COVER NOTE: ROAD SAFETY ENFORCEMENT REVIEWS **10 January 2025**

Phase 1: Academic Enforcement Review (completed by Newcastle University in April 2024)

The appended review was financed from the former Police, Fire and Crime Commissioner's road safety fund, on behalf of the York and North Yorkshire Road Safety Partnership. It is a complex, statistical study which was produced for use by experienced road safety practitioners.

The review's primary objective was to assess the effectiveness of the current enforcement strategy (mobile safety camera vans) on mitigating the frequency and severity of road traffic collisions, involving personal injury on the roads within York and North Yorkshire.

The review was based on a sample of 50 sites[1] selected across York and North Yorkshire, featuring a mix of speed limits and urban/rural settings. Sites were selected based on the availability of substantial data to support a robust analysis of collisions over the past decade. The aim was to assess the overall effectiveness of the current approach, rather than to identify the need for alternative enforcement methods at specific sites.

The review reported that the current enforcement approach using mobile safety camera vans had significantly reduced casualties from road traffic collisions. It concluded that there is a case for further study into the merits of introducing average/fixed speed cameras in York and North Yorkshire as it was noted that fixed cameras (in other areas) have shown similar success in reducing road traffic collisions and public perception of average speed cameras is more positive than traditional (fixed) cameras, but they are the costliest to operate.

Following this, the Road Safety Partnership has agreed to commission a further study (Phase 2) commencing in 2025, to determine the economic sustainability and effectiveness of a blended enforcement approach including some average and/or fixed speed cameras.

Phase 2: Enforcement – Economic Investment Appraisal (commencing in January 2025)

Would the introduction of fixed and/or average speed cameras be effective in reducing collisions in York and North Yorkshire? and if so

Can this be achieved through a sustainable self-financing funding model that covers operational costs and provides income to invest into further partnership casualty reduction activity and initiatives?

This appraisal will help establish prioritised site selection criteria to identify the optimal locations for fixed and average cameras, should they be deemed effective in further reducing collisions in York and North Yorkshire.

[1] there are over 800 live mobile safety camera van sites across York and North Yorkshire

At present, there has been no formal partner engagement or collective partnership endorsement of the introduction of fixed and/or average cameras in York and North Yorkshire. Therefore, once Phase 2 is complete, road safety partners will be able to consider these findings and next steps.

Roles and Responsibilities

Enforcement of all speed offences, including those detected by safety cameras, is the responsibility of North Yorkshire Police.

As local highway authority, installation of any infrastructure on the local road network, including fixed and average speed cameras, would require local authority approval. Similarly, local authorities cannot install them without police approval.

In those areas across the Country, where fixed and average speed cameras operate, they do so under a partnership approach, with the police still retaining their lead authority enforcement function.

Assessing the effectiveness of present and potential enforcement strategies for mitigating the frequency and severity of road traffic incidents in York and North Yorkshire

Newcastle University Project
NU-017326 North Yorkshire Traffic
Lee Fawcett
Joseph T. Matthews
Nicola K. Hewett

Executive Summary

In this report we perform extensive analyses on raw collision data provided by North Yorkshire Council, mapped to 50 designated mobile road safety camera sites across North Yorkshire and the City of York and dating back to the year 2000. We also analyse data on speeding violations provided by North Yorkshire Police. One aim of this report is to provide a thorough evaluation of mobile road safety cameras across North Yorkshire and the City of York since 2013, with a detailed literature review providing some context in terms of similar evaluations in other jurisdictions, both in the UK and further afield. The literature review also compares the effectiveness of mobile safety cameras to other speed enforcement systems, including fixed safety cameras, average speed cameras and TASCAR.

An exploratory data analysis reveals interesting and important features in the data, including significant trends in collisions and casualties through time; some evidence of *regression to mean* (RTM); and noticeable changes depending on time of year, pre/post camera deployment period, urban/rural location, council area and local authority. Such features in the data support an empirical Bayes modelling approach to evaluate the effectiveness of the mobile safety cameras. Specifying 5-year pre/post deployment periods reveals that after accounting for confounding effects of RTM and trend, since 2013 mobile safety cameras in North Yorkshire and the City of York have resulted in a 36% reduction in casualties as a result of road traffic collisions, with an average value of prevention of around £11.3 M. Preliminary analyses of data on speeding violations reveals an association with data on collisions, and statistical modelling potential that could support a more proactive approach to the identification of road safety hotspots. We note that there are a small number of sites that warrant further investigation, with a significant *increase* in collisions and casualties post deployment.

In the context of other mobile safety camera evaluations, the evaluation of cameras in North Yorkshire is extremely positive. In the UK, typically casualty reductions of between 30%–40% are noted; however, we report just a 20% reduction in a previous study of mobile safety cameras in North Yorkshire and just a 7% reduction in a study of mobile cameras in the Northumbria Police

Force area. Further afield, a 20% reduction in collisions was estimated in a survey of mobile safety cameras in Tallinn, Estonia.

Although studies on fixed cameras reveal (on average) a similar level of success to mobile cameras, studies on the effectiveness of fixed cameras are more plentiful in the literature. The public perception of average speed cameras is more positive than traditional (fixed) cameras, in terms of their effectiveness, with supporting evidence of their efficacy. Although it is accepted that average cameras have the most significant impact on the reduction of speed-related collisions, they are the most costly to operate. We believe there is a case for further study into the merits of average speed cameras in North Yorkshire; with the caveat that a mix of fixed and average speed cameras may be required to ensure a sustainable business model.

Contents

1 Introduction and Background

Road casualty or collision reduction is a key aim of transport policy and relies heavily on the implementation of effective road safety countermeasures at known collision hotspots. This usually requires significant financial investment from finite available budgets. Road safety practitioners are therefore very keen to understand the impact that these countermeasures are having, particularly for guiding future investment decisions. Building on previous collaborative work between the Newcastle University Statistics & Road Safety Group (NUSRG) and North Yorkshire Police (NYP)/North Yorkshire Council (NYC) (see Section 1.2 for full details), in this report we investigate the effectiveness of mobile road safety cameras in the council areas of North Yorkshire and the City of York (often collectively referred to as "North Yorkshire" in this report) in reducing speed in the area, and therefore reducing the frequency and severity of road traffic incidents. There are two major contributions to this report: (i) A comprehensive analysis of data provided by NYP/NYC, linked to sites at which mobile speed detection systems have been deployed; (ii) a literature review element that aims to contextualise the findings from our data analysis and extend our investigation to consider other speed enforcement systems currently in use in the UK, including fixed unmanned instantaneous speed cameras, average speed cameras and Temporary Automatic Speed Cameras At Roadworks (TASCAR).

In particular, through our data analysis and literature review, the report will address questions including:

To what extent do safety camera/hand-held deployments prove effective in mitigating excessive speed and other offenses that fall within the category of the fatal 5? How effective are mobile speed detection systems in general (for example, across the UK) based on a review of the existing evidence?

Is it appropriate to implement other enforcement systems, such as fixed cameras and/or average speed cameras in York and North Yorkshire, to enforce speed limits and eliminate anti-social road use, and how do these compare in terms of efficacy?

1.1 Methods and Data

Given the skills of the NUSRG team, comprehensive literature reviews will be performed to both contextualise any findings from our data analyses relating to the use of mobile safety cameras in North Yorkshire, but also to examine the effectiveness of such countermeasures relative to other speed enforcement systems currently in use in the UK. In the main body of this report, key references will be highlighted at various points in the discussion; however, the reader is referred to Section 3.1 for a more detailed evaluation of relevant literature. Publications from both academic and practitioner-focused literature will be surveyed, including official reports and magazine articles.

Similarly, only brief descriptions of any statistical methods used will be given in the main body of the report, with the reader being referred to Appendix A.2 and external references for full methodological details should they be interested. Generally, all data analysis methods have been tried-and-tested with data provided by other local authorities and practitioner partners, including collaborators at the Traffic Accident Data Unit at Gateshead Council; Buckinghamshire County Council, in partnership with consulting firm *Agilysis*; National Highways; Traffic Scotland; the Estonian Transport Administration; and the US State Department of Transportation in New York. However, the abundance of data provided by NYP and NYC in this current study has resulted in a more robust treatment of, for example, regression-to-mean (RTM) and trend (see for example, Hauer (1980) and Appendix A.1).

General methods include basic data exploration with appropriate numerical and graphical summaries for visualisation through to advanced modelling techniques, utilising a Bayesian estimation framework to perform predictive analytics and uncertainty quantification. Where relevant, NUSRG's road safety analytics dashboard *RAPTOR* will be used (Reactive Analytic Predictive Toolkit for Road safety), providing many of the graphics used in this report and an interactive summary dashboard for readers. The most relevant external references for the statistical methods used in this report are Fawcett and Thorpe (2013); Fawcett et al. (2017), and Matthews et al. (2019).

For the current project, we have the co-ordinates of 50 sites at which mobile safety cameras have been deployed at some point since the year 2013; see Fig. 1 for a map of these locations across the North Yorkshire region. These data have been provided by colleagues at NYP. We have the precise date on which these sites became 'active', that is, the date on which a mobile speed detection system started being used; we also have the site descriptors shown in List 1 below.

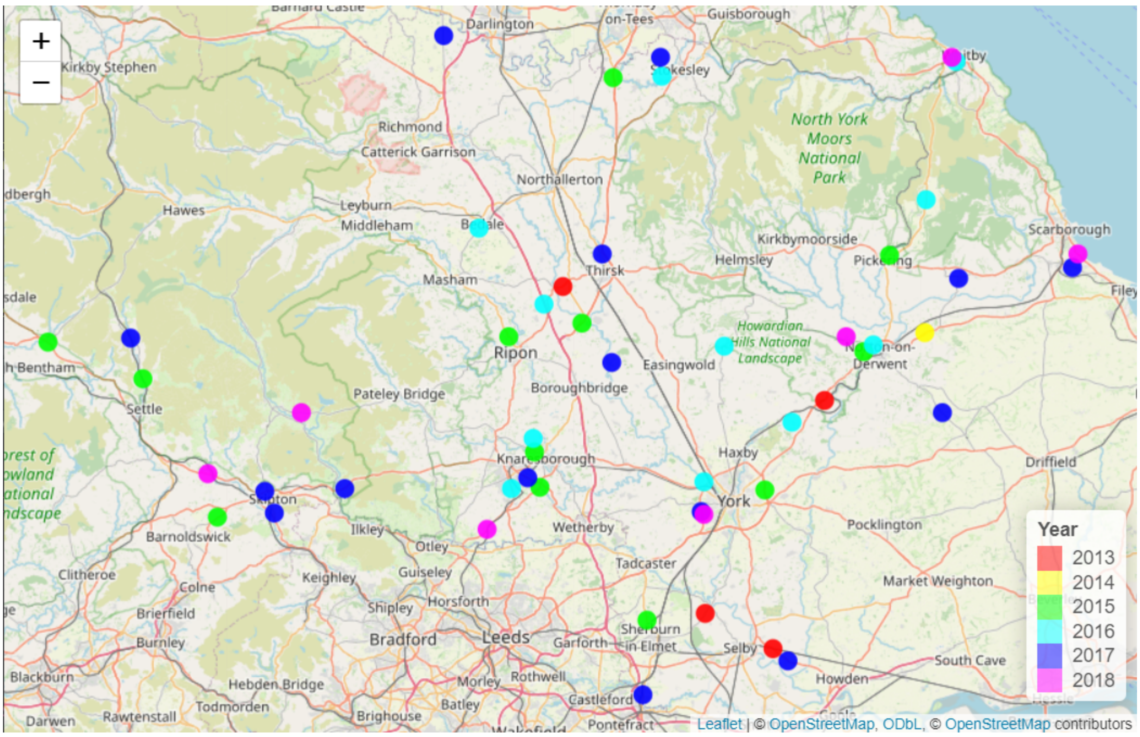

Figure 1: Map showing the locations of all 50 mobile safety camera sites in North Yorkshire/City of York. The colour used indicates the year in which the site became "active".

- - - *List 1: Data for our 50 designated mobile safety camera sites* - - -

Data provided by NYP

- Date on which the site became active
- The Local Authority in which the site resides
- The speed limit at the site
- The type of enforcement vehicle used at the site, since the site became 'active': 'Big van'/'Small van'/'Motorcycle'/A combination of these vehicles
- Site type: 'Killed or Seriously Injured'/'Community Concern'/'Displacement'

Data provided by NYC

- Annual collision counts dating back to the year 2000; also casualty counts, categorised by severity: "Slight" / "Serious" / "Fatal"
- Causation factors associated with collisions, including "Vehicle Factor", "Hazard in Carriageway", "Light Condition", "Road Surface", "Weather Condition"
- Road classification (A/B/Unclassified)
- Urban/Rural identifier
- Council area: North Yorkshire/City of York

- - - *List 2: Variables associated with violations* - - -

Data provided by NYP

- Precise dates and times of visits to each site
- The number of speeding violations observed at each visit
- The type of penalty issued for each violation:
  - SAC: Speed Awareness Course
  - CO: Conditional Offer–Fine and Points
  - RFS: Report for Summons
- Data on other reported violations (for example, mobile phone usage or seatbelt violations)
- A binary variable indicating whether or not a mobile safety camera was active at the time of each violation

Colleagues at NYC have undertaken an extensive mapping exercise, allocating raw collision data from STATS-19 records to our 50 mobile safety camera sites if their co-ordinates fell within a 500 metre catchment radius of these sites. This exercise extracted raw collisions from the year 2000 onwards; once collisions for each mobile safety camera site were obtained, raw counts were aggregated by calendar year to give annual collision counts for each of our 50 sites (although we can easily disaggregate, if necessary, for example to explore seasonal patterns in the data). It is often the case that each raw collision includes multiple casualties, and so we also have annual casualty counts for each of our 50 sites (classified by severity – "slight" / "serious" / "fatal"). In addition to the site-specific descriptors provided by NYP shown in List 1, to help build a general picture of road safety across the North Yorkshire road network the NYC STATS-19 data extraction exercise also provided some further site-specific descriptors (also shown in List 1).

For each of our 50 mobile safety camera sites, NYP has also provided extensive violation data-files relating to 19,566 monitoring incidents between 2013–2023, including data shown in List 2.

Section 2.1 provides a high-level exploratory analysis of these data in which we describe some of the more interesting findings from our initial analysis; a full range of summaries and tables of results is available in Appendices B and C.

1.2 NUSRG/North Yorkshire Previous Collaboration: Mobile Cameras

Evaluation of road safety countermeasures is often performed through B/A (B/A) comparisons of casualty or collision rates pre/post intervention; for example, comparisons of collision counts at a particular location during a fixed period before, and after, the deployment of a mobile road safety camera. However, such simplistic analyses are vulnerable to the effects of confounders, specifically regression-to-mean (RTM) and trend (see for example, Hauer (1997), and the discussion in Appendix A.1), and failure to account for the effects of such confounders has been shown to seriously over-estimate the effectiveness of road safety countermeasures. Between 2011-2012, NUSRG developed novel methods for separating genuine treatment effects from the effects of confounders such as RTM, with these methods being embedded within their road safety analytics dashboard *RAPTOR*; see Thorpe and Fawcett (2012) and Fawcett and Thorpe (2013) for a discussion of the underpinning methodology and an application to mobile safety camera data in the Northumbria Police Force area, and Matthews et al. (2019) for a description of the NUSRG *RAPTOR* dashboard.

