Are speed enforcement cameras more effective than other speed management measures?
An evaluation of the relationship between speed and accident reductions

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Abstract

In this paper, models are developed which enable a prediction of how the impact of speed management schemes on accidents varies both with speed changes and with site and scheme characteristics. It was found that, the impact of schemes with vertical deflections is independent of the change in mean speed: an accident reduction of 44% is predicted by the model irrespective of the impact on speed. For cameras and other types of engineering schemes, a simple relationship between the change in mean speed and the consequent change in accidents is available. For the range of mean speeds typically found on 30 mph roads, the percentage accident reduction per 1mph speed reduction is around 4% for cameras and 7–8% for schemes with horizontal features. While larger percentage accident reductions are achieved per 1 mph speed reduction on lower speed roads, larger speed reductions and larger overall percentage accident reductions are obtained on roads with higher before mean speeds. It is possible to predict both changes in speeds and accidents before treatment using the models derived from this study and these models confirm that schemes with vertical deflections are most effective in reducing both speeds and accidents.

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1. Introduction

Although there is evidence that inappropriate speed is a major factor affecting road accident frequency and severity, the effectiveness of speed management schemes in reducing speeds and accidents, and the nature of the relationship between these reductions, is not well understood. It has been suggested that a progressive relationship exists between reductions in accidents and reductions in mean speed (see for example, Finch et al., 1994; Webster and Mackie, 1996; Taylor et al., 2000). A 5% reduction in accidents for each 1mph reduction in mean speed is widely quoted although Taylor et al. (2000) suggest that the actual percentage accident reduction depends on the nature of the road and the before mean speed: with larger reductions on urban roads with low average speeds and smaller reductions on higher speed roads. However, these findings must be treated with some caution. Cross-sectional studies of roads with different speed and accident distributions (for example, Finch et al., 1994 and Taylor et al., 2000) examine how differences in the distributions of speeds on different roads may affect accidents but, since these roads have no speed management schemes in place, such studies cannot examine how a specific treatment intervention may impact on speeds, or how this change in speed might relate to changes in accidents. Numerous before-and-after studies of specific speed management schemes have been published but few have had available both accident and speed data and, until recently, none have fully separated the accident changes attributable to the effects of speed changes from those due to the various confounding factors that hamper the analysis of before-and-after accident
data (for example, Webster and Mackie, 1996). Thus, the true relationship between the speed changes associated with various types of speed management measures and their consequent accident changes have yet to be established.

The aim of the research on which this paper is based, was thus to investigate this issue, comparing the impact of a range of speed management schemes on both accidents and speed distributions, taking proper account of non-scheme effects on accidents. A separate paper presented details of the average effects of such schemes (Mountain et al., 2005). It was found that the median impact of the various types of speed management schemes reduced accidents although not all schemes were successful. Engineering schemes with vertical deflections (such as speed humps, tables or cushions (see, for example, County Surveyors Society, 1994)) offered the largest and most consistent percentage accident reductions: an overall fall in personal injury accidents (PIAs) attributable to scheme effects of 44%, of which a 38% fall was attributable to speed changes and the remaining 6% due to traffic diversion away from the speed managed section. The impact of vertical deflections on accidents was twice that at sites where safety cameras were used to control speeds: an overall fall in PIAs of 22%, of which a fall of 17% was attributable to speed reductions. Schemes with vertical deflections were also the only type of scheme to have a significant impact on fatal and serious accidents. Other types of engineering schemes (with a fall in PIAs of 29%) were, on average, less effective in reducing accidents than schemes with vertical features but more effective than cameras. It was also shown that, on average, all types of speed management scheme were successful in reducing vehicle speeds. Schemes with vertical deflections had the greatest impact on speed: an average reduction in the mean speed of 8.4 mph and a reduction in the percentage of drivers exceeding the speed limit from 56% to only 16%.

This analysis was concerned with the average effect of the various types of speed management scheme on accident frequencies and speeds. The variation in the reduction in annual accidents within each scheme type was, however, considerable, as was the impact on speed. It was thus of interest to attempt to understand the underlying causes of this variation with a view to establishing which type of speed management scheme was most effective for any given set of site conditions. This paper thus describes the next stage of the analysis: to develop models that would enable a prediction of how the impact of treatment on accidents varies both with speed changes and with site and scheme characteristics.

