, max = 0.82). The reference for these CMFs is a study of Gan et al. (2005).

Gitelman et al. (2014), is the unique previous study investigating specifically the safety effectiveness of upgrading old barriers with new ones meeting the EU standard. Results pointed out safety benefits only for dual carriageway roads and total fatal and injury crashes with a net reduction of 15% and benefit-cost ratio ranging from 1.11 to 2.51. The crash reduction was estimated from the coefficient of models developed by using a multivariate analysis. This approach can't be classified as an appropriate before–after study because the regression coefficients may be affected by unknown exogenous variable not included in the model and the statistical technique is not able to address regression to the mean bias, as well.

In summary, despite differences in the value of CMF, all the above studies indicate that road guardrails are effective in reducing target crashes, while shown a negligible effect on total crashes. However, these CMFs may not be appropriate for the scenario under consideration in this paper. For example, the only 3 ones in the CMF clearinghouse related to an improvement of guardrail are not specific to motorways, and in particular not to motorway barriers meeting the new

Table 2 – Details of the database used to estimate models for the different crash typology.

Crash type	Period	AADT (veh/d)	Injury crash		Injury crash rate (million veh·km)	
			TG	RG	TG	RG
Total	Before	8696–32,998	63	216	0.27	0.11
	After	7651–37,052	48	193	0.14	0.12
Ran-off-road	Before	–	50	95	0.20	0.05
	After	–	10	95	0.03	0.10

EU standard. Furthermore, not all the studies reported above address regression to the mean effects.

3. Data analysis and segmentation approach

The data used for this investigation are based on an Italian rural motorway, the "A18" Messina-Catania, which is approximately 76 km (47.2 miles) long. The cross section is made up of two 3.75-m travel lanes and a 3-m emergency lane in each direction. Carriageways are divided by a median with barriers. The analysis periods are from 2000 to 2004 for the before period and from 2006 to 2010 for the period after the barriers were installed in 2005. In the ten years of analysis, 580 severe (fatal and injury) crashes occurred as reported in the official statistics on motor vehicle collisions provided by the Italian National Institute of Statistics (ISTAT, 2010). In Italy, property damage only crashes are not recorded. The data were divided into two different datasets.

a) Reference group (RG), made up by untreated road segments.
b) Treated group (TG) in the before and after periods made up by the segments in which the barriers were changed in the 2005, with separate datasets for the before and after periods.

The latter datasets contain segments where the median barrier, the lateral one, or both, were retrofitted. Only the road segments between interchanges were analyzed and segmentation was carried out to achieve homogeneous segments with respect to barrier typology (Cafiso et al., 2013; D'Agostino, 2014).

Table 2 presents the basic traffic and crash statistics for the treatment and non-treatment sites. It is evident that there was a treated site selection bias, in that sites with higher crash rates tended to be selected for treatment. This would result in regression to the mean and, as reported later in the paper, it brings to not negligible differences in the results based on the chosen methodology of analysis, and justify the use of a more complex analysis methodology such as the empirical Bayes. AADT is annual average daily traffic.

The suitability of a reference group was determined by performing a test of comparability for the treated group and potential reference groups that was suggested by Hauer (1997).

The comparability test for total crashes and for ran-off-road crashes showed that both datasets are suitable as reference groups, with a mean value of 1.03 and 0.96 for total and ran-off-road crashes respectively, and 95% confidence intervals that include 1 (if sample mean is not sufficiently close to 1.0, and the 95% confidence interval does not include 1.0, then the candidate reference group is unsuitable).

4. Observational before–after analysis

This section describes the methodology used and the models required for the three before–after analysis used in the elaboration and the results. All the methodologies described differ each other for the estimation of the number of crashes than would have occurred in the after period if the treatment were not implemented.

4.1. *Before–after with comparison group and naive before–after approach*

A before–after with comparison group study uses an untreated comparison group of sites similar to the treated ones to account for changes in crashes unrelated to the treatment such as time and traffic volume trends. The comparison group is used to calculate the ratio of observed crash frequency in the after period to that in the before period. The observed crash frequency in the before period at a treated site group is multiplied by this comparison ratio to provide an estimate of expected crashes at the treated group which had no treatment been applied. This is then compared to the observed crashes in the after period at the treated site group to estimate the safety effects of the treatment.