In 2016, NUSRG conducted a retrospective, small-scale B/A analysis of data from 22 sites in North Yorkshire at which mobile safety camera vans had been deployed, with equal-length B/A periods between 2011-2014. Although a 28% raw reduction in casualties was observed after the deployment of the mobile safety cameras, NUSRG estimated a reduction owing to the cameras to be just 20% after accounting for the effects of RTM and general trends. Full findings are available in the 2017 report *Newcastle University Evaluation of Mobile Road Safety Cameras in North Yorkshire: Summary of Methods and Key Findings* (North Yorkshire Police, 2017). A similar analysis of 56 mobile safety camera sites in the Northumbria Police Force region, performed by NUSRG, reported a 32% raw reduction in casualties post-intervention, reducing to just 7% attributable to the cameras themselves after accounting for RTM and trend (see Fawcett and Thorpe (2013)). Across the UK, where analyses have been performed to separate genuine treatment effects of mobile safety cameras from those of RTM and trend, treatment effects anywhere between a 2% reduction and a

40% reduction in casualties have been reported, although typically we might see reductions owing to the cameras of between 20-30% (see, for example, Hirst et al. (2004)).

Following the original evaluation of mobile safety cameras in North Yorkshire between 2011-2014, NYP expanded their fleet of safety camera vans to further reduce the number of collisions, deaths, and serious injuries on the region's roads; for full details, see *Public report by the North Yorkshire Police & Crime Commissioner: Making North Yorkshire's Roads Safer* (Police and Crime Commissioner North Yorkshire, 2017). A subsequent collaboration with NUSRG consisting of a 3-year B/A analysis, 2014-2017/2017-2020, revealed an improving picture regarding the effectiveness of mobile safety cameras in North Yorkshire, rising from a 20% reduction in casualties in our trial analysis on data from 2011-2014 to a 24% overall reduction in casualties at the same 22 locations in the updated analysis.

1.3 Structure of This Report

In Section 2 we perform detailed data analyses of the collision and violations data described in Lists 1 and 2 on page 7. Specifically, we perform a basic exploratory analysis on the casualty and collisions data (Section 2.1.1), as well as the violations data (Section 2.1.2). We then perform a more detailed statistical analysis to investigate the effectiveness of the mobile safety cameras at the 50 designated signs shown in Fig. 1 (Section 2.2.1), as well as a more in-depth analysis of the violations data (Section 2.2.2). We then set our North Yorkshire mobile safety camera evaluation in the context of other such evaluations (Section 2.3), before presenting the results of a more detailed literature review in which the efficacy of mobile safety cameras is set alongside that of fixed speed cameras and average speed cameras (Section 3). We complete this report with a summary of our findings in terms of prioritising the use of different speed camera deployments.

2 Data Analysis: Mobile Safety Cameras in North Yorkshire

In Section 2.1 we perform basic exploratory data analyses using the data-files provided by NYP and NYC (as outlined in Section 1.1). A high-level overview of our findings is reported here, with the most interesting plots and patterns in the data discussed; see our interactive summary dashboard for a full suite of plots. The aim here is to give an overview of the datasets we are working with and to form initial insights that support our more detailed analyses in Section 2.2, in which we use statistical methods to identify genuine effects attributable to the mobile safety cameras deployed in both the collision and violations datasets. In Section 2.3 we then draw on our literature review to contextualise our data analyses, in terms of how our conclusions from this, and previous collaborations with colleagues in North Yorkshire (see Section 1.2), compare to mobile safety camera studies in other parts of the UK.

Data cleaning/potential data issues

Note that, of the 50 mobile safety camera sites discussed in Section 1.1 and displayed in Fig. 1, one site was removed altogether due to it having no collisions allocated over the full observation period 2000–2023. Also, two raw collisions did not map to any of our designated mobile safety camera sites, and of the 19,566 monitoring incidents in the violations data-files, 26 incidents were discarded due to the recorded length of time of a monitoring incident being 0 minutes. Other than this, no issues were found with the data as provided by NYP and NYC.

Throughout this section we are assuming raw collision data have been recorded accurately, specifically their longitude and latitude. These co-ordinates have been used in the initial mapping exercise by NYC to allocated collisions to mobile safety camera sites; our subsequent analyses cannot account for changes in the quality of such spatial mapping through time.

2.1 Exploratory Data Analysis

2.1.1 Collision/casualty data

In this section we perform exploratory data analyses on both collisions and casualties, although attention is drawn to casualties as this is the main focus of our analysis in Section 2.2.1: Any modelling aimed at identifying a treatment effect might then proceed to a costing exercise (see towards the end of Section 2.2.1), in which casualty severity plays an important role.

Trend and mean reversion

Fig. 2 shows time series plots of annual casualty counts, since the year 2000, averaged over our full raw collision dataset obtained from STATS-19 (top-left); it also shows raw counts through time for three of our 49 mobile safety camera sites (a full suite of plots, for each site, can be accessed via our dashboard). Obvious from most of these plots are the decreasing trends in counts, which in many cases are statistically significant (i.e. $p = 6.14 \times 10^{-15}$ for the negative trend displayed in the plot for all sites) and almost linear through time; see, in particular, the plot for all sites. However, there are site-specific deviations from this general global trend; for example, the plot for the A65 Skipton site displays a far less significant trend in casualties than we see across the road network generally, and at the A64 Middlecave site there might be some evidence of an *increasing* trend in casualties through time. From an analysis point-of-view, and in particular our work in Section 2.2.1, identifying such general and site-specific trends is extremely important, especially any significant trend that was present throughout the time before a mobile safety camera site became "active": Assuming this trend is decreasing and would have continued into the period after site activation, any estimation of treatment effect via a pre/post comparison of casualty data is prone to exaggeration if such trend is not properly accounted for.

Also evident from the time series plots in Fig. 2 are the effects of RTM through time (see Appendix A.1 for a full account of RTM). For example, the 7 casualties observed at the A64 Westbound Murton site in 2010, which are immediately followed by zero count casualties – or at least, counts that lie within the 95% confidence bands of the expected trend line. More generally in these time series plots, for many sites we often see abnormally high casualty counts being followed by counts that are back in-line with the expected trend (or below).

In similar studies conducted by the NUSRG team, including their earlier collaboration with NYP (see Section 1.2), such longitudinal data has not been available. It is more often the case that data from reference sites and other sources must be sought in order to account for the contribution of trend and RTM in any pre/post treatment analysis; although statistical tests are available to help ensure trends observed from other sources are applicable to the safety camera sites being studied, such a "leap of faith" does of course add extra uncertainty to any analysis (with such uncertainty propagating through to any estimated treatment effects).

Fig. 3 shows the same information as that in Fig. 2, but for casualty counts broken down by their severity. Considering average counts across all sites, we still observe negative trends through time, for both slight and serious casualties; numbers are too small and data to few too discern any real trends in fatal casualties. The same might be said for site-specific casualty counts, regardless of their severity; as the other plots in Fig. 3 show, at a site level counts are too small and data too few to detect any real trends. However, evident here might be the effects of RTM; for example, at the A64 Westbound Murton, the unusually high casualty count in the year 2001 perhaps reverting to an underlying mean level in subsequent years.

Although not shown in the main body of this report, time series plots could be produced at the local authority level. At both a site and local authority level, thankfully collisions leading to serious casualties and fatalities are relatively relatively rare occurrences. However, there are some interesting observations to make – for example:

- In Ryedale in 2009 there were more than three times as many serious casualties as slight casualties. There was also a relatively large number of fatal casualties in Ryedale in 2013 (but with much fewer since then)
- York observed its lowest annual count of slight casualties in 2017, but since then there has been an increasing trend, which is statistically significant ($p = 0.034$)
- Richmondshire appears relatively safe, with a maximum 6 slight casualties in 2016 and only ever seeing one serious casualty

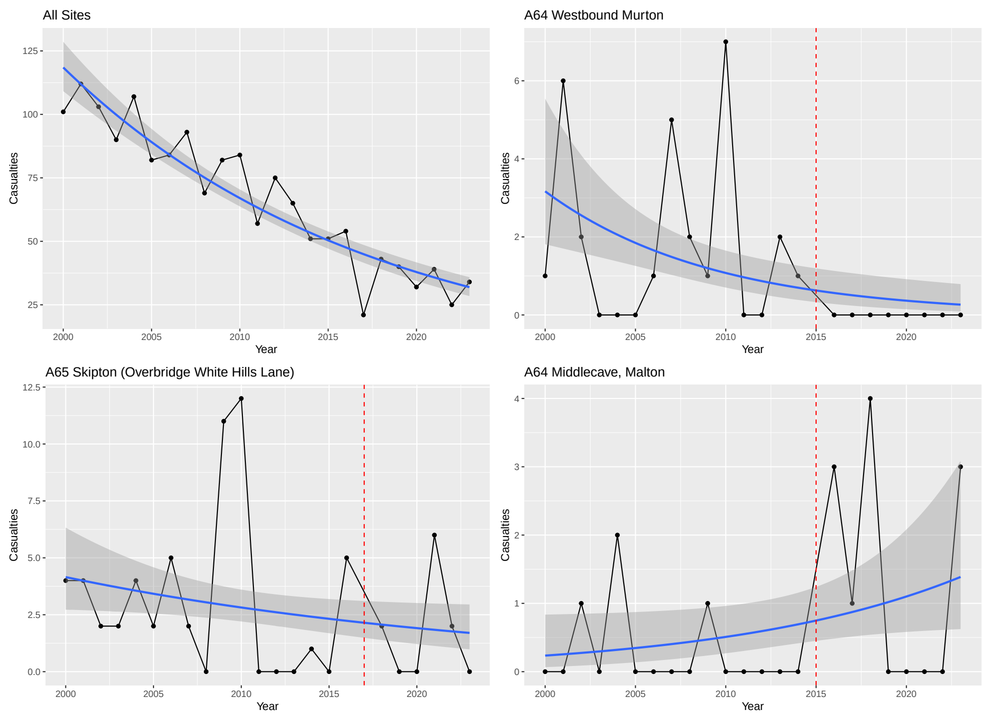

Figure 2: Time series plot showing total annual casualties across all sites, between the years 2000–2023 (inclusive; top-left); and for three of our 49 mobile safety camera sites selected at random. The blue line indicates a fitted trend line, with associated 95% confidence intervals given by the shaded region around this line. The red vertical (dotted) lines indicate the boundary of the B/A periods.

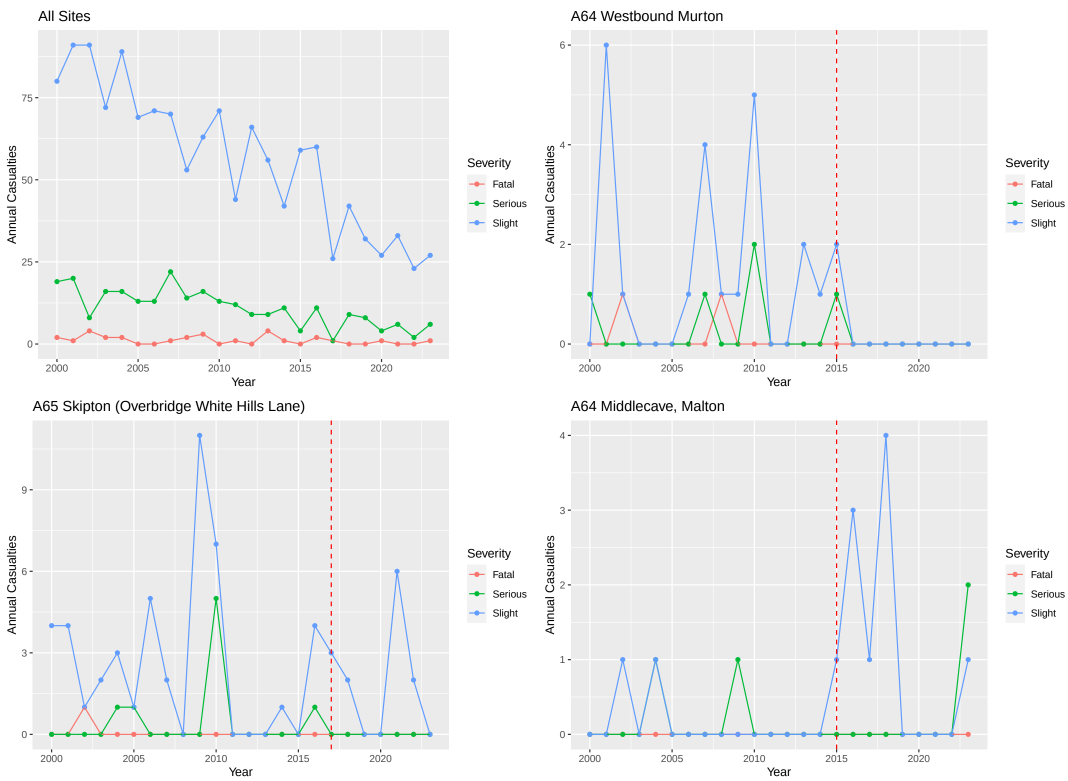

Figure 3: Time series plot showing total annual casualties across all sites, between the years 2000–2023, disaggregated by casualty severity (inclusive; top-left); and for three of our 49 mobile safety camera sites selected at random.

Seasonal variability

It could be that time of year, or season, might play an important role in casualty or collision prediction and might therefore inform any analyses we perform. Fig. 4 shows total casualties by month of the year, and disaggregated by casualty severity. There are some changes noticeable according to the time of year, with some statistically significant differences in casualty counts between months. For example, performing an Analysis of Variance on monthly total casualty counts indicates significant changes ($p = 0.025$); as does an analysis investigating changes in slight casualties across months ($p = 0.045$). However, no significant monthly changes are detected when looking at casualties in the serious or fatal categories ($p > 0.1$ in both cases). In terms of total casualties, follow-up test procedures indicate a higher number of casualties–on average–in the months of July, August and December, with some noticeably high counts detected as significant outliers in March and July. In other studies conducted by the NUSRG team, where significant deviations in casualty or collision counts by season have been identified, seasonal structure in the data has then been exploited in the modelling to lend increased precision to the analysis; for example, see the dynamic linear model analysis of collision data in Florida, discussed in Hewett et al. (2023), and the random effects analysis of UK collision data in Hewett (2023). However, both of these studies covered a substantially larger geographic area and thus monthly collision counts were much higher than what we see in Fig. 4; even where significant seasonal deviation has been identified, the scale of the data might make analyses on (for example) monthly disaggregations difficult.

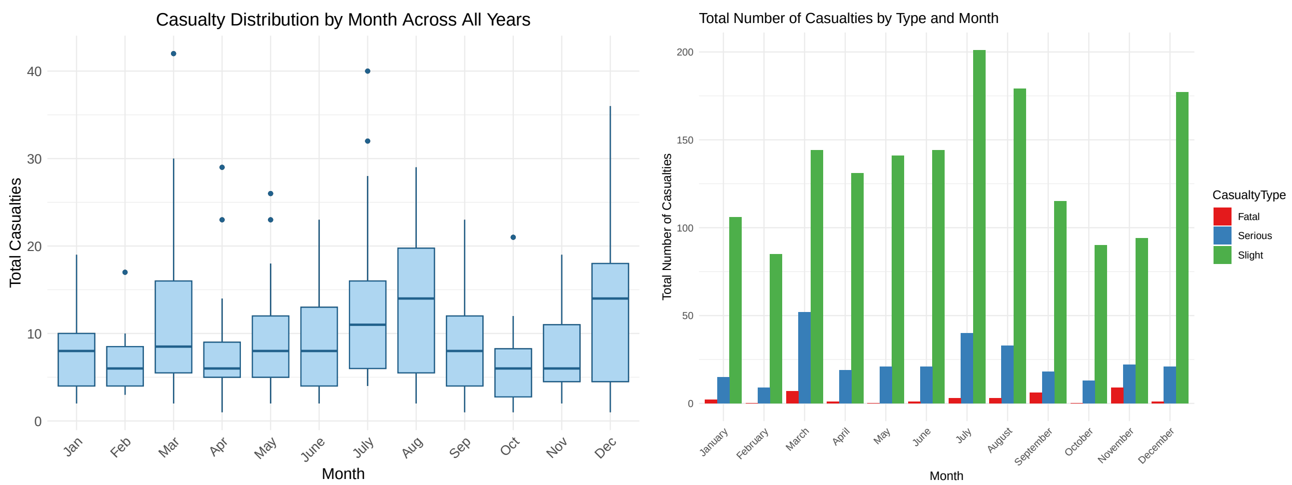

Figure 4: Boxplots of total casualties across all sites, for the years 2000-2023 (inclusive), by month of year (left); barplots showing monthly casualties disaggregated by casualty severity (right).