2. Data

The data for this study relate to 149 speed management schemes on 30mph roads throughout Great Britain (Mountain et al., 2005). These schemes include 79 speed enforcement cameras (17 mobile and 62 fixed cameras) and 70 engineering schemes of various types. The engineering schemes were split into two categories: “vertical deflections” and “horizontal features”. The first category comprised the 39 schemes that included any form of vertical deflection. The remaining 31 schemes were classified as schemes with horizontal features and included a range of scheme types (narrowing, mini-roundabouts, chicanes and speed-activated signs (see, for example, County Surveyors Society, 1994 for more details of the nature of the schemes typically used)).

The accident data obtained for each scheme comprised details of all PIAs (some 3500 accidents) occurring during the 3 years prior to scheme implementation and for up to 3 years after implementation (an average after period of 2.5 years). For engineering schemes this included all PIAs occurring within the treated section. Similarly, for mobile cameras, the accidents were those occurring within the full section over which the cameras could be deployed as indicated by the relevant police authority. For fixed cameras the choice of a monitoring length for accidents was more difficult as few studies have examined the area of influence of cameras. As part of the study described here, an initial analysis of accident changes over various distances was carried out (Mountain et al., 2004) and it was found that fixed cameras can improve safety over a distance of up to 1 km. Thus, the data for fixed cameras in this paper include all available recorded PIAs up to 1 km either side of the camera.

Various measures of before and after speed were obtained (mean, 85th percentile, standard deviation, percentage exceeding the speed limit and the mean speed of speeders) although not all measures of speed were available for all sites (Mountain et al., 2005). At least one measure of traffic flow was also obtained during the periods before and after scheme implementation.

3. Estimation of confounding factors

A detailed description of the approach to the accident analysis is given elsewhere (Hirst et al., 2004a,b; Mountain et al., 2005). A review of existing methodologies for estimating confounding factors in observational before and after accident studies was carried out (Hirst et al., 2004a). While the empirical Bayes (EB) method appeared to have the greatest potential to allow for RTM effects, in its simplest form potential sources of error were identified. In particular, it was noted that some of the change in accidents attributable to a scheme may arise due to a reduction in flow rather than a reduction in speed and that the accident prediction models used in the EB method tend to be outdated due to trends in accident risk.

Clearly, in attempting to establish the relationship between the impact of schemes on accidents and speeds, it is important to separately estimate those accident changes attributable to speed changes. Since speed management schemes can give rise to significant traffic diversion away from the speed managed section, a procedure was devised to estimate the impact on accidents of any such change in flow separate from the impact of speed changes while avoiding any double counting (Hirst et al., 2004a). In addition, whilst the errors arising due
to trends in accidents during the study period have previously been accounted for in the implementation of the EB method, the effects of trend on the predictive accident models used to obtain EB estimates have invariably been ignored. The problem arises because accident risk has tended to decline over time in recent years, while the majority of predictive models assume that accident risk per unit of exposure is constant. The models thus tend to become outdated and the estimated treatment effect is then exaggerated. Since predictive models are based on past accident history, often for a period many years prior to the study period, the effects of outdated models on estimates of treatment effectiveness can be substantial.

A correction procedure was derived (Hirst et al., 2004b). An extensive simulation study was undertaken and it was demonstrated that this procedure could effectively eliminate the bias in EB estimation due to outdated prediction models. Thus, the estimation procedure used in this study allowed the observed accident changes to be disaggregated according to the separate effects of speed and flow changes, as well as trend and RTM effects (Mountain et al., 2005).

4. Treatment effect models

In order to model the safety effect of speed management schemes it is necessary to model accidents in the period after the scheme has been implemented. This is not straightforward. The usual negative binomial (NB) model for analysing annual accident counts, \( Y_n \), for \( n \) sites is of the form:

\[
Y_n \sim\text{NB}(\mu_n, K) \quad \text{where} \quad \log(\mu_n) = \log(t_i) + f(Z_i\beta) \quad \text{for} \quad i = 1, \ldots, n. \quad \text{(Model 1)}
\]

\( K \) is the shape parameter, \( Z_i \) is the vector of explanatory variables and \( \beta \) is the vector of coefficients. In this model, the offset is the logarithm of the total years of the observation for each site (log(\( t_i \))).