This method will not account for regression-to-mean unless treatment and comparison sites are also matched on the basis of the observed crash frequency in the before period. Specifically, a control site would need to be matched to each treated site based on the annual crashes in the before period. There are immense practical difficulties in achieving an ideal comparison group to account for regression-to-mean (i.e., matching on the basis of crash occurrence) as illustrated in Pendleton (1996). In addition, the necessary assumption that the comparison group is unaffected by the treatment is difficult to test and can be an unreasonable assumption in some situations.

The CMF for a given crash type at a treated site is estimated by first summing the observed crashes for both the treated and comparison groups for the two time periods by using Eqs. (2) and (3) to estimate the variance.

$$\mathrm{CMF} = \left(N_{\mathrm{observed,T,A}} \big/ N_{\mathrm{expected,T,A}}\right) \Big/ \left\{1 + \left[\mathrm{Var}\left(N_{\mathrm{expected,T,A}}\right) \Big/ N^2_{\mathrm{expected,T,A}}\right]\right\} \tag{2}$$

$$\mathrm{Variance}(\mathrm{CMF}) = \mathrm{CMF}^2 \left\{1 \Big/ N_{\mathrm{observed,T,A}} + \left[\mathrm{Var}\left(N_{\mathrm{expected,T,A}}\right) \Big/ N^2_{\mathrm{expected,T,A}}\right]\right\} \Big/ \left[1 + \mathrm{Var}\left(N_{\mathrm{expected,T,A}}\right) \Big/ N^2_{\mathrm{expected,T,A}}\right]^2 \tag{3}$$

$$N_{\text{expected,T,A}} = N_{\text{observed,T,B}}\left(N_{\text{observed,C,A}}/N_{\text{observed,C,B}}\right)$$

$$\text{Var}\left(N_{\text{expected,T,A}}\right) = N^2_{\text{expected,T,A}}\left(1/N_{\text{observed,T,B}} + 1/N_{\text{observed,C,B}} + 1/N_{\text{observed,C,A}}\right)$$

where $N_{\text{observed,T,A}}$ is the observed number of crashes in the after period for the treated group, $N_{\text{observed,C,B}}$ is the observed number of crashes in the before period in the comparison group, $N_{\text{observed,C,A}}$ is the observed number of crashes in the after period in the comparison group, $N_{\text{observed,T,B}}$ is the observed number of crashes in the before period for the treated group.

The comparison ratio ($N_{\text{observed,C,A}}/N_{\text{observed,C,B}}$) indicates how crash counts are expected to change in the absence of treatment (i.e., due to factors other than the treatment of interest). This is estimated from the comparison group as the number of crashes in the after period divided by the number of crashes in the before period. $N_{\text{expected,T,A}}$ represents the expected number of crashes for the treated group that would have occurred in the after period without treatment. In its simplest form, an observational before–after study consists of comparing the counts occurring in the before period to its count in the after period. The term naive stands for the fact that counts in the before period is used as predictor of the expected crashes occurring in the after period without treatment. In other terms the CMF can be evaluated using just the numerator of Eq. (2), considering that $N_{\text{expected,T,A}}$ is equal to the observed crashes in the before period.

4.2. *Empirical Bayes before–after approach*

In an empirical Bayes before–after study, the change in safety is given by the comparison between the number of reported crashes in the after period (A) and the expected number of crashes that would have occurred in the “after” period without the treatment (B). Because of changes in safety that may result from external factors like traffic volume or, as is the case for this study, regression-to-mean caused by selection bias, or from time trends in crashes and other factors, the count of crashes before a treatment by itself is not a good estimate of B (Hauer, 1997). Instead, B is estimated from an empirical Bayes (EB) procedure in which a safety performance function (SPF) is used to first estimate the number of crashes predicted at the treated sites based on comparison sites with similar traffic and physical characteristics ($N_{\text{predicted,Ti,B}}$) (Frank et al., 2010). In each section i, the sum of these annual SPF estimates ($N_{\text{predicted,Ti,B}}$) is then combined with the count of crashes ($N_{\text{observed,Ti,B}}$) in the before period at the treated site i to obtain an empirical Bayes estimate of the expected number of crashes ($N_{\text{expected,Ti,B}}$) before the treatment. This estimate of $N_{\text{expected,Ti,B}}$ is shown in Eq. (4).

$$N_{\text{expected,Ti,B}} = w_i N_{\text{predicted,Ti,B}} + (1 - w_i) N_{\text{observed,Ti,B}} \tag{4}$$

The weight (w) is estimated with Eq. (5).

$$w_i = \frac{1}{1 + k_i N_{\text{predicted,Ti,B}}} \tag{5}$$

where k_i is the dispersion parameter of the negative binomial distribution of the SPF in section i, $N_{\text{predicted,Ti,B}}$ is the estimated number of crashes from SPF in section i, $N_{\text{observed,Ti,B}}$ is the count of crashes in section i.