Before/After and other comparisons

Our analysis in Section 2.2.1 formally evaluates the effectiveness of the mobile safety cameras deployed throughout North Yorkshire; here, we make informal assessments using simple graphical and numerical summaries of our data, including casualty counts before and after the implementation of a mobile safety camera (we use 5-year before and after periods), but also according to data on some other variables shown in List 1, to assess the suitability of these variables in the modelling approach adopted in Section 2.2.1.

Fig. 5 and Table 1 show, on average, higher casualty counts in the period before safety camera implementation than in the period after, with significantly reduced variability in our data in the after period. At a site-level, we might (again, informally) get a handle on any treatment effect owing to the mobile safety camera by examining time series plots such as those shown in Figs. 2 and 3; for example, the plot for the A64 Westbound Murton in Fig. 2 might be indicative of a treatment effect, with casualties reducing to zero every year after the site became live.

Similarly, raw counts seem higher in urban areas than rural, and in sites within North Yorkshire Council than those in the City of York (although, *on average*, counts are higher in the City of York). Performing simple hypothesis tests in each of these cases (for example, Mann-Whitney tests) reveals that the difference in median casualties between B/A treatment, between urban and rural locations, and between locations in North Yorkshire and City of York councils to all be highly statistically significant ($p = 4.25 \times 10^{-11}$, $p = 8.60 \times 10^{-9}$ and $p = 7.8 \times 10^{-4}$ respectively). A Kruskal-Wallis test again shows a highly statistically significant difference in average casualty counts between local authorities ($p = 1.49 \times 10^{-14}$). A post-hoc Dunn test reveals Harrogate, Scarborough and York to have statistically significantly higher rates of casualties compared with the other local authorities, with Scarborough significantly higher than Harrogate, although neither significantly different from York. Detecting such associations paves the way for building regression models in Section 2.2.1.

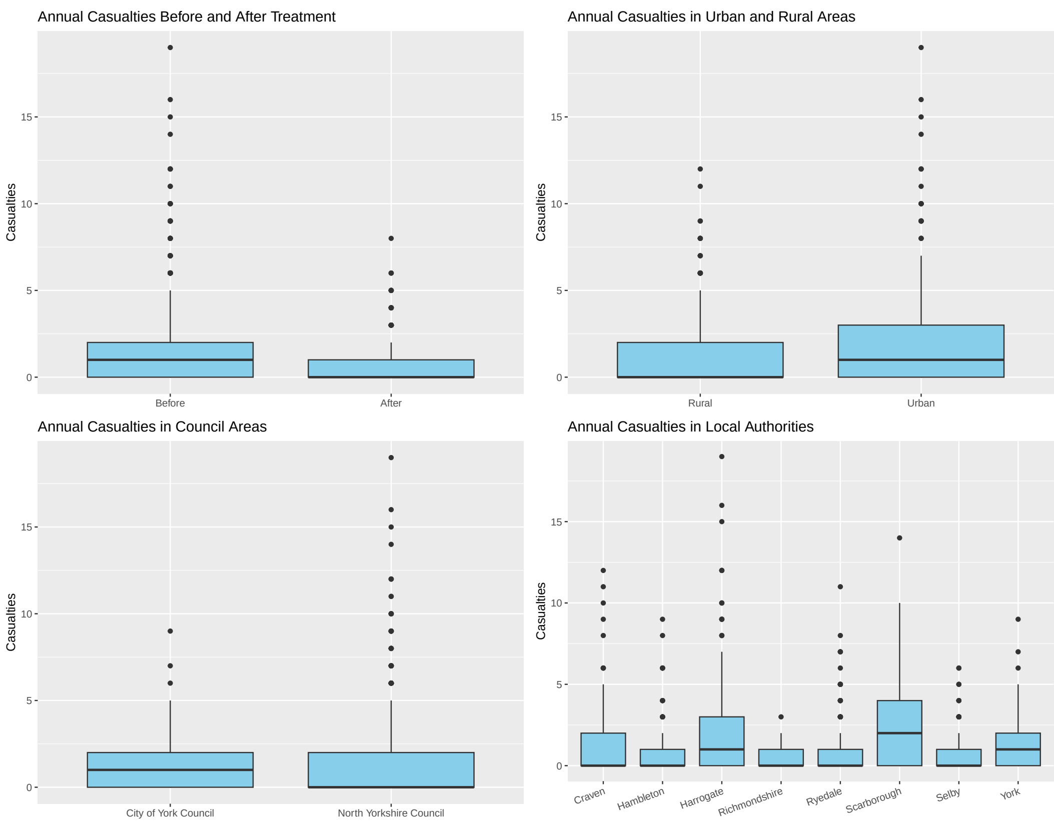

Figure 5: Boxplots of annual casualties across all sites, for the years 2000-2023 (inclusive), shown by period (before/after mobile safety camera implementation; top-left); urban/rural identifier (top-right); council area (bottom-left); and local authority (bottom-right).

		Mean	St. Dev.	Range
Treatment	Before	1.70	2.54	(0,19)
	After	0.75	1.32	(0,8)
Area	Urban	1.81	2.66	(0,19)
	Rural	1.03	1.78	(0,12)
Council	City of York	1.67	1.80	(0,9)
	North Yorkshire	1.39	2.33	(0,19)

Table 1: Summaries of casualty counts for the years 2000-2023 across all mobile safety camera sites.

Collisions

Throughout this exploratory data analysis section so far, we have focused on casualties as opposed to collisions. Here, we are looking ahead to our analysis in Section 2.2.1 in which we model casualties, and assess the deployment of mobile safety cameras in terms of casualties, in order to extend our analysis to consider casualty severity and the associated costs of prevention. Fig. 6 shows the same information as Fig. 5, but for collisions rather than casualties. As we might expect, these plots are very similar: We see, on average, higher collision counts in the period before safety camera deployment than in the period after, with reduced variability in the after period; we see higher collision counts in urban areas compared to rural areas; higher counts (on average) in the City of York compared to North Yorkshire (although some higher raw counts in North Yorkshire); and similar differences in collisions between local authorities as we noted for casualties in our earlier discussion.

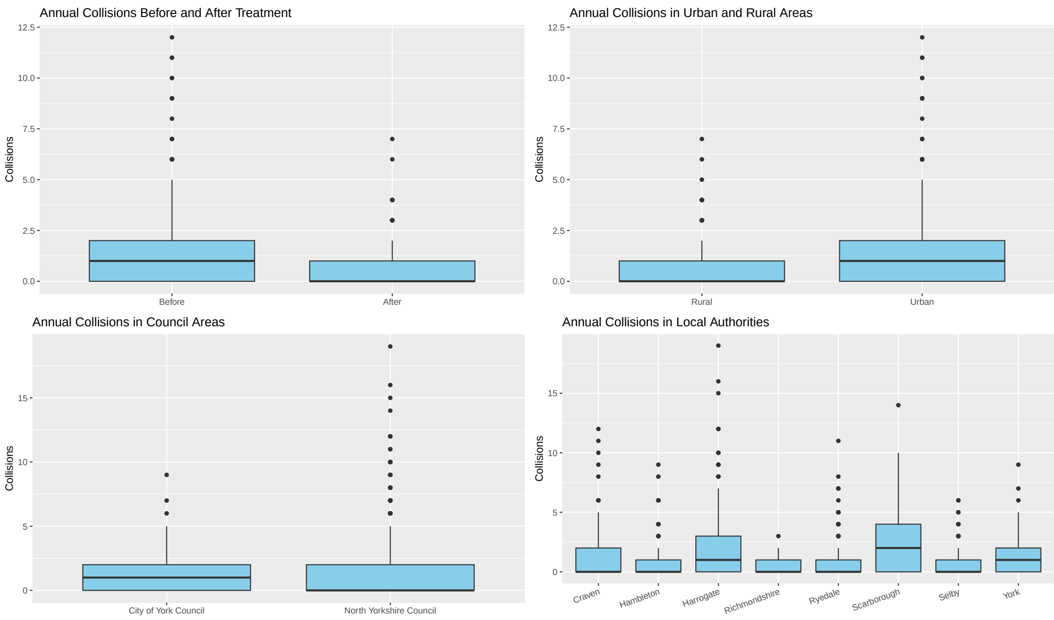

Figure 6: Boxplots of annual collisions across all sites, for the years 2000-2023 (inclusive), shown by period (before/after mobile safety camera implementation; top-left); urban/rural identifier (top-right); council area (bottom-left); and local authority (bottom-right).

2.1.2 Violations data

For exploratory analysis purposes, we standardise the number of violations (see List 2 on page 7 of this report) by the length of the monitoring period in minutes, to calculate the *violations per hour* (VPH):

$$\text{VPH} = 60 \times \frac{\text{Violations}}{\text{Minutes}}.$$

Comparing VPH across monitoring periods taken with and without a camera being present, gives the results shown in Fig. 7. Although for some local authorities we do not have data for our 5-year before periods (Harrogate, Richmondshire and Selby), looking at the boxplots for sites across the

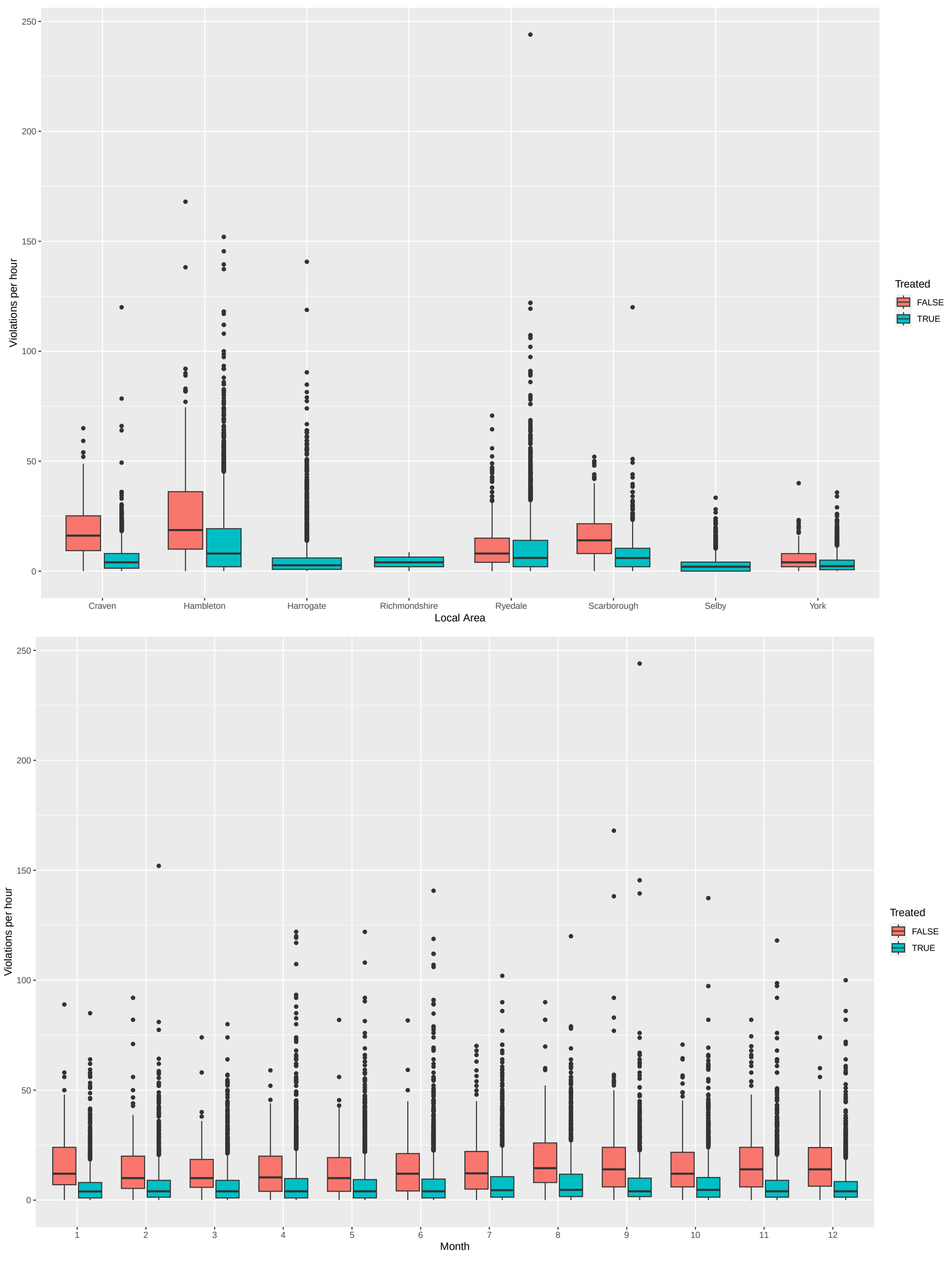

Figure 7: Boxplots showing the derived VPH for incidents where a camera was present (TRUE) or not present (FALSE); broken down by local authority (top) and month (bottom).

other five local authorities shows a clear reduction in VPH during periods when safety cameras were active – espeally for Craven, Hambleton and Scarborough (and here we have statistically significant decreases in VPH, with $p < 2.2 \times 10^{-16}$ for each test). It is worth noting that there are many outliers across these boxplots, usually due to short recording windows (e.g. the highest VPH with a camera corresponded to a monitoring window of 15 minutes which observed 61 violations). Checking for seasonal differences, Fig. 7 also shows very little deviations in VPH from month-to-month, with similar changes between periods when cameras were/were not present noted for each month of the year. A more detailed analysis of the violations data will be considered in Section 2.2.2.

2.1.3 Summary

The aim of the exploratory data analysis presented in this section was to investigate, informally, any patterns in the datasets on casualties, collisions and violations with a view to supporting the more formal analyses in Section 2.2. Of course, given the size of the datasets and the number of variables present, there are many more plots and summaries that might have been produced than we discuss in this section of the report; here, we focus on the most interesting patterns and assoations, but readers are referred to our interactive dashboard for more summaries. Some key findings include:

- Significant trend in total casualty and collision counts through time at many of our mobile safety camera sites, and across the network of mobile safety camera sites as a whole. More often than not this trend is decreasing through time, but for some sites we have an increasing trend (for example, increasing casualties at the A64 Middlecave site; and in the ty of York since 2017).
- The time trends observed across total casualty counts are reflected in those observed for slight and serious casualties, when aggregating across all mobile safety camera sites. However, it is difficult to detect anything meaningful in terms of trends in fatal casualties; similarly, trends in any casualty severity classification at a site level are difficult to detect due to sparsity of data.
- Some evidence of RTM at many sites, with apparently abnormally high counts in casualties or collisions being immediately followed by counts that are consistent with the overall trend observed at these sites.
- Some significant differences in total casualty and collision counts according to month of the year; similarly for slight casualty counts. The months of July, August and December seem to have the highest number of casualties and collisions, with significantly high outliers also being observed in March and July.
- On average, higher casualty and collision counts are observed in our 5-year before periods than in our 5-year after periods. These differences are statistically significant. Although some reduction is bound to be due to trend and RTM, ad discussed above, there might also be some reduction due to the effects of the mobile safety cameras themselves (which we will investigate further in Section 2.2.1).