In modelling accidents in the period after a treatment intervention it is, however, useful to consider a different offset in the model. Denoting by \( Y_{Ai} \) the after accident count for the \( i \)th site, the model has the form:

\[
Y_{Ai} \sim\text{NB}(\mu_{Ai}, K) \quad \text{where} \quad \log(\mu_{Ai}) = \log(\hat{M}_{Ai}) + f(Z_i\beta) + b_i \quad \text{where} \quad b_i \sim N(0, \text{var}(\log(\hat{M}_{Ai}))) \quad \text{(Model 2)}
\]

Here \( \hat{M}_{Ai} \) is the EB estimate of total accidents in the after period given a suitable accident prediction model for before accidents and accounting for trend and flow effects (Mountain et al., 2005). Since the estimate of after accidents is already adjusted for what it would have been if there was no scheme in place, it would be expected that a simple intercept model (where \( f(Z_i\beta) = \beta_0 \)) with the more complicated offset (Model 2) would give much more predictive power than with the usual form (Model 1). This model form also allows estimation of the treatment effect (defined here as the ratio of observed after accidents to expected after accidents, \( \frac{Y_{Ai}}{\hat{M}_{Ai}} \)) for each site according to covariates:

\[
\frac{Y_{Ai}}{\hat{M}_{Ai}} = \exp(f(Z_i\beta)).
\]

This expectation is confirmed as, for the simple intercept model (where \( f(Z_i\beta) = \beta_0 \)), the residual mean square error (defined for these models as the average squared difference between observed and fitted annual after accidents) in Model 1 is 11.9 compared to 3.8 for Model 2. The extent of over-dispersion is also reduced for Model 2, with the estimate of \( K \) increased from 1.2 to 7.0.

However, a concern over using the offset \( \log(\hat{M}_{Ai}) \) is that \( \hat{M}_{Ai} \) is a variable and has an associated variation. It is desirable to incorporate this. Assuming that \( \log(\hat{M}_{Ai}) \) is approximately normally distributed a preferable model is:

\[
Y_{Ai} \sim\text{NB}(\mu_{Ai}, K) \quad \text{where} \quad \log(\mu_{Ai}) = \log(\hat{M}_{Ai}) + f(Z_i\beta) + b_i \quad \text{where} \quad b_i \sim N(0, \text{var}(\log(\hat{M}_{Ai}))) \quad \text{(Model 3)}
\]

where it can be shown that \( \text{var}(\log(\hat{M}_{Ai})) = (1 - a_i)/\hat{M}_{Ai} \) (\( a_i \) is the weight for the individual site EB calculations and \( \hat{M}_{Ai} \) is the EB estimate of before accidents).

Attention then turns to the problem of how to fit Model 3 incorporating the individual random error surrounding the offset. Traditional maximum likelihood methods in standard statistical analysis software are unable to deal with this more complicated form of the NB model. However, the fit can be accomplished via Bayesian modelling using the Markov chain Monte Carlo Gibbs sampling package WinBUGS (Spiegelhalter et al., 2003). The base code for fitting negative binomial models in WinBUGS is taken from Sprague (2001) and amended to fit Model 3. The mean of the posterior distributions are used as the point estimates for model parameters; the 2.5th and 97.5th percentiles give 95% credibility intervals for inference on the model parameters.

For the simple intercept model (where \( f(Z_i\beta) = \beta_0 \)), Model 3 (with the random error term around the offset) has the same residual mean square error (3.8) as Model 2 (where the offset is fixed) but the estimate of \( K \) increases to 14.7 indicating part of the overall between site variation is due to uncertainty around the estimate of \( \hat{M}_{Ai} \).

One of the main objectives of this study was to establish the form of the relationship (if any) between the impact of the schemes on safety and their impact on the distribution of speeds. Although data for five speed variables were obtained for this study (Mountain et al., 2005), some (such as the mean speed and 85th percentile speed) were closely correlated and could not be considered simultaneously due to concerns over collinearity. Changes in other variables were not closely correlated with accident changes. Previous work (Taylor et al., 2000) suggests, however, that accident frequencies depend on both the mean speed and the spread of speeds. Consequently it was decided that consideration would be given in
the modelling to changes in mean speed (using $V_A$ and $V_B$ to
denote the before and after mean speeds in mph) and standard
deviation of speeds (using $\sigma_A$ and $\sigma_B$ to denote the before
and after standard deviation of speeds in mph).

The form of covariate function used in the initial fit was:

$$f(Z \beta) = \beta_0 + \beta_1 \log \left( \frac{V_A}{V_B} \right) + \beta_2 \left( \sigma_A - \sigma_B \right)$$

where $j = 1, 2, 3$ for the three different treatment types (safety
cameras, schemes with horizontal features and schemes with
vertical deflections).