A comparison ratio (C_i) between the sums of SPF predicted values in the after period $N_{\text{predicted,Ti,A}}$ and the before period ($N_{\text{predicted,Ti,B}}$), is applied to Eq. (5) to account for the differences between the before and after period in terms of length of analysis period, changes in traffic volume, and time trend.

$$C_i = N_{\text{predicted,Ti,A}}/N_{\text{predicted,Ti,B}} \tag{6}$$

The result, after applying this factor, is an estimate of the number of crashes that would have been expected in the treated section without treatment in the after period. The estimate of B is then summed over all road sections in the treated group of interest (to obtain B_{sum}).

$$B_{\text{sum}} = \sum C_i N_{\text{expected,Ti,B}} \tag{7}$$

Compared with the count of crashes during the after period in that group (A_{sum}).

$$A_{\text{sum}} = \sum N_{\text{observed,Ti,B}} \tag{8}$$

The procedure also produces an estimate of the variance of B_{sum}, calculated as Eq. (9).

$$\text{Var}(B_{\text{sum}}) = \sum C_i m_i (1 - w_i) \tag{9}$$

The CMF is estimated as Eq. (10).

$$\text{CMF} = \frac{A_{\text{sum}}/B_{\text{sum}}}{1 + \left[\text{Var}(B_{\text{sum}})/B^2_{\text{sum}}\right]} \tag{10}$$

The standard deviation (SD) of CMF is given by Eq. (11).

$$\text{SD}(\text{CMF}) = \left\{\frac{\text{CMF}^2\left[\text{Var}(A_{\text{sum}})/A^2_{\text{sum}} + \text{Var}(B_{\text{sum}})/B^2_{\text{sum}}\right]}{\left[1 + \text{Var}(B_{\text{sum}})/B^2_{\text{sum}}\right]^2}\right\}^{0.5} \tag{11}$$

5. Indices computation

This section reports the various phase for the computation of indices described above before presenting the results.

Table 3 – Value of regression parameters, (standard error) and [*p*-value] for the SPF calibrated.

		Total	Ran-off-road
Intercept		−14.1368 (2.153) [<0.0001]	−13.3460 (2.444) [<0.0001]
AADT		0.9631 (0.224) [<0.0001]	0.7862 (0.254) [0.002]
Year	2000	1.05	1.33
	2001	0.91	0.85
	2002	1.00	1.15
	2003	1.27	1.58
	2004	1.16	1.35
	2006	1.08	1.47
	2007	0.82	1.07
	2008	0.75	0.95
	2009	0.79	1.03
	2010	0.91	1.29
k		$5.6L^{-0.8}$	$6.1L^{-0.85}$

5.1. *Safety performance functions*

As indicated above, the EB analysis requires the use of a safety performance function (SPF). The generalized linear modeling (GLM) approach was used to estimate the SPFs, using the Statistical Analysis System software package (Cafiso and D'Agostino, 2012; Lord and Persaud, 2007; SAS Institute Inc., 2008).

To consider time trend in the estimation of the CMF, a post SPF calibration procedure was applied. The SPF was calibrated considering an average AADT value for the whole period of analysis (7 years) and the sums of crashes for each segment. The estimation obtained for each year was than corrected with a multiplier given by the ratio of the sums of yearly observed crashes and the SPF estimates for the comparison sites.