- On average, casualty and collision counts are higher in urban areas than in rural areas, with these differences being statistically significant.
- Casualty and collision counts are higher, on average, in the City of York council area than they are in the North Yorkshire Council area. However, we observe some larger raw casualty and collision counts in the North Yorkshire Council area, with bigger outliers.
- Some significant differences in casualty and collision counts are noted between local authority areas; in particular, Harrogate, Scarborough and York appear to have significantly higher rates of casualties and collisions than the other local authorities.
- In terms of violations, in order to make relative comparisons we work with violations per hour. Looking at our VPH data across different local authorities and different months of the year, we see some differences between local authorities but no noticeable difference according to VPH in different months of the year. However, where violations data are available in our 5-year before and after periods, we see significant decreases in VPH once sites within a local authority became active – especially in Craven, Hambleton and Scarborough.

2.2 Statistical Modelling

2.2.1 Collision data

As described in Appendix A.2, in our analysis of the collision data we follow the gold standard empirical Bayes (EB) methodology to identify any significant treatment effects due to the presence of the mobile safety cameras at our designated mobile safety camera sites across North Yorkshire. Given our discussion in the exploratory data analysis section (see Section 2.1.1 in particular), our analysis will focus on the use of total casualties rather than separate analyses by casualty severity. However, we will consider the implications of casualty severity in our subsequent analysis investigating the value of prevention of the mobile safety cameras in North Yorkshire.

Empirical Bayes analysis: Outline

There are four main steps in our EB analysis, which we outline briefly here (but with full mathematical detail being provided in Appendix A.2); note that, for each site, we take our before period to be the five years immediately prior to the site becoming active, and the after period to be the first five years afterwards.

1. **Fit a regression model to data from untreated sites** in order to predict the casualty count at each of the camera sites in the period before the camera became active.

   For example, if we focus on the A64 Westbound Murton site, shown in the top-right plot of Fig. 2: This site became active in 2015, and so we consider data from the years 2010–2014 (inclusive) to be from our before period at this site. The purpose of fitting a regression model to estimate casualty counts in the before period is to smooth through any abnormally high (or low) counts we might see at our site of interest – for example, the 8 casualties observed in the year 2010 at the A64 Westbound Murton. Typically this regression model is built using a pool of 'control' or 'reference' sites, which are distinct from the sites where cameras are deployed (see, for example, Fawcett and Thorpe (2013)). Here, however, as we have historic data at each of our camera sites, we can use data from the sites themselves, from a time interval before the official 5-year before period, to build our model. So in the case of the A64 Westbound Murton site, we use data from the period 2005–2009 to estimate casualty counts in the before period of 2010–2014, along with similar data from all other non-treated sites during this period.

In another example, focus on the A65 Skipton site in the bottom-left of Fig. 2, which became active in 2017: Our official five year before period might seem abnormally safe relative to the full casualty time series at this site, or indeed the casualty count in 2016 might seem abnormally high – regardless, a model that has been built using data from 2007–2011 at this site and all other non-treated sites during this period will provide an estimated casualty count for the before period 2012–2016 that will smooth through these 'blips'.

The model estimates the number of casualties we would expect to see at a typical site with a given set of characteristics (those described in List 1 in Section 1.1 – for example, local authority, urban/rural etc.), with year included as a predictor to account for any trends in time (such as those shown in Fig. 2). This model also provides insight into which variables appear to affect casualty counts across the network. A full table of results is given in Appendix B.1, with a headline discussion below.

2. **Use a Bayesian model** to update the estimate from step 1. Although step 1 will provide an estimate of what we might expect to see in our before period, at each site, we cannot simply ignore the casualty counts that have been observed at these sites – even if they appeared to be abnormally high or low. The EB approach (see Appendix A.2) produces a weighted average of the estimated casualty count obtained from step 1 and the casualty count that was actually observed during the before period. We take this to be our casualty count in the before period after removing the RTM effect.

3. **Adjust for trend** by fitting a regression model to the data before the official 5-year before period (the same data used to build the regression model in step 1, except just for each individual site) which includes "Year" as a predictor. We then use the modelled effect of "Year" at that site to adjust our estimate from Step 2 (for example, if the model says there is an 8% reduction due to trend, we would multiply our estimate by 0.92). The result of this is our estimated casualty count in the after period, if there had been no camera deployed.

4. **Compute the treatment effect**. We estimate the effect of the camera by taking the difference between our estimated value if there had been no camera deployed, obtained in step 3, and the actual observed count when the camera has been deployed.

Empirical Bayes analysis: Headline results

Table 2 in Appendix B.1 shows the results of step 1 of our analysis. In summary, it appears that the following variables from List 1 are all statistically significant predictors of casualties in the North Yorkshire area:

- Road Class (Class A roads having higher casualties)

- Local Authority (Scarborough highest, Ryedale lowest casualty rates)
- Urban/Rural indicator (urban has higher rates)
- Year (negative trend in time)

In more detail, and as examples of how we interpret this model and the results shown in Table 2:

- The sign of the estimated Road Class coefficients suggests the impact of the Road Class on casualty counts, relative to the Road Class that has been set as a baseline (here, Road Class A). Thus, with negative estimated regression coefficients for both Road Class B and Road Class C (–0.4694 and –2.0482), we are less likely to see casualties for both of these Road Classifications than we are for Road Class A, and both effects are statistically significant with *p*-values of 0.0041 and 0.0112 respectively (considerably less than the usual 5% cutoff).
- The sign of the estimated local authority coefficients suggests the impact of the local authority on casualty counts, relative to the local authority that has been set as a baseline (here, local authority 1–Craven). Thus, with a negative estimated regression coefficient (–0.246), we are less likely to see collisions in Hambleton than we are Craven, although with a *p*-value of 0.2880 this is not statistically significant. However, Ryedale has the largest (negative) estimated coefficient, which *is* statistically significant, indicating that casualties in Ryedale are significantly lower than Craven and lower (on average) than elsewhere. Conversely, the positive estimated regression coefficient for Scarborough (0.4989) indicates that we are more likely to see collisions in Scarborough than Craven, and with a *p*-value of 0.0201 this is statistically significant. Further, Scarborough has the largest (positive) estimated coefficient, indicating that casualties in Scarborough are higher (on average) than elsewhere.
- The Urban/Rural indicator has a positive regression coefficient (0.4177). Again, having used "Rural" as a baseline, the positive coefficient suggests that we are more likely to see casualties as a result of road traffic collisions in urban areas. Further, this is a statistically significant finding, with a *p*-value of just 0.0024 (considerably less than the usual 5% cutoff).
- Globally, across all sites in North Yorkshire, there is a significant negative trend in casualty counts.

Table 3 in Appendix B.2 shows results from steps 2–4 of our analysis, reporting:

- Raw total casualty counts in the 5-year before and 5-year after periods for each site ("before" and "after" respectively)
- The estimated casualty count for the before period, obtained from the Bayesian model in step 2 ("post.est")
- The estimated "RTM" effect, obtained by subtracting "post.est" from "before"
- The estimated trend effect ("trend.effect"), obtained from step 3
- From the raw reduction in casualties ("before" − "after"), we subtract the estimated "RTM" and "trend.effect", to leave us with the estimated treatment effect ("treat.est")

- 95% confidence intervals on our estimated treatment effects to quantify our uncertainty
- Relative percentage changes in casualties due to the mobile safety cameras

An extract from Table 3 is shown below to explain some of these results in more detail. For example:

Site	before	after	post.est	RTM	trend.effect	treat.est	Lower	Upper
30	27.00	16.00	25.50	-1.50	-0.78	-8.72	-18.93	-0.64
34	33.00	7.00	31.93	-1.07	-0.35	-24.8	-35.28	-14.57
48	2.00	4.00	2.46	0.46	-0.28	1.82	-2.13	3.37

- Site 30 (ID 6267 – B1261 - Cayton Low Road, Eastfield): There were 27 observed casualties in the before period (2012-2016) and 16 in the after period (2018-2022)
  - This gives an overall raw decrease of **11 casualties**
  - The Bayesian model suggests around **1.50** of this difference is due to RTM (a small effect), and would not have happened anyway – the difference between the raw "before" value and the "post.est" from the EB analysis
  - Our analysis for this site also suggests that a further **0.78** casualties would not have happened anyway due to trend
  - Thus, the estimated treatment effect for this site is 11 – 1.50 – 0.78 = **8.72 casualties**, reported as **–8.72** to indicate a reduction in casualties
  - This is our mean estimated treatment effect; after accounting for uncertainty, our 95% confidence interval around this mean is **(–18.93, –0.64)**. As this is wholly negative (only just!), we might say that our treatment effect is statistically significant
- Site 34 (ID 6151 – A61 Leeds Road): This site saw the greatest reduction in casualties. There were 33 observed casualties in the before period (2011-2015) and 7 in the after period (2017-2021).
  - This gives an overall raw decrease of **26 casualties**
  - The Bayesian model suggests around **1.07** of this difference is due to RTM (a small effect), and would not have happened anyway – the difference between the raw "before" value and the "post.est" from the EB analysis
  - Our analysis for this site also suggests that a further **0.35** casualties would not have happened anyway due to trend
  - Thus, the estimated treatment effect for this site is 26 – 1.07 – 0.35 = **24.58 casualties**, reported as **–24.58** to indicate a reduction in casualties
  - This is our mean estimated treatment effect; after accounting for uncertainty, our 95% confidence interval around this mean is **(–35.28, –14.57)**. As this is wholly negative, we might say that our treatment effect is statistically significant
- Site 48 (ID 6536 – Askham Lane, Acomb): There were 2 observed casualties in the before period (2013-2017) and 4 in the after period (2019-2023)

- This gives an overall raw <u>increase</u> of **2 casualties**
- The Bayesian model suggests we would have seen around 2.46 casualties anyway, without a mobile safety camera, indicating an RTM effect of (+)**0.46** casualties
- Our analysis for this site also suggests that **0.28** casualties would not have happened anyway due to trend
- Thus, the estimated treatment effect for this site is $-2 + 0.46 - 0.28 =$ **1.82 casualties**, reported as (+)**1.82** to indicate an increase in casualties
- This is our mean estimated treatment effect; after accounting for uncertainty, our 95% confidence interval around this mean is **(–2.13, 3.37)**; as this covers zero, we might say that any change in casualties due to the treatment (an increase here) is not statistically significant

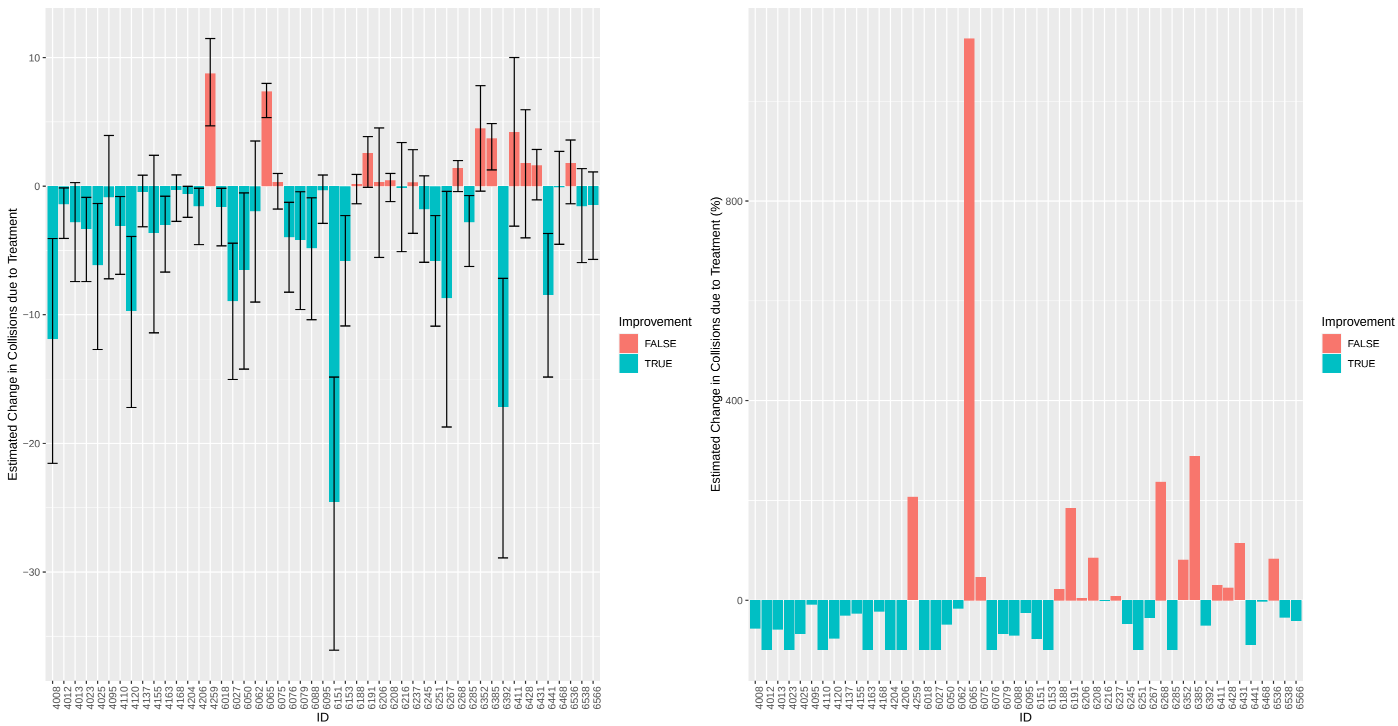

Figure 8: Bars showing estimated change in casualties due to mobile safety cameras as a raw figure (left) and as a percentage of expected collisions (right). Green bars represent a site with a reduction in casualties due to the camera according to the model.

All estimated treatment effects from our model are displayed in Fig. 8, where we see that the majority of sites (34 out of 49) have an estimated reduction in casualties due to the cameras in the 5-year period following implementation. Across all mobile safety camera sites, there was a total of 339 casualties in the before periods and 209 in the after periods, giving a raw reduction between before and after periods of 130 casualties; our analysis suggests that a reduction of around 120 casualties might be attributable to the mobile safety cameras themselves, after accounting for RTM and site-specific trends. The reduction owing to RTM here is considerably smaller than noted in some other studies (for example, see our discussion in Appendix A.1), with a correspondingly higher reduction in casualties due to the mobile safety cameras here: For example:

- In an analysis of mobile safety cameras in the Northumbria Police Force region, Fawcett and Thorpe (2013) cite an overall RTM/trend reduction in casualties of around 26%, with a reduction owing to the mobile safety cameras of just 7%.

- In a previous (considerably smaller) analysis of mobile safety cameras in North Yorkshire (see Section 1.2), an overall RTM/trend reduction in casualties of around 11% was noted, with a reduction owing to the mobile safety cameras of around 20%.

- In this study, we have an overall TRM/trend reduction in casualties of just 7%, with a reduction owing to the mobile safety cameras of around 36%.

Breaking down the estimated treatment effects by road class, local authority, and urban/rural gives the results shown in Fig. 9. From this we can see that while there is some variability in the treatment effects across the different groups, these don't appear to be significant, particularly when we consider the relatively small sample sizes. We can however conclude that there doesn't appear to be any type of site for which the treatments do not appear to have any effect. Tables 4, 5 and 6 in Appendix B.2 summarise such findings numerically, comparing mean treatment effects for different road classifications; council areas; and local authorities, respectively. Although none of these effects are significantly different across different groups, it is interesting to note the relative size of treatment effects – for example, from one local authority to another (Harrogate versus Ryedale in Table 6, for example).