This corresponds to a model for treatment effect:

$$\frac{V_A}{M_A} = \exp(\beta_0) \left( \frac{V_A}{V_B} \right)^{\beta_1} \exp(\beta_2 (\sigma_A - \sigma_B))$$

for $j = 1, 2, 3$.

Mean speed data were available for some 140 sites while
the standard deviation of speed was available for 111. As
no obvious method is available to predict missing values of
mean speed with any accuracy, the models are restricted to
140 of the 149 possible observations. For the 29 sites that
lacked observed values of either $\sigma_B$ or $\sigma_A$, an estimate was obtained using this
fitted relationship. Therefore, in subsequent analyses, an esti-
mated value was used where necessary for $\sigma_B$ or $\sigma_A$ (together
with the standard error of the estimate, as given by the residual
standard error from the fit in Fig. 1). This is easily included
in the fitting of models using WinBUGS (Spiegelhalter et al.,
2003).

The coefficients for the full covariate model described
above are shown in Table 1 (Model 3(i)). It would appear that
for cameras and schemes with horizontal features the in-
tercept is not different from zero, implying that no change in
the distribution of speeds leads to a treatment effect of 1. This
is not the case for schemes with vertical deflections, where
which all three measures were available, together with the
best fit least squares line. Hence, for sites that lacked an ob-
served value of $\sigma_B$ or $\sigma_A$, an estimate was obtained using this
fitted relationship. Therefore, in subsequent analyses, an esti-
mated value was used where necessary for $\sigma_B$ or $\sigma_A$ (together
with the standard error of the estimate, as given by the residual
standard error from the fit in Fig. 1). This is easily included
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tercept is not different from zero, implying that no change in
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is not the case for schemes with vertical deflections, where

Table 1

<table>
<thead>
<tr>
<th>Scheme type</th>
<th>Intercept</th>
<th>log($V_A / V_B$)</th>
<th>$\sigma_B - \sigma_A$</th>
<th>$\kappa$ (95% CI)</th>
<th>Residual MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 3(i)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cameras</td>
<td>$\beta_0 = -0.20 (-0.48, 0.02)$</td>
<td>$\beta_1 = 0.63 (-0.66, 1.89)$</td>
<td>$\beta_2 = 0.07 (0.007, 0.13)$</td>
<td>17.2 (7.2, 38.1)</td>
<td>3.1</td>
</tr>
<tr>
<td>Horizontal</td>
<td>$\beta_0 = -0.17 (-0.52, 0.17)$</td>
<td>$\beta_1 = 1.46 (-0.69, 3.06)$</td>
<td>$\beta_2 = -0.06 (-0.35, 0.16)$</td>
<td>$\beta_3 = 0.19 (-0.06, 0.44)$</td>
<td></td>
</tr>
<tr>
<td>Vertical</td>
<td>$\beta_0 = -0.56 (-0.95, -0.17)$</td>
<td>$\beta_1 = 0.45 (-0.49, 1.73)$</td>
<td>$\beta_2 = 0.07 (0.007, 0.12)$</td>
<td>15.5 (6.6, 34.0)</td>
<td>3.0</td>
</tr>
<tr>
<td>Model 3(ii)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cameras</td>
<td>$\beta_0 = 0$</td>
<td>$\beta_1 = 1.59 (0.75, 2.44)$</td>
<td>$\beta_2 = 0.06 (-0.01, 0.12)$</td>
<td>15.5 (6.6, 34.0)</td>
<td>3.0</td>
</tr>
<tr>
<td>Horizontal</td>
<td>$\beta_0 = 0$</td>
<td>$\beta_1 = 2.08 (1.33, 3.04)$</td>
<td>$\beta_2 = -0.13 (-0.36, 0.10)$</td>
<td>$\beta_3 = 0.19 (-0.06, 0.46)$</td>
<td></td>
</tr>
<tr>
<td>Vertical</td>
<td>$\beta_0 = -0.58 (-0.99, -0.17)$</td>
<td>$\beta_1 = 0.38 (-0.84, 1.70)$</td>
<td>$\beta_2 = 0.35 (-0.16, 0.66)$</td>
<td>14.9 (6.4, 32.5)</td>
<td>3.1</td>
</tr>
<tr>
<td>Model 3(iii)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cameras</td>
<td>$\beta_0 = 0$</td>
<td>$\beta_1 = 1.30 (0.54, 2.07)$</td>
<td>$\beta_2 = 0$</td>
<td>14.9 (6.4, 32.5)</td>
<td>3.1</td>
</tr>
<tr>
<td>Horizontal</td>
<td>$\beta_0 = 0$</td>
<td>$\beta_1 = 2.57 (1.10, 4.13)$</td>
<td>$\beta_2 = 0$</td>
<td>15.2 (6.5, 33.1)</td>
<td>3.1</td>
</tr>
<tr>
<td>Vertical</td>
<td>$\beta_0 = -0.59 (-0.82, -0.36)$</td>
<td>$\beta_1 = 0$</td>
<td>15.2 (6.5, 33.1)</td>
<td>3.1</td>
<td></td>
</tr>
</tbody>
</table>