Consistent with the state of research in developing these models, the negative binomial error distribution was assumed for the count of observed crashes (Hauer, 1997). For the empirical Bayes evaluation, the negative binomial dispersion parameter was estimated from the calibration of the SPF using a maximum likelihood methodology. Some recent studies (Hauer, 2001; Heydecker and Wu, 2001; Higle and Witkowski, 1988; Miaou and Lord, 2003), suggested that the dispersion parameter, contrary to earlier research, is not constant for a given data set but actually varies from site to site depending on the length of a roadway segment. The varying form in applications such as the Highway Safety Manual is such that the dispersion parameter for certain classes of road segments is inversely proportional to segment length. This form was first suggested by Hauer (2001) who argued logically that shorter segments have a higher crash frequency variance and, consequently, should have a higher dispersion parameter than longer segments, and that this variation should influence the long-term estimate of a segment's safety. For this study, following Cafiso et al. (2010), we did not, a priori, assume proportionality. Instead, the chosen equation for the calibration of the variable dispersion parameter was as following Eq. (12).

$$k = \alpha L^{\beta} \tag{12}$$

where α and β are regression terms, k is the overdispersion parameter, L is the segment length (m).

The maximization of the log-likelihood function required an iterative process to calibrate both the SPF coefficients and the two coefficients for the exponential function for k. To this end, an iterative calculation algorithm was developed and implemented. The results of the model calibration for three crash types are shown in Table 3, based on the SPF model form shown in Eq. (13).

$$E(Y) = y_j e^{a} L \cdot \mathrm{AADT}^{b} \tag{13}$$

where $E(Y)$ is expected annual (fatal and injury) crash frequency of random variable Y (crashes/year), AADT is average annual daily traffic (veh/d), a and b are regression terms, y_j is the time trend coefficient in the year j.

The goodness of fit (g.o.f.) of the models was evaluated by the way of the cumulative residuals (CURE) plot (Hauer and Bamfo, 1997) which resulted in reasonable good fits of the models to the data not exceeding the ±2σ bounds (Fig. 2).

6. Results and discussions

Table 4 reports the crash modification factors estimated on the data for the total and ran-off-road crashes by using the three methodologies.

As it is clear looking at Table 4, there are notable differences between the results delivered by the EB–BA

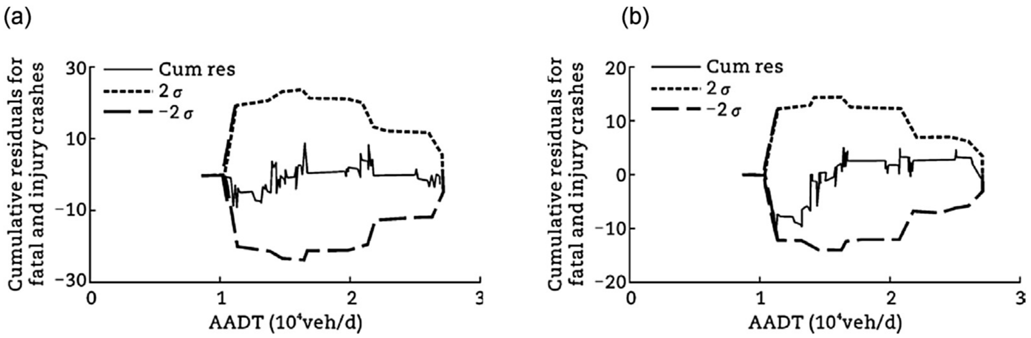

Fig. 2 – CURE plots with ±2σ. (a) Total crashes. (b) Ran-off-road crashes.

Table 4 – CMF estimation for total and ran-off-road crashes using EB–BA, BA with comparison group, and naive BA analyses.

Methodology	EB–BA		Before–after with comparison group		Naive before–after	
	Total	Ran-off-road	Total	Ran-off-road	Total	Ran-off-road
Var(B_{sum})	15.39	20.21	81.39	102.63	–	–
B_{sum}	57.59	35.11	56.29	50.00	63.00	50.00
A_{sum}	48	10	48	10	48	10
CMF	0.83	0.28	0.83	0.20	0.75	0.20
SD	0.13	0.11	0.17	0.07	–	–
95% confidence interval	0.57 1.08	0.06 0.49	0.50 1.16	0.06 0.33	– –	– –

methodologies when compared with the naive and the BA with comparison group. For the ran-off-road crashes either the naive or the BA with comparison group provide an overestimation of the safety benefit of the treatment of about 10%, while for the total crashes just the naive overestimate the CMF. This can be explained consider the selection bias effects that, as expected, are stronger for the target crashes. While its effects on total crashes results less significant for the presence of other crash typologies which are not influenced by safety barriers.