Of particular interest might be the sites displayed in Tables 7 and 8 in Appendix B.2. The sites reported in these tables all have treatment effects that are "positive", i.e., after accounting for RTM and trend we have estimated an increase in casualties rather than a decrease. However, these positive treatment effects are not all significant; the treatment effect 95% confidence intervals for many of the sites shown in Table 7 cover zero (as is the case for site 48 – Askham Lane, Acomb, as

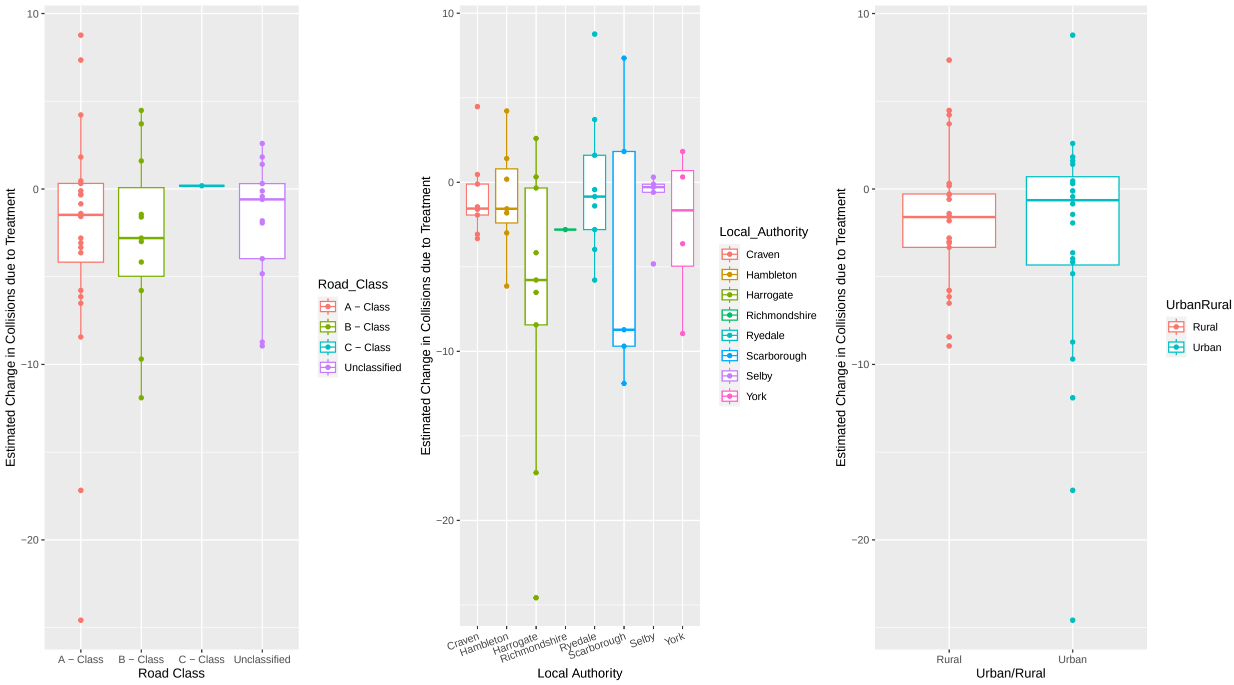

Figure 9: Boxplots showing the estimated change in casualties due to cameras, broken down by site characteristics.

discussed above), indicating no significant treatment effect. Only for three sites (as shown in Table 8) do we estimate significant increases in casualties, after mobile safety camera deployment and after accounting for RTM and trend. These three sites – A64 Middlecave, Malton; A64 Rillington; and B125 South of Ebbertson, might warrant further investigation.

Estimated cost of prevention

For each site, Fig. 8 and Table 3 (Appendix B.2) show the estimated treatment effect, in terms of casualties prevented due to the deployment of mobile safety cameras. Using historic data on casualty severity at each site, we can then estimate the proportion of casualties – prevented due to the presence of mobile safety cameras – that would have been classified as "slight", "serious" or "fatal" had they indeed materialised. Multiplying these proportions by the estimated casualty prevention figures for each site, and then by standard Department for Transport figures relating to the average value of prevention for road traffic casualties in each severity category (Department for Transport (2012)), leads to the estimated total value of prevention at each site as shown in the last two columns of Table 10. Although these are based on 2012 casualty prevention valuations, and our estimates for each site relate to varying 5-year post-deployment periods ranging from (2013–2017) to (2018–2022), these figures are nonetheless informative: Summing across all sites, we have an estimated total value of prevention owing to the mobile safety cameras in our study of our £8.2 M; appropriate scaling gives a 2024 valuation of around £11.3 M. Note that these estimates include police costs, medical and ambulance costs, property damage costs, insurance and administration costs, and human costs including pain, grief and suffering.

2.2.2 Violations data

Table 11 in Appendix C shows the results of a negative binomial regression linking VPH (see Section 2.1.2) to prospective predictor variables, as shown in List 1 on page 7. As can be seen, almost all variables displayed in this table appear important, with p-values less than the nominal 5% cutoff for statistical significance. As with the discussion in Section 2.2.1 relating to Table 2, we see that, for example:

- Relative to the baseline month (month 1, January), all months (except December) have a higher VPH due to their positive estimated coefficients, and all monthly effects except for March and December are significant in the model.
- Relative to the baseline local authority (Craven), all local authorities except Hambleton have a lower VPH due to their negative estimated coefficients, although effects for Scarborough and Richmondshire are marginal (their p-values fall between 5% and 10%).
- The variable "year" is statistically significant, with a negative estimated coefficient, indicating a significant negative trend through time in VPH across the network.
- We can also see that in areas for which we have VPH data before and after the deployment of mobile safety cameras, there are significant changes in VPH post-treatment.

Although beyond the scope of the current study, we observe a correlation between data on violations and data on casualties and collisions. A more detailed analysis of violations data, including the use of hotspot prediction methodology such as that described in Fawcett et al. (2017), might be of interest here: Using violations as a proxy for collisions would support a much more proactive approach to road safety hotspot identification and subsequent treatment (e.g. with mobile road safety cameras), as we are not dependent on waiting until collisions occur (with their associated high societal and financial costs).

2.2.3 Summary

North Yorkshire and the City of York should feel assured that their mobile safety cameras have been performing well, in terms of reducing collisions and casualties across the designated safety camera sites shown in Fig. 1.

- Our analysis in Section 2.2.1 shows that, after accounting for the confounding effects of RTM and trend, there was a reduction in casualties between our 5-year before and after periods of around 36%, and this reduction is statistically significant.
- Although our previous collaboration (see the discussion in Section 1.2) analysed data from a smaller subset of these sites, with shorter before and after periods, relative comparisons can still be made; in our previous collaboration we reported just a 20% reduction in casualties due to the mobile safety cameras.
- Reductions of between 20%–30% after accounting for RTM and trend are typical (see, for example, Hirst et al. (2004)), so a reduction of 36% across North Yorkshire and the City of York is a very positive outcome.
- This is especially pleasing when set against the effectiveness of mobile road safety cameras in some other jurisdictions (for example, the 7% treatment effect observed in the Northumbria Police Force area, as reported in Fawcett and Thorpe (2013)).
- The estimated treatment effect of 36% translates to a reduction of 120 casualties as a result of the mobile safety cameras. An analysis of historic casualty severity data, and linking this to standard Department for Transport figures (Department for Transport (2012)) relating to the average value of prevention for road traffic casualties, suggests a total value of prevention of around £11.3 M in 2024 figures.

At a site-specific level, for most sites there has been a significant decrease in casualties as a result of the mobile safety cameras. However, some sites have been flagged in our analysis as a potential cause for concern.

- The 15 sites Listed in Table 7 all observed an *increase* in casualties in the period following mobile safety camera deployment, after accounting for RTM and trend.
- However, only for three of these sites was the increase in casualties significant:
  - A64 Middlecave, Malton

  - A64 Rillington
  - B12 South of Ebberston (near Electric Sub Station)

- We would recommend further investigation into the effectiveness of the mobile safety cameras at these sites.

We believe that analyses of violations data might be crucial in implementing a more proactive approach to the identification of future sites for mobile safety camera treatment. Our investigations reveal a positive correlation between our data on violations and our data on collisions/casualties. The analysis in Section 2.2.2 shows significant associations between site-wise violation rates and various predictor variables, most notably month of the year, local authority, the year itself (i.e. indicating a trend in violations through time) and, most crucially, significant differences in violation rates between our before and after periods (for areas in which we have violations data for both periods). Thus, there is potential for a statistical modelling approach similar to that used in Fawcett et al. (2017) in which such data can be used to predict future violations and to therefore support a proactive approach to the identification of sites for treatment. Using violations as a proxy for collisions or casualties in this way has much lower costs – both societal and financial – than an analysis relying on collisions or casualties.

2.3 Other Evaluations of Mobile Road Safety Cameras

In Section 2.2.1 we made some comparisons of the current B/A study of mobile safety cameras in North Yorkshire to another evaluation of mobile safety cameras performed by the NUSRG team in conjunction with the Northumbria Safety Camera Partnership. As discussed, once confounding effects have been properly accounted for, reductions owing to road safety countermeasures as identified from such retrospective B/A studies are typically in the range of 20%–30% (Hirst et al. (2004)); with a reduction of around 36% in the current study and just 7% in the NUSRG Northumbria study (Fawcett and Thorpe (2013)). We now set the current project alongside some other studies of mobile safety cameras both in the UK and further afield. It should be noted that examples of robust evaluations of mobile safety cameras in the literature are limited; most evaluations that attempt to separate genuine treatment effects from the effects of confounders such as RTM and trend are based on fixed speed cameras. In this report we avoid any comparisons from B/A studies that neglect to identify confounding effects.

Christie et al. (2003) aimed to compare the various methods (circles and routes of various sizes) for assessing local effectiveness of mobile safety cameras, and then to use the most appropriate of those methods to investigate the effectiveness of mobile cameras by time after intervention, time of day, speed limit, and type of road user injured, using a controlled before-after method of investigation. They studied 101 sites in South Wales and demonstrated a notable decrease in injurious crashes within the vicinity of the designated mobile safety camera sites. Specifically, within 100 metres, there was a 73% reduction, and within 100-300 metres, a 24% reduction was observed. Utilising a 500-metre route method, overall crash rates declined by 51%. The route-based method proved more effective, particularly over a 500-metre linear route, revealing a greater reduction in crashes compared to the circular method. This approach allowed for a more nuanced understanding of the cameras' impact, which remained consistent over time and across different speed zones. Notably, pedestrian injuries saw the largest decrease, with a 78% reduction. However, the study's reliance on limited traffic volume and route diversion data might have influenced the precision of these findings, posing a potential limitation to the model used. Notice that the reported treatment effects here are substantially larger than those reported above. We note that this study is unlike most of the other retrospective B/A studies in the literature (including ours in this report); properly designed, controlled B/A studies are superior to retrospective B/A studies as they can avoid RTM biases altogether, therefore avoiding the need for post-hoc estimation of such effects.

Jones et al. (2008) evaluated road traffic accidents in Norfolk before and after the implementation of speed cameras at 29 sites, chosen due to their high injury crash rates. Most sites had speed limits over 60 mph, primarily outside urban areas. Following the introduction of cameras, overall crashes on these roads fell by 1%, and fatal or serious crashes decreased by 9%. At the camera sites, total crashes reduced by 19%, and fatal and serious crashes by 44%. This decrease was significantly greater than what could be attributed to the regression to the mean, indicating a positive impact of speed cameras on road safety.

Kokkuvotte (2019), in conjunction with the NUSRG team, used a standard empirical Bayes analysis to evaluate mobile cameras deployed to 30 sites in Tallinn, Estonia. Across these sites, a reduction on collisions of around 20% was estimated owing to the mobile safety cameras; a 17% reduction due to RTM was estimated, with a further reduction of around 10% due to trend.

3 Literature Review: Other Speed Enforcement Systems

3.1 Road Safety and Speed

Despite the United Kingdom having one of the highest standards of road safety in Europe, it has been reported that annually, around 3,000 individuals lose their lives and more than 40,000 suffer serious injuries in road accidents in the UK (Bartlett et al., 2008). A significant number of these accidents involve inappropriate or excessive vehicle speed as a contributing factor (Barker et al., 1998, DETR, 2000, Graham, 1997, Quimby et al., 1999, Taylor, 2001, Taylor et al., 2000)). The link between speed and the likelihood of accidents is complex, yet extensive research indicates that lower speeds on the roads correlates with a decrease in both the frequency and severity of accidents. A notable meta-analysis of European studies by Finch et al. (1994) demonstrated that a reduction in average traffic speed by one mile per hour can lead to a 5% reduction in accident rates. A safety measure that is commonly implemented to combat excessive speeds is speed cameras, and mobile road safety cameras are playing an increasing role here.

3.2 Confounding Factors

Most road safety schemes like speed cameras are evaluated retrospectively through B/A studies (Hauer, 1997). These studies identify potential intervention sites, termed 'sites with promise', through continuous monitoring of road networks. During a predetermined 'before' period, extensive data, including accidents, traffic volume, and speed, are collected. Post-observation, sites exceeding a certain accident threshold undergo treatment, followed by 'after' period data collection. However, attributing reductions solely to interventions overlooks the RTM phenomenon and selection bias, which can account for a 20-30% reduction in collision counts (Fawcett and Thorpe (2013), Hauer (1980), Hirst et al. (2004)). This necessitates considering trends and other confounding factors in evaluations.

Temporal trends also play a crucial role in road safety, influenced by factors like traffic volume and vehicle safety improvements. Not accounting for these trends can bias treatment effect estimates (Guo et al. (2019), Yanmaz-Tuzel and Ozbay (2010)). UK data shows varying trends in accident severity, with a consistent number of fatalities since 2010, a decrease in slight accidents since 2014, and a recent increase in serious injuries, partly due to reporting changes (Department for Transport, 2020). These trends highlight the importance of considering accident severity in predictive models. Elvik (2002) shows that not controlling for confounding factors leads to an overestimation of the effects of road safety measures.

The importance of choosing the correct model and accounting for confounding factors is shown via the huge differences in the evaluated effectiveness of speed cameras. It is also noted that estimates of the effectiveness of speed cameras vary substantially across different studies. In a survey of existing literature, Wilson et al. (2010) found that after implementation of speed cameras, the relative reduction in average speed ranged from 1-15% in the 35 studies included in the review; the reduction of proportion of speeding vehicles ranged from 14-65%; and the reduction in road traffic crashes ranged from 8-49%. This can even be prominent when using variations of the same model, for instance, empirical Bayes (EB). For more information on EB, see Hauer (1997).

Hirst et al. (2004) discuss sources of error in road safety scheme evaluation. They compare current methods in which they include examples of the change in the effectiveness of speed camera intervention from the inclusion of certain error factors. They calculate the reduction of accidents from the before and after periods and compare the percentage reduction evaluated through methods which include accounting for trends, RTM effects and traffic flow changes. Methods compared include a simple B/A study, B/A with comparison group, "simple EB", EB with a comparison group and EB with comparison group and flow correction. Depending on the method used, the treatment effect was found to reduce the number of all accidents by between 32.1–36% and for KSIs between 42.8–48.8% over the 50 sites. When evaluating the effectiveness of any safety measure it's important to account for any confounding factors, such as trend and RTM. We might also assume that the implementation of a speed camera may persuade drivers to use alternate routes and hence, traffic volume and distances in the surrounding areas may provide key information on the fluctuation of the number of crashes in the before and after periods.

3.3 Advantages of Speed Cameras

Although there are discrepancies in the reporting of how effective speed cameras are, there's a general consensus that speed cameras are indeed effective in reducing excess speed and subsequently the number of traffic collisions. By decreasing the number of collisions, speed cameras also contribute to substantial economic savings through reduced social and healthcare costs. The economic implications of road accidents are substantial, encompassing hidden social costs such as productivity loss, medical and legal expenses, pain, suffering, and property damage. Estimates suggest a fatal casualty as a result of a road traffic accident incurs costs of approximately £2 million; a serious casualty around £220,000; and a slight casualty £25,000. In response, a system introduced in 2000 allowed pilot areas to fund speed and red-light cameras through fines, later expanding nationally. Gains et al. (2005) analysed its effectiveness over three years in 24 areas, concluding a positive cost-benefit ratio of around 4:1. By the third year, the benefits to society from avoided injuries exceeded £221 million, compared to enforcement costs of about £54 million.