* Horizontal = schemes with horizontal features, vertical = schemes with vertical deflections with or without horizontal features.
The suggestion is that simply implementing the scheme itself will have an impact on accidents.

The model was thus re-fitted with \( \beta_01 \) and \( \beta_02 \) fixed at zero (Table 1, Model 3(ii)). Naturally forcing the intercept leads to a substantial increase in \( \beta_11 \) and \( \beta_12 \). However, it was felt that, as there was no evidence of a deviation from the assumption that no change in speed leads to no change in accidents, this was the preferred model form. The coefficients for the reduction in the standard deviation of speeds indicate, perhaps counter-intuitively that, for cameras and schemes with vertical deflections, a reduction in standard deviation for the same mean speed reduction would lead to a decrease in treatment effectiveness. This phenomenon has been discussed as a possibility elsewhere (Taylor et al., 2000). However, all the coefficients for the reduction in the standard deviation of speeds have credibility intervals that span 0 and hence can be removed from the model (Table 1, Model 3(iii)). Whilst the intercept remained important for schemes with vertical deflections after the removal of the term relating the reduction in standard deviation to after accidents, the coefficient for \( \log(V_A/V_B) \) was virtually zero. The final model was thus fitted with \( \beta_13 \) forced to zero (Table 1, Model 3(iv)).

The residual mean square error was reduced from 3.8 in the simple intercept model (where \( f(Z, \beta) = \beta_0 \)) to 3.1 in the final model. Thus, the average difference between the observed and fitted after annual accidents is 1.76. This perhaps suggests that, whilst there is a relationship between changes in speed and treatment effect for cameras and engineering schemes with horizontal features, other unmeasured variables are also important.

Fig. 2 shows the observed and fitted annual after accidents for the 140 schemes based on these models and the corresponding observed and fitted treatment effects (\( Y_A/\hat{M}_A \)).
The indication would seem to be that more research is needed into why some schemes reduce accidents much more than others for similar changes in speed, and also why some schemes are not at all successful in reducing accidents. Intuitively, it might be thought that schemes would be less likely to be successful if the observed accident frequency in the before period was less than would be expected given the characteristics of the site (i.e. less than estimated by the predictive accident models). However, this does not appear to be borne out by the data: in this study a third of the schemes were implemented at locations where the accident frequency in the before period was lower than expected but the success rate for these schemes (77% of them reduced accidents) was marginally higher than the success rate of 71% for schemes where the before accident frequency was higher than expected.

For prediction purposes, Fig. 3 shows the estimates of treatment effect across the range of mean speed ratios for schemes with horizontal features and cameras, together with the corresponding upper and lower 95% credibility interval. The values for schemes with vertical deflections were constant across the range of mean speed ratios (0.4–1.1): an estimated treatment effect of 0.56 (i.e. an accident reduction of 44%) for all speed ratios and a 95% credibility interval of 0.44–0.70.

5. Predictive models

With the exception of the model for schemes with vertical deflections, the models described above require measurements of mean speeds after scheme implementation. Since after speeds can be measured soon after scheme implementation, while useful accident data takes several years to accumulate, they can be used predictively in the early life of a scheme. It may, however, also be useful to predict the likely treatment effect prior to scheme implementation. The next stage in the modelling was thus to investigate the possibility of fitting treatment effect models which use only quantities which can be measured before treatment as explanatory variables.

These models again take the form of Model 3:

\[
Y \sim NB(\mu, K) \quad \text{where} \\
\log(\mu_i) = \log(\hat{M}_A^i) + f(Z_i \beta) + b_i \quad \text{where} \\
b_i \sim N(0, \text{var}(\log(\hat{M}_A^i)))
\]

However, in this case the function of linear predictors \(f(Z_i \beta)\) comprises schemes and site variables that can be measured before implementing the scheme. Possible variables were the number of minor junctions across the length of the scheme (denoted \(J\)), whether the scheme was in an urban or village location, the road class (A road or not A road), before mean flow (millions of vehicles/