For the importance of variance in the estimation of CMF (Cafiso and D'Agostino, 2015, 2016), it worth to look at those delivered by the three methodologies. The before–after with comparison group approach produced an approximated value of the variance of the expected number of crashes in the after period. In the case of ran-off-road crashes the standard deviations evaluated with the BA with comparison group approach is almost half of the standard deviation of the EB–BA approach, while for the total, the estimation of variance results similar with the two methodologies. This is why the comparison group alone is not "ideal" in terms of tracking variation in crash distribution over year of the treated group. The naive BA is not able to provide an estimation of variance and therefore the statistical error remains unknown.

To evaluate whether the crash reductions would justify the considerable retrofit costs, a benefit-cost (B/C) analysis for the treatments implementations in this study was conducted. For this, average costs of €1,600,000.00, and €350,000.00 for fatal and injury crashes were assumed respectively, based on information provided by the Italian Ministry of Transportation. Considering the relative frequencies of these crash types in the after period, a weighted crash cost of €295,000.00 is obtained.

The cost of treatment implementation of €250,000.00/km was taken by the technical specifications of Italian National Road Authority (ANAS). Considering a discount rate of 3%, either for treatment or for crashes, and a service life of 20 years for the new barriers an annualized implementation cost of €16,815/km is obtained.

The total crash reduction was calculated by subtracting the actual crashes in the after period from the expected crashes when the treatment had not been implemented. The number of crashes saved per kilometer per year was 0.29 and 0.48 ran-off-road crashes for the EB–BA and others methodologies, respectively. Those values were obtained by dividing the total crash reduction (25 for EB–BA and 40 for the other methodologies) by the number of after period kilometer per year per site (85).

The annual benefits (i.e., crash savings) per kilometer of €87,708 and €140,560 for EB–BA and the other methodologies respectively are the product of the crash reduction per kilometer per year (0.29 and 0.48) and the cost of a crash. The benefit-cost ratio (B/C) is calculated as the ratio of the annual benefit per kilometer to the annual cost per kilometer. The B/C ratios are estimated to be 5.20 for EB–BA and 8.36 for the other methodologies. These results suggest that the treatment is highly cost effective, even consider the unbiased value of the CMF. It is value of noted that a relatively smaller difference of 10% in the CMF estimation lead to a great difference in benefit estimation (benefit estimated the EB–BA are about 60% of the safety benefit estimated using a naive BA and a BA with comparison group). Moreover, it can be pointed out that this overestimation of benefits is uncontrolled (i.e., should be higher in other applications) and therefore makes the naive methods unreliable.

7. Conclusions

Where there is no regression-to-mean and where a suitable comparison group is available, the comparison group methodology can be a simple alternative to the more complex empirical Bayes approach. This may be true in cases where 1) crash frequency is not considered in selecting a site for safety treatment, 2) the safety evaluation is strictly related to a change implemented for operational reasons, 3) a blanket treatment is applied to all sites of a given type. In practice, except for blanket treatments, it is difficult to ascertain that there is no selection bias which will enforce regression-to-mean. This is generally true on whatsoever dataset used for before–after analysis because the typical approach of agencies is to implement a safety treatment "where needed". In other terms the selection bias is always present and it shows its effects more on the target crashes. In the present research work, using data from a motorway in Italy, the state of the art of empirical Bayes before–after approach which account for regression to the mean and temporal trend effects was applied to the estimation of CMFs and results were compared with observational comparison group and the naive approaches, which are simplest methodologies but exposed to uncontrolled errors.

Also in the present research work the effects of the regression to the mean on the estimation of the safety benefit due to the retrofit of roadway segment with new barriers meeting the EU standard may be determinant in the safety treatment selection and analysis. The selection bias, combined with a time trend which the comparison group is not always able to catch in the treated sites bring to an overestimation of the safety benefit of about 10%. Using the estimated CMFs to evaluate the benefit-cost ratio of the treatment it varying from 5.20 for the one evaluated using the EB–BA and 8.36 for the others methodologies. Even more a remarkable difference is delivered in the evaluation of the annual benefits (i.e., crash savings) per kilometer which resulted of €87,708 and €140,560 for EB–BA and the other methodologies respectively, despite a difference of "only" 10% in the estimation of safety benefit delivered by the treatment.

From the analysis of results, the effects of selection bias can bring to wrong decision in safety treatment implementing with wrong use of resources. Using unreliable observational before–after analysis methodologies to evaluate the safety effects of a treatment, the expected results are to overestimate by an uncertain value the safety performance and as a consequence, to save less human lives than expected.

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