Transport Research Laboratory (2021) provide a discussion on the evolution of methodologies for calculating collision costs, originally established by O'Reilly (1993) and Hopkins and Simpson (1995), and suggest potential improvements for more accurately capturing the economic effects of road traffic collisions. Building on this, Fawcett and Thorpe (2013) demonstrate that, after adjusting for trends, the implementation of safety cameras not only saves lives but also contributes to economic savings. Their analysis shows a reduction in total casualties translating to a median prevention value of over £1.2 million at 56 sites over a two-year period, underscoring the significant dual benefits of safety cameras in both human life protection and economic efficiency.

3.3.1 Fixed safety cameras

The effects of fixed speed cameras are most commonly studied. There are many examples of the use of EB to evaluate the effectiveness of fixed speed cameras. De Pauw et al. (2014) evaluate the traffic safety effects of 65 fixed speed cameras, installed between 2002 and 2007, on highways in Flanders-Belgium using EB. The article illustrated an 8% decline in the occurrence of injury crashes, which was not statistically significance. In contrast, in instances of more severe crashes involving serious or fatal injuries, a significant reduction of 29% was identified at the 5% significance level. An advantageous impact was observed across all road user categories encompassing car occupants, cyclists, moped riders, motorcyclists, and pedestrians.

Høye (2015) assessed the safety impact of 223 fixed speed cameras, in Norway, installed from 2000 to 2010 using a B/A EB method. Benefits included a 22% reduction in injury crashes near camera sites. However, for severe cases involving fatalities or severe injuries, no significant change was observed. The safety effects were more pronounced for cameras installed after 2004, but diminished with increasing distance from the cameras. The method accounted for general trends, traffic volumes, and changes in speed limits to provide a more accurate understanding of the cameras' effects. EB still remains in common usage with Høye (2015), Park and Abdel-Aty (2015), Wang et al. (2017) providing examples of studies carried out in the last several years relying on an EB methodology for inference.

Li et al. (2013) use the propensity score matching (PSM) method to evaluate the impacts of speed limit enforcement cameras on reducing road accidents in the UK by accounting for both confounding factors and the selection of proper reference groups. A naive B/A approach and the EB method were compared with the PSM method. A total of 771 sites and 4787 sites for the treatment and the potential reference groups respectively were observed for a period of 9 years in England. Speed cameras were found to be most effective in reducing accidents up to 200 metres from camera sites and no evidence of accident migration was found.

3.3.2 Average speed cameras

An RAC survey revealed that 79% of people believe average speed cameras are more effective at slowing traffic than traditional fixed ones (RAC, 2018). Notably, 86% of respondents acknowledge the effectiveness of average speed cameras in reducing vehicle speeds, contrasting with 70% for fixed cameras, which are perceived to have limited impact beyond their immediate location. Furthermore, Owen et al. (2016) provide compelling evidence on the efficacy of average speed cameras in Great Britain. Analysing 51 sites installed between 2000 and June 2015, they observed notable reductions in road collisions: fatal and serious collisions dropped by 25-46%, and personal injury collisions by 9-22%. Covering 294km across 25 sites, the study also highlights a significant decrease in installation costs — from £1.5 million in 2000 to £100,000 per mile in 2016 — suggesting a potential rise in the adoption of such safety measures due to more affordable technology and competitive market pricing. Soole et al. (2013) provide a review of multiple studies on the effectiveness of average speed cameras across Europe and Australia.

3.3.3 TASCAR

The introduction of TASCAR significantly improved safety and traffic flow in roadwork zones on highways. Traditional enforcement methods, such as spot speed cameras and hand-held speed guns, often lead to sudden braking, congestion, and collisions due to their immediate and localised nature. In contrast, the advent of SPECS Average Speed Cameras, first prototyped in 1994 on the M20 in Kent and further developed for the M62 in 2002, allowed for the calculation of vehicles' average speed over longer distances. This system effectively reduced the erratic driving behaviours associated with older technologies. Recognised by the Department for Transport in

2005 with the approval of a specific sign for SPECS controlled zones, these average speed cameras have become the default enforcement technology in major roadworks since 2007. This approach enables more efficient traffic management, reducing the impact on journey times while ensuring safety within extended work zones. Over 400 major TASCAR projects in the UK have demonstrated the benefits of this technology, allowing for smoother and safer traffic flow through construction areas (TASCAR, 2024).

Sgt Paul Preston of Nottinghamshire Police emphasised the transformative impact of SPECS average speed cameras, debunking the notion they serve as mere revenue tools. Instead, these cameras have become a cornerstone for traffic safety, offering unparalleled consistency in driving behaviour over long distances. Nottinghamshire's early embrace of this technology, resulting in the deployment of over 36 pairs of permanent cameras, has been pivotal in achieving significant advancements in driving compliance and road safety. The comprehensive influence of SPECS cameras extends beyond mere enforcement; they cultivate a driving environment characterised by stability, minimal speed variations, and heightened focus. By diminishing the urge for competitive lane changes and reducing response to roadside distractions, these cameras engender a collective compliance effect, leading to safer and more predictable road conditions. This collective adherence, coupled with an increased awareness of enforcement presence, underscores the critical role of average speed cameras in fostering safer driving behaviours and enhancing traffic management efficiency (Charlesworth, 2008).

3.3.4 Speed cameras as safety measures

More generally, studies show the advantage of implementing speed cameras as safety measures. College of Policing (2017) reviewed 51 studies and found no significant difference in the effectiveness of speed cameras between urban and rural areas. However, it did find some evidence of greater reductions in crashes during rainy and wet conditions, during the day compared to night, and on weekdays compared to weekends. Notably, fixed cameras showed a slightly greater effect on all road traffic crashes and those resulting in fatalities or severe injuries than mobile cameras. The full review can be found in Steinbach et al. (2016). The review included 16 new evaluations alongside 35 from a previous review (Wilson et al., 2010). The findings demonstrate that speed camera programs significantly reduce average speeds by 7% (95% confidence interval 0-13%), the percentage of vehicles exceeding speed limits by 57% (95% confidence interval: 50%–64%), overall crashes by 19% (95% confidence interval: 14%–24%), injury crashes by 18% (95% confidence interval: 13%–23%), and severe or fatal crashes by 21% (95% confidence interval: 13%–29%). Notably, the review found little variation in the effectiveness of different types of speed cameras, such as fixed versus mobile or overt versus covert. However, there was some evidence suggesting that fixed cameras may have a slightly greater impact on reducing overall road traffic crashes and those resulting in fatalities or severe injuries compared to mobile cameras.

The Royal Society for the Prevention of Accidents (2021) offers a detailed assessment of the role of speed cameras in reducing road accidents, focusing on multiple studies and different types of cameras. It underscores that higher speeds significantly increase the likelihood and severity of accidents, with 2019 data revealing a notable contribution of inappropriate speed to road accidents in the UK. The article elaborates on various speed camera types, particularly fixed and average speed cameras, highlighting their effectiveness in curbing speeding behaviours. Fixed speed cameras showed a 70% reduction in vehicles exceeding speed limits and a 91% decrease in excessive speeding, while the rate of people killed or seriously injured dropped by 42% at camera sites. The document also references multiple international studies, consistently indicating that the presence of speed cameras leads to substantial reductions in collisions, injuries, and fatalities.

Allsop (2013) primarily highlights the significant reduction in collisions following the establishment of speed cameras across the UK, in a report authored for the RAC Foundation. The analysis found a 27% reduction in fatal or serious collisions (FSC) and up to a 32% decrease in personal injury collisions (PIC), with an average reduction of 25% in PIC. These findings underscore the effectiveness of speed cameras in enhancing road safety. Additionally, the study observed a reduction in speeds around camera sites, further supporting the cameras' role in promoting safer driving behaviours. For the analysis, the study used a comprehensive dataset covering various regions and periods before and after the camera installations. The statistical model, accounted for year-on-year changes and controlled for RTM. This approach effectively isolated the impact of speed cameras from other factors, providing a robust assessment of their influence on reducing collisions and speeds.

Additionally, Li et al. (2021) focuses on assessing the effectiveness of speed cameras in the UK, particularly examining the criteria used for selecting camera sites. The study involved 332 speed cameras and 2513 control sites, utilising both Propensity Score Matching (PSM) and Empirical Bayes (EB) whilst also controlling for regression to the mean and other confounding factors. The study suggests that a site length of 500 meters is optimal for achieving the best safety effects of speed cameras and speed cameras are most effective in reducing crashes when the minimum number of historical killed and seriously injured collisions (KSIs) is met (criterion 1). Specifically, sites with at least 3 KSIs in the baseline years showed the most significant reductions. The study found that speed cameras are more effective with a risk value greater than or equal to 30, as opposed to the recommended risk value of 22 (criterion 2). In terms of reduction in collisions, the study found that the absolute number of Personal Injury Collisions (PICs) per km per year reduced by 0.597 to 1.147 at sites meeting criterion 1, and by 0.313 to 0.357 at sites not meeting it. For criterion 2, reductions in PICs per km were 0.293 for up to 500 meters, 0.203 for up to 1000 meters, and 0.186 for up to 1500 meters. The study also indicates that a road length of 500 meters is most effective, with reductions of 15.63% for criterion 1 and 16.85% for criterion 2. Overall, the study underscores the importance of careful site selection based on specific criteria for maximising the effectiveness of speed cameras in reducing road traffic accidents and injuries.

3.4 Identification of Camera Deployment Strategy

As discussed throughout this section, there are relative strengths and drawbacks to each type of camera deployment (here we consider fixed, mobile, and average speed cameras), which must be considered when deciding on which type of camera to allocate where. It is generally accepted that average speed cameras have the most significant impact in reducing the number of speed related collisions, however these are also the most expensive camera scheme to operate, and require the usage of a dedicated police unit to process the data (one unit per speed limit in the area), leading to significant cost. Furthermore, because of their effectiveness, along with the fact they allow drivers to correct their speed before the end of the camera area, they typically do not generate much revenue in terms of speeding fines, making them difficult to justify from a financial cost-effectiveness perspective. So whilst their effectiveness at reducing collisions is well accepted, a strategy of solely using average speed cameras is unlikely to ever be viable due to financial constraints, not to mention logistical issues of average speed cameras needing to be deployed on a road where average speed can easily be estimated, without too many junction points between the start and end of the zone etc. In contrast to this, fixed and mobile cameras are relatively cheap to set up and run, and because they focus on a driver's speed at a specific point, are much more successful in recording speed violations and therefore generating revenue through speeding fines. This is particularly true where mobile cameras are moved around frequently, to reduce the 'halo effect' which affects fixed (and non-moving mobile) cameras, whereby motorists are aware of the presence of the camera, and so speed limit compliance improves within a given radius of the camera (but is unchanged further away).

We can therefore look to combine these two camera types and effects into a single strategy, where fixed/mobile cameras are preferred at locations which have high numbers of speed violations but low numbers of collisions/casualties, and average speed cameras are preferred where there are high numbers of collisions relative to the number of violations. This allows the fixed/mobile cameras to target high violation areas, and in the process generate revenue to finance the average speed cameras which can target areas where the threat to safety is at its highest.

Acknowledgements

The NUSRG project team would like to thank Dr. Keith Newman for his support in producing the interactive graphics dashboard to support this report. The team would like to thank James Stoker at NYC for very promptly responding to data requests, and to the wider team at both NYC and NYP for very useful discussions and insights.

Appendices

A Methodology for the Evaluation of Road Safety Interventions

A.1 Regression To (the) Mean (RTM)

When evaluating safety schemes, it is important to take into consideration trends and many other confounding factors such as RTM. In road safety, practitioners make decisions on the implementation of safety schemes based upon data. However, issues in collecting data cause problems with the implementation or retention of safety schemes. Common issues include problems with sparsity of data, temporal trends or regression to the mean (RTM). Regression to the mean is a concept which refers to the fact that when a sample from a random variable is extreme, eventually the following samples will return closer to the mean value. This can significantly impact road safety studies. The RTM phenomenon is well-known and well-documented (Fawcett and Thorpe, 2013, Galton, 1889, Hauer, 1980).

When selecting sites for safety interventions, areas with unusually high collision or casualty rates are often chosen. However, these high rates might partly be due to random fluctuations, and over time, they might naturally decrease to the average level, a process known as RTM. Without accounting for RTM, any reduction in accidents after implementing a safety measure, such as speed cameras, could be mistakenly attributed entirely to the intervention, when in fact, some of the reduction would have occurred naturally.

To accurately assess the impact of safety interventions, it's crucial to distinguish the effects of RTM from the actual effects of the intervention. This is typically done by using control groups - sites similar to the intervention sites but without the safety measures. By comparing the before-and-after changes in collision or casualty rates at both the intervention and control sites, analysts can more reliably determine the portion of the change that can be attributed to the intervention, as opposed to RTM. Incorporating an understanding of RTM into road safety analysis ensures a more accurate and reliable evaluation of safety interventions, preventing overestimation of their effectiveness and leading to better-informed decisions in road safety management.

The first significant investigation into the RTM effect, in the context of road safety, was by Ezra Hauer (Hauer, 1980, 1986) and can be defined in this context as *selection bias* when a treatment is applied non-randomly based on the responses on the individuals that are treated (see also, Elvik (1997), Mountain et al. (1998)). The RTM effect varies but in some instances, the reduction in collision counts owing to RTM has been shown to be as much as 20–30% (Elvik, 2002, Fawcett and Thorpe, 2013, Hauer, 1997, Mountain et al., 1998). This might be viewed as the exaggerated effects of the road safety intervention, as often reported by police or in the media (Brooker and North, 2007). Hence, it is vital that this is accounted for when evaluating schemes when almost a third of the reduction could be inevitable.

A.2 Empirical Bayes/Full Bayes Methodology

It is common that B/A evaluations are performed via an empirical Bayes (EB) approach, proposed by Hauer (1997). In fact, in recent years this has become the 'gold standard' in road safety scheme evaluation. In the EB method for evaluating the effectiveness of safety cameras, the analysis is not only confined to the locations where safety cameras are deployed ('treatment sites') but also includes data from similar locations without safety cameras ('control sites'). These control sites are chosen for their similarities in traffic and road characteristics to the treatment sites, yet remain unaffected by the deployment of safety cameras. Data on accidents, incidents or collisions are collected from both sets of sites for periods before and after the safety cameras are deployed. The method then involves a detailed comparison of changes in accident, collision or casualty rates at the treatment sites against those at the control sites. This comparison is crucial as it helps to isolate the specific effect of safety cameras from other influencing factors like changes in traffic volume or road conditions. Additionally, the EB method incorporates prior knowledge or assumptions about accident rates and traffic patterns, both for treatment and control sites. This blending of observed data with established patterns allows for a more refined estimation of the camera's effectiveness. By comparing the adjusted accident/collision/casualty rates from the treatment and control sites, the method provides a comprehensive and accurate assessment of the true impact of safety cameras on road safety, ensuring that the conclusions drawn about their effectiveness are robust and reliable.

When using EB, we use standard techniques to estimate the regression coefficients in the accident prediction model (APM).This model helps us understand the relationship between various factors and the number of collisions, as illustrated by the equation:

$$\mu = \exp\{\beta_0 + \beta_1 x_{speedlimit} + \beta_2 x_{trafficvolume} + \cdots\} \tag{1}$$

Here, the regression coefficients (β_i) are initially estimated using maximum likelihood, and these estimates are then incorporated into the Bayesian analysis within the EB framework.

From this point forward our discussion focuses on casualties, as it is changes in casualties that we assess in Section 2.2.1. We let Y_j represent casualty counts at site j in the before period, and we assume that Y_j (taking observations y_j) is Poisson-distributed with mean m_j. In a Bayesian analysis, we then adopt a *prior distribution* for the parameter in our model – here, the Poisson rate m_j at each site j, which we assume itself is gamma-distributed with mean μ_j. A Bayesian analysis then incorporates *prior information* into the analysis, along with our observed data (casualty counts in the before period), to obtain our *posterior distribution*; our updated beliefs about the rate m_j having combined our prior beliefs with the observed data.

This is where the reference sites usually come into play; the model in Eq. 1 is constructed using data at the reference sites, before being applied to data at the treated sites – essentially giving an estimate of casualty counts at the treated sites but based on data observed at sites that were not treated, and therefore sites with casualty counts that are *not* excessively high. This estimate is then combined with the actual observed casualty count in the before period, to give the *Empirical Bayes estimate of casualty frequency*:

$$y_{EB,j} = \text{Mean}(m_j) = \alpha_j \mu_j + (1 - \alpha_j) y_j,$$

where the weight α_j is estimated as part of the initial regression analysis. Note that this is a weighted sum of what we might expect to see at site j, based on information at the references sites, and what we have actually observed; any abnormally high observations will be tempered by what we expect through the regression modelling part of the analysis.

In a truly Bayesian setting, we have the ability to include prior/expert knowledge about the parameters to help inform the model, and simulation-based procedures might be needed to estimate all parameters within a 'fully Bayesian' (FB) context. Doing so could more reaListically quantify our uncertainty in estimates of RTM and treatment effects by acknowledging our uncertainty in the estimated APM, although for the purposes of our analysis in this report we use adopt standard EB procedures, focusing on average changes in casualties due to treatment.

Previous reluctance to embrace an FB methodology in industry can be explained by the enhanced level of computing and statistical ability needed to implement this method, fortunately advances of computing and software applications greatly improve the accessibility and hence, FB methods are becoming more commonplace (El-Basyouny and Sayed, 2012, Heydari et al., 2014). As an example, Bayesian methodology is used by PTV group in their software VISUM and by Gateshead council through *RAPTOR*. The *RAPTOR* suite of software applications was developed by the Newcastle road safety team to allow practitioners to implement Bayesian methods, without any technical or computational requirements (Matthews et al., 2019). The advantage stems from use of diffuse prior distributions for the coefficients in the regression equation. This allows for more reaListic standard deviations and doesn't accept the estimated regression coefficients as fixed (known) values. In addition, it also allows for change of priors omitting the need for the Poisson-gamma conjugacy. Despite FB methods being accepted in the literature for a while, with Schlüter et al. (1997) providing support for a hierarchical model to replace EB in the 1990s, EB still remains in common usage currently with Høye (2015), Park and Abdel-Aty (2015), Wang et al. (2017) providing examples of studies carried out in the last several years still relying on an EB methodology for inference. For more examples in favour of a fully Bayes analyses, see Kitali and Sando (2017), Lan et al. (2009), Yanmaz-Tuzel and Ozbay (2010).

B Empirical Bayes Results

B.1 Regression Model

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	74.6711	35.8659	2.08	0.0373
Road_ClassB - Class	-0.4694	0.1636	-2.87	0.0041
Road_ClassC - Class	-2.0482	0.8080	-2.54	0.0112
Road_ClassUnclassified	-0.6016	0.1764	-3.41	0.0006
Local_AuthorityHambleton	-0.2460	0.2317	-1.06	0.2883
Local_AuthorityHarrogate	0.2918	0.1846	1.58	0.1139
Local_AuthorityRichmondshire	-0.3143	0.4929	-0.64	0.5237
Local_AuthorityRyedale	-0.4409	0.1994	-2.21	0.0270
Local_AuthorityScarborough	0.4989	0.2146	2.32	0.0201
Local_AuthoritySelby	-0.2374	0.2704	-0.88	0.3799
Local_AuthorityYork	0.1286	0.2451	0.52	0.5998
UrbanRuralUrban	0.4177	0.1376	3.04	0.0024
Year	-0.0370	0.0179	-2.07	0.0389

Table 2: Regression table showing results for step 1. Shown here are the estimated regression coefficients, their standard errors, and their *p*-values, where *p*-values less than 0.05 indicate a statistically significant predictor variable.

B.2 Empirical Bayes Analysis

Site	before	after	post.est	RTM	trend.effect	treat.est	Lower	Upper	treat.perc
1	3.00	0.00	3.40	0.40	-0.08	-3.33	-6.68	-0.93	-100.00
2	9.00	3.00	8.54	-0.46	0.60	-6.14	-12.16	-1.38	-67.17
3	14.00	7.00	13.63	-0.37	-0.11	-6.51	-13.41	-0.40	-48.20
4	5.00	2.00	4.89	-0.11	-0.09	-2.80	-6.32	0.33	-58.31
5	0.00	8.00	0.74	0.74	-0.09	7.35	4.50	7.93	1125.73
6	11.00	9.00	10.64	-0.36	-0.79	-0.85	-5.91	4.20	-8.60
7	10.00	0.00	9.12	-0.88	-0.17	-8.95	-14.91	-4.56	-100.00
8	1.00	0.00	1.52	0.52	0.08	-1.60	-4.40	-0.27	-100.00
9	6.00	10.00	5.68	-0.32	-0.15	4.48	1.21	8.01	81.05
10	1.00	1.00	1.65	0.65	-0.31	-0.34	-3.37	0.73	-25.27
11	1.00	0.00	1.58	0.58	-0.01	-1.57	-5.02	-0.31	-100.00
12	1.00	0.00	1.51	0.51	-0.12	-1.40	-4.02	-0.25	-100.00
13	6.00	0.00	5.20	-0.80	0.59	-5.79	-9.45	-2.14	-100.00
14	6.00	0.00	6.24	0.24	-0.46	-5.78	-10.83	-2.45	-100.00
15	3.00	0.00	2.99	-0.01	-0.19	-2.80	-5.97	-0.83	-100.00
16	0.00	0.00	0.64	0.64	-0.04	-0.59	-2.61	-0.05	-100.00
17	8.00	8.00	7.93	-0.07	-0.25	0.32	-5.28	4.42	4.11
18	3.00	0.00	3.38	0.38	-0.30	-3.07	-6.22	-0.87	-100.00
19	7.00	9.00	7.41	0.41	-0.24	1.82	-4.43	.62	25.39
20	1.00	1.00	1.58	0.58	-0.30	-0.28	-2.46	0.79	-22.14
21	7.00	2.00	6.64	-0.36	0.19	-4.83	-9.41	-0.84	-70.71
22	4.00	4.00	4.04	0.04	-0.34	0.31	-3.35	2.74	8.29
23	13.00	10.00	12.13	-0.87	-0.19	-1.94	-7.55	3.86	-16.22
24	3.00	2.00	3.34	0.34	0.11	-1.45	-5.51	0.95	-42.01
25	6.00	2.00	6.23	0.23	-0.07	-4.17	-9.95	-0.70	-67.56
26	1.00	4.00	1.62	0.62	-0.21	2.59	-0.87	3.70	184.52
27	0.00	1.00	0.75	0.75	-0.07	0.32	-2.77	0.92	46.75
28	1.00	1.00	0.82	-0.18	-0.01	0.18	-1.57	0.84	22.38
29	4.00	0.00	3.95	-0.05	0.02	-3.97	-8.22	-1.41	-100.00
30	27.00	16.00	25.50	-1.50	-0.78	-8.72	-18.93	-0.64	-35.28
31	0.00	1.00	0.73	0.73	-0.20	0.46	-1.74	0.94	85.79
32	4.00	4.00	4.42	0.42	-0.32	-0.10	-4.30	2.57	-2.55
33	5.00	3.00	5.16	0.16	-0.60	-1.55	-4.87	1.42	-34.12
34	33.00	7.00	31.93	-1.07	-0.35	-24.58	-35.28	-14.57	-77.83
35	37.00	17.00	35.63	-1.37	-1.46	-17.18	-28.08	-6.85	-50.26
36	10.00	1.00	9.85	-0.15	-0.42	-8.43	-14.54	-3.7	-89.40
37	16.00	18.00	14.51	-1.49	-0.73	4.22	-2.23	10.20	30.64
38	3.00	0.00	3.05	0.05	-0.06	-3.00	-6.93	-0.97	-100.00
39	4.00	2.00	3.72	-0.28	0.09	-1.81	-6.46	0.54	-47.57
40	21.00	9.00	20.15	-0.85	0.75	-11.90	-21.48	-4.20	-56.94
41	1.00	3.00	1.48	0.48	-0.08	1.60	-1.42	2.73	114.11
42	13.00	3.00	12.82	-0.18	-0.13	-9.69	-17.31	-4.11	-76.37
43	5.00	13.00	5.21	0.21	-0.97	8.77	5.05	11.41	207.11
44	7.00	6.00	6.56	-0.44	-0.45	-0.11	-4.33	3.43	-1.86
45	14.00	10.00	13.84	-0.16	-0.21	-3.63	-11.33	2.26	-26.66
46	1.00	1.00	1.47	0.47	-0.03	-0.43	-3.63	0.71	-30.24
47	0.00	2.00	0.67	0.67	-0.07	1.41	-1.42	1.93	237.62
48	2.00	4.00	2.46	0.46	-0.28	1.82	-2.13	3.37	83.73
49	1.00	5.00	1.37	0.37	-0.08	3.71	1.32	4.77	288.17

Table 3: Full results for the Empirical Bayes analysis, with discussion provided in Section 2.2.1.

	Road_Class	mean(treat.est)
1	A - Class	-2.62
2	B - Class	-2.79
3	C - Class	0.01
4	Unclassified	-2.04

Table 4: Mean treatment effects by road classification.

	Council_Area	mean(treat.est)
1	City of York Council	-2.76
2	North Yorkshire Council	-2.43

Table 5: Mean treatment effects by council area.

	Local_Authority	mean(treat.est)
1	Craven	-0.71
2	Hambleton	-1.11
3	Harrogate	-7.15
4	Richmondshire	-2.81
5	Ryedale	-0.04
6	Scarborough	-4.49
7	Selby	-1.01
8	York	-2.76

Table 6: Mean treatment effects by local authority.

	ID	Location	Road_Class	Local_Authority	Council_Area	UrbanRural	Before	After	treat.est	Treat.low	Treat.upp
1	6065	A64 Middlecave, Malton	A - Class	Scarborough	North Yorkshire Council	Rural	0.00	8.00	7.35	5.34	7.99
2	6352	A65 Skipton (Overbridge White Hills Ln)	B - Class	Craven	North Yorkshire Council	Rural	6.00	10.00	4.48	-0.39	7.82
3	6206	A1237 Westfield	A - Class	York	City of York Council	Rural	8.00	8.00	0.32	-5.53	4.52
4	6428	A165 Osgodby	A - Class	Scarborough	North Yorkshire Council	Urban	7.00	9.00	1.82	-4.03	5.94
5	6237	A63 Hemingbrough	Unclassified	Selby	North Yorkshire Council	Urban	4.00	4.00	0.31	-3.66	2.84
6	6191	Market Flat Lane, Knaresborough	Unclassified	Harrogate	North Yorkshire Council	Urban	1.00	4.00	2.59	-0.08	3.86
7	6075	A6108 High Common	A - Class	Harrogate	North Yorkshire Council	Urban	0.00	1.00	0.32	-1.78	0.99
8	6188	Tame Bridge, Stokesley	C - Class	Hambleton	North Yorkshire Council	Rural	1.00	1.00	0.18	-1.37	0.92
9	6208	B6479 Horton in Ribblesdale	A - Class	Craven	North Yorkshire Council	Urban	0.00	1.00	0.46	-1.20	0.99
10	6411	A61 South Kilvington Village (South)	A - Class	Hambleton	North Yorkshire Council	Rural	16.00	18.00	4.22	-3.11	10.00
11	6431	Main Street, Amotherby	B - Class	Ryedale	North Yorkshire Council	Urban	1.00	3.00	1.60	-1.07	2.86
12	4259	A64 Rillington	A - Class	Ryedale	North Yorkshire Council	Urban	5.00	13.00	8.77	4.69	11.48
13	6268	Main Street, Helperby North	Unclassified	Hambleton	North Yorkshire Council	Urban	0.00	2.00	1.41	-0.42	1.99
14	6536	Askham Lane, Acomb	Unclassified	York	City of York Council	Urban	2.00	4.00	1.82	-1.37	3.59
15	6385	B1258 South of Ebbertson	B - Class	Ryedale	North Yorkshire Council	Rural	1.00	5.00	3.71	1.26	4.87

Table 7: Sites with positive estimated treatment effect, that is, treatment effects indicating an increase in casualties after RTM and trend.

	Site	ID	Location	Road_Class	Local_Authority	Council_Area	UrbanRural	Before	After	treat.est	Treat.low	Treat.upp
1	5.00	6065	A64 Middlecave, Malton	A - Class	Scarborough	North Yorkshire Council	Rural	0.00	8.00	7.35	5.34	7.99
2	43.00	4259	A64 Rillington	A - Class	Ryedale	North Yorkshire Council	Urban	5.00	13.00	8.77	4.69	11.48
3	49.00	6385	B1258 South of Ebbertson	B - Class	Ryedale	North Yorkshire Council	Rural	1.00	5.00	3.71	1.26	4.87

Table 8: Sites with 95% treatment effect confidence intervals all above 0 (i.e. significant increase in casualties after the removal of RTM and trend).

	ID	Location	Before	After	treat.est	Treat.low	Treat.upp
1	6065	A64 Middlecave, Malton	0.00	3.00	1.48	-1.12	2.80
2	4259	A64 Rillington	5.00	10.00	5.89	2.37	8.33
3	6385	B1258 South of Ebbertson	1.00	2.00	0.76	-0.93	1.73

Table 9: Results of collisions based EB analysis for 3 'definitely positive' sites from casualties analysis.

	ID	Fatal.Prop	Serious.Prop	Slight.Prop	Fatal.Change	Serious.Change	Slight.Change	Cost2012	Cost2024
1	4023	0.00	0.11	0.89	-0.00	-0.37	-2.96	114516.15	156738.26
2	4025	0.00	0.08	0.92	-0.00	-0.51	-5.63	181098.34	247869.29
3	6050	0.00	0.21	0.79	-0.00	-1.36	-5.16	335932.61	459790.97
4	4013	0.17	0.00	0.83	-0.47	-0.00	-2.33	828387.08	1133813.39
5	6065	0.00	0.50	0.50	0.00	3.67	3.67	-757663.30	-1037013.76
6	4095	0.03	0.43	0.54	-0.02	-0.37	-0.46	116023.47	158801.32
7	6027	0.11	0.11	0.78	-0.99	-0.99	-6.96	1986614.36	2719079.08
8	6018	0.00	0.50	0.50	-0.00	-0.80	-0.80	164978.40	225805.94
9	6352	0.02	0.15	0.83	0.09	0.65	3.73	-338535.68	-463353.78
10	6095	0.21	0.14	0.64	-0.07	-0.05	-0.22	135068.40	184868.12
11	4206	0.00	0.38	0.62	-0.00	-0.59	-0.98	126838.82	173604.29
12	4012	0.00	0.80	0.20	-0.00	-1.12	-0.28	217982.21	298352.25
13	6251	0.12	0.62	0.25	-0.72	-3.62	-1.45	1945551.96	2662876.96
14	6153	0.00	0.17	0.83	-0.00	-0.96	-4.82	255684.01	349954.71
15	6285	0.00	0.30	0.70	-0.00	-0.84	-1.96	189552.30	259440.23
16	4204	0.00	0.00	1.00	-0.00	-0.00	-0.59	8737.92	11959.59
17	6206	0.10	0.30	0.60	0.03	0.10	0.19	-75500.96	-103338.16
18	4110	0.00	0.00	1.00	-0.00	-0.00	-3.07	45357.48	62080.78
19	6428	0.00	0.16	0.84	0.00	0.29	1.53	-78858.16	-107933.17
20	4168	0.00	0.00	1.00	-0.00	-0.00	-0.28	4191.84	5737.37
21	6088	0.00	0.25	0.75	-0.00	-1.21	-3.62	284556.56	389472.56
22	6237	0.00	0.12	0.88	0.00	0.04	0.27	-10877.87	-14888.54
23	6062	0.05	0.29	0.67	-0.09	-0.55	-1.29	281685.92	385543.51
24	6566	0.00	0.00	1.00	-0.00	-0.00	-1.45	21387.24	29272.72
25	6079	0.00	0.00	1.00	-0.00	-0.00	-4.17	61490.16	84161.58
26	6191	0.00	0.00	1.00	0.00	0.00	2.59	-38287.44	-52404.02
27	6075	0.25	0.00	0.75	0.08	0.00	0.24	-139833.48	-191390.08
28	6188	0.00	0.00	1.00	0.00	0.00	0.18	-2701.08	-3696.97
29	6076	0.00	0.40	0.60	-0.00	-1.59	-2.38	339422.55	464567.64
30	6267	0.01	0.20	0.79	-0.11	-1.70	-6.91	619819.24	848346.59
31	6208	0.00	0.33	0.67	0.00	0.15	0.31	-34031.38	-46578.75
32	6468	0.00	0.23	0.77	-0.00	-0.02	-0.08	5775.91	7905.49
33	6538	0.03	0.11	0.86	-0.04	-0.17	-1.34	123563.79	169121.76
34	6151	0.00	0.07	0.93	-0.00	-1.78	-22.80	677464.56	927245.75
35	6392	0.00	0.07	0.93	-0.00	-1.24	-15.94	472290.83	646424.46
36	6441	0.00	0.09	0.91	-0.00	-0.77	-7.67	260017.04	355885.32
37	6411	0.00	0.08	0.92	0.00	0.33	3.89	-121158.82	-165830.08
38	4163	0.00	0.17	0.83	-0.00	-0.50	-2.50	132395.76	181210.07
39	6245	0.00	0.25	0.75	-0.00	-0.45	-1.36	107012.56	146468.09
40	4008	0.00	0.07	0.94	-0.00	-0.77	-11.13	311351.90	426147.35
41	6431	0.00	0.18	0.82	0.00	0.29	1.31	-75021.81	-102682.35
42	4120	0.00	0.16	0.84	-0.00	-1.55	-8.14	417149.79	570952.92
43	4259	0.00	0.16	0.84	0.00	1.40	7.36	-377315.23	-516431.35
44	6216	0.00	0.16	0.84	-0.00	-0.02	-0.10	4863.29	6656.39
45	4155	0.03	0.17	0.81	-0.10	-0.61	-2.93	331329.98	453491.34
46	4137	0.00	0.50	0.50	-0.00	-0.22	-0.22	44750.39	61249.86
47	6268	0.00	0.33	0.67	0.00	0.47	0.94	-103641.03	-141853.47
48	6536	0.00	0.00	1.00	0.00	0.00	1.82	-26907.48	-36828.27
49	6385	0.08	0.31	0.61	0.29	1.14	2.28	-739655.96	-1012367.12

Table 10: Historic severity trends by site, estimated change is casualty numbers by severity, total cost saved by treatment in 2012 figures, and adjusted for 2024 inflation (positive cost = saving).

C Violations Results

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	221.5303	7.4748	29.64	0.0000
month2	0.1115	0.0451	2.47	0.0135
month3	0.0613	0.0440	1.39	0.1639
month4	0.1499	0.0418	3.59	0.0003
month5	0.1452	0.0415	3.50	0.0005
month6	0.2149	0.0416	5.16	0.0000
month7	0.1921	0.0414	4.64	0.0000
month8	0.2661	0.0418	6.37	0.0000
month9	0.1815	0.0425	4.27	0.0000
month10	0.1675	0.0421	3.98	0.0001
month11	0.1313	0.0443	2.96	0.0031
month12	-0.0026	0.0449	-0.06	0.9529
areaHambleton	0.3439	0.0705	4.88	0.0000
areaHarrogate	-0.0786	0.0315	-2.50	0.0126
areaRichmondshire	-0.3846	0.2200	-1.75	0.0804
areaRyedale	-0.5403	0.0706	-7.66	0.0000
areaScarborough	-0.1474	0.0848	-1.74	0.0820
areaSelby	-0.7355	0.0376	-19.57	0.0000
areaYork	-1.1654	0.0910	-12.81	0.0000
year	-0.1109	0.0037	-29.85	0.0000
TreatedTRUE	-0.5943	0.0537	-11.07	0.0000
logmin	1.1564	0.0203	56.94	0.0000
areaHambleton:TreatedTRUE	0.3780	0.0760	4.98	0.0000
areaRyedale:TreatedTRUE	0.9805	0.0746	13.14	0.0000
areaScarborough:TreatedTRUE	0.3563	0.0941	3.79	0.0002
areaYork:TreatedTRUE	0.6397	0.0974	6.57	0.0000

Table 11: Regression table showing result for a regression model on the violations dataset.

References

Allsop, R. (2013). Guidance on use of speed camera transparency data. https://www.racfoundation.org/assets/rac_foundation/content/downloadables/speed_camera_data-allsop-may2013.pdf. Accessed: 2024-01-25.

Barker, J., Farmer, S., and Nicholls, D. (1998). Injury accidents on rural single-carriageway roads, 1994-95: An analysis of stats19 data. Technical report, Transport Research Laboratory (TRL).

Bartlett, P., Allen, P., Tranter, M., and Bhagat, A. (2008). Road casualties great britain: 2007-annual report. Technical report, Welsh Assembly Government, Scottish Government, Department for Transport, England.

Brooker, C. and North, R. (2007). Speed cameras: the twisted truth. https://www.telegraph.co.uk/motoring/road-safety/2749419/Speed-cameras-the-twisted-truth.html. [Online; accessed 24-May-2021].

Charlesworth, K. (2008). The effect of average speed enforcement on driver behaviour. In IET Road Transport Information and Control - RTIC 2008 and ITS United Kingdom Members' Conference, pages 1–5.

Christie, S., Lyons, R. A., Dunstan, F. D., and Jones, S. J. (2003). Are mobile speed cameras effective? a controlled before and after study. Injury Prevention, 9(4):302–306.

College of Policing (2017). Speed cameras. https://www.college.police.uk/research/crime-reduction-toolkit/speed-cameras#:~:text=The%20review%20notes%20that%20there%20was%20some%20evidence%20to%20suggest,5%20studies)%20than%20mobile%20cameras. [Online; accessed 09-Nov-2023].

De Pauw, E., Daniels, S., Brijs, T., Hermans, E., and Wets, G. (2014). An evaluation of the traffic safety effect of fixed speed cameras. Safety Science, 62:168–174.

Department for Transport (2012). A valuation of road accidents and casualties in great britain: Methodology note. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/995110/rrcgb-valuation-methodology.pdf.

Department for Transport (2020). Reported road casualties in great britain: 2019 annual report. https://assets.publishing.service.gov.uk/media/5f735c2fd3bf7f286abc0748/reported-road-casualties-annual-report-2019.pdf. [Online; accessed 26-Oct-2023].

DETR (2000). Tomorrow's roads—safer for everyone. the government's road safety strategy and casualty reduction targets for 2010.

El-Basyouny, K. and Sayed, T. (2012). Measuring direct and indirect treatment effects using safety performance intervention functions. Safety science, 50(4):1125–1132.

Elvik, R. (1997). Evaluations of road accident blackspot treatment: A case of the iron law of evaluation studies? Accident Analysis & Prevention, 29(2):191–199.

Elvik, R. (2002). The importance of confounding in observational before-and-after studies of road safety measures. Accident Analysis & Prevention, 34(5):631–635.

Fawcett, L. and Thorpe, N. (2013). Mobile safety cameras: estimating casualty reductions and the demand for secondary healthcare. Journal of Applied Statistics, 40(11):2385–2406.

Fawcett, L., Thorpe, N., Matthews, J., and Kremer, K. (2017). A novel bayesian hierarchical model for road safety hotspot prediction. Accident Analysis & Prevention, 99:262–271.

Finch, D., Kompfner, P., Lockwood, C., and Maycock, G. (1994). Speed, speed limits and accidents. TRL project report.

Gains, A., Nordstrom, M., Heydecker, B., and Shrewsbury, J. (2005). The national safety camera programme: Four-year evaluation report. Technical report, Department for Transport, London. Accessed: [02-02-2023].

Galton, F. (1889). Natural Inheritance, volume 42. Macmillan.

Graham, S. (1997). Why do people speed? Traffic Safety (Chicago), 97(6).

Guo, X., Wu, L., Zou, Y., and Fawcett, L. (2019). Comparative analysis of empirical bayes and bayesian hierarchical models in hotspot identification. Transportation Research Record, 2673(7):111–121.

Hauer, E. (1980). Bias-by-selection: Overestimation of the effectiveness of safety countermeasures caused by the process of selection for treatment. Accident Analysis & Prevention, 12(2):113–117.

Hauer, E. (1986). On the estimation of the expected number of accidents. Accident Analysis & Prevention, 18(1):1–12.

Hauer, E. (1997). Observational before/after studies in road safety. estimating the effect of highway and traffic engineering measures on road safety. Emerald Group Publishing Limited.

Hewett, N. (2023). Bayesian inference for enhanced road safety analysis. PhD thesis.

Hewett, N., Golightly, A., Fawcett, L., and Thorpe, N. (2023). Bayesian inference for a spatio-temporal model of road traffic collision data.

Heydari, S., Miranda-Moreno, L. F., and Liping, F. (2014). Speed limit reduction in urban areas: A before–after study using bayesian generalized mixed linear models. Accident Analysis & Prevention, 73:252–261.

Hirst, W., Mountain, L., and Maher, M. (2004). Sources of error in road safety scheme evaluation: a quantified comparison of current methods. Accident Analysis & Prevention, 36(5):705–715.

Hopkins, M. J. and Simpson, H. F. (1995). Valuation of road accidents. TRL Report 163, Transport Research Laboratory, Crowthorne.

Høye, A. (2015). Safety effects of fixed speed cameras—an empirical bayes evaluation. Accident Analysis & Prevention, 82:263–269.

Jones, A. P., Sauerzapf, V., and Haynes, R. (2008). The effects of mobile speed camera introduction on road traffic crashes and casualties in a rural county of england. Journal of Safety Research, 39(1):101–110.

Kitali, A. E. and Sando, P. T. (2017). A full bayesian approach to appraise the safety effects of pedestrian countdown signals to drivers. Accident Analysis & Prevention, 106:327–335.

Kokkuvotte (2019). Riigiteedel rakendatud statsionaarse automaatse kiirusjärelevalve mõju liiklusõnnetustele. Transpordiamet Estonia. [Online; accessed 26-Feb-2024].

Lan, B., Persaud, B., Lyon, C., and Bhim, R. (2009). Validation of a full bayes methodology for observational before–after road safety studies and application to evaluation of rural signal conversions. Accident Analysis & Prevention, 41(3):574–580.

Li, H., Graham, D. J., and Majumdar, A. (2013). The impacts of speed cameras on road accidents: An application of propensity score matching methods. Accident Analysis & Prevention, 60:148–157.

Li, H., Zhu, M., Graham, D. J., and Ren, G. (2021). Evaluating the speed camera sites selection criteria in the uk. Journal of Safety Research, 76:90–100.

Matthews, J., Newman, K., Green, A., Fawcett, L., Thorpe, N., and Kremer, K. (2019). A decision support toolkit to inform road safety investment decisions. Proceedings of the Institution of Civil Engineers - Municipal Engineer, 172(1):53–67.

Mountain, L., Maher, M., and Fawaz, B. (1998). Improved estimates of the safety effects of accident remedial schemes. Traffic Engineering & Control, 39(10).

North Yorkshire Police (2017). Evaluation of mobile road safety cameras in north yorkshire: Summary of method and key findings. https://northyorkshire.police.uk/content/uploads/2017/12/Newcastle-University-Evaluation-of-Mobile-Road-Safety-Cameras-in-North-Yorkshire.pdf.

O'Reilly, D. M. (1993). Costing road traffic accidents: The value of lost output. TRL Working Paper WP/SRC/09/93.

Owen, R., Ursachi, G., and Allsop, R. (2016). The effectiveness of average speed cameras in great britain. https://www.racfoundation.org/wp-content/uploads/2017/11/Average_speed_camera_effectiveness_Owen_Ursachi_Allsop_September_2016.pdf. Accessed: 2024-01-25.

Park, J. and Abdel-Aty, M. (2015). Development of adjustment functions to assess combined safety effects of multiple treatments on rural two-lane roadways. Accident Analysis & Prevention, 75:310–319.

Police and Crime Commissioner North Yorkshire (2017). Making north yorkshire's roads safer: Overview & impact – 2017. https://www.northyorkshire-pfcc.gov.uk/wp-content/uploads/2018/09/Report-Making-North-Yorkshires-Roads-Safer.pdf.

Quimby, A., Maycock, G., Palmer, C., and Buttress, S. (1999). The Factors the Influence a Driver's Choice of Speed: A Questionnaire Study. Citeseer.

RAC (2018). Average speed cameras more effective at slowing vehicles down than traditional single location, fixed ones. https://www.rac.co.uk/press-centre#/pressreleases/average-speed-cameras-more-effective-at-slowing-vehicles-down-than-traditional-single-location-fixed-ones-2562126. Accessed: 2024-01-25.

Schlüter, P., Deely, J., and Nicholson, A. (1997). Ranking and selecting motor vehicle accident sites by using a hierarchical bayesian model. Journal of the Royal Statistical Society: Series D (The Statistician), 46(3):293–316.

Soole, D. W., Watson, B. C., and Fleiter, J. J. (2013). Effects of average speed enforcement on speed compliance and crashes: A review of the literature. Accident Analysis & Prevention, 54:46–56.

Steinbach, R., Perkins, C., Edwards, P., Beecher, D., and Roberts, I. (2016). What works: crime reduction systematic review. https://library.college.police.uk/docs/what-works/SR8-Speed-Cameras-2017.pdf.

TASCAR (2024). Traffic average speed camera and recording (tascar) system. https://www.tascar.co.uk/. Accessed: 2024-02-20.

Taylor, M. (2001). Managing vehicle speeds for safety: Why? how? Traffic engineering and control, 42(7):226–229.

Taylor, M. C., Lynam, D., and Baruya, A. (2000). The effects of drivers' speed on the frequency of road accidents. Transport Research Laboratory Crowthorne.

The Royal Society for the Prevention of Accidents (2021). Road safety factsheet: Speed cameras. https://www.rospa.com/media/documents/road-safety/speed-cameras-factsheet.pdf. Accessed: 2024-01-25.

Thorpe, N. and Fawcett, L. (2012). Linking road casualty and clinical data to assess the effectiveness of mobile safety enforcement cameras: a before and after study. BMJ Open, 2(6):e001304.

Transport Research Laboratory (2021). Improving our understanding of cost of injuries on the road. https://trl.co.uk/uploads/trl/documents/PPR996_Improving-Our-Understanding-of-Cost-of-Injuries-on-the-Road.pdf. Accessed: 2024-02-02.

Wang, J.-H., Abdel-Aty, M., and Wang, L. (2017). Examination of the reliability of the crash modification factors using empirical bayes method with resampling technique. Accident Analysis & Prevention, 104:96–105.

Wilson, C., Willis, C., Hendrikz, J. K., Le Brocque, R., and Bellamy, N. (2010). Speed cameras for the prevention of road traffic injuries and deaths. Cochrane Database of Systematic Reviews, 2010(10):CD004607.

Yanmaz-Tuzel, O. and Ozbay, K. (2010). A comparative full bayesian before-and-after analysis and application to urban road safety countermeasures in new jersey. Accident Analysis & Prevention, 42(6):2099–2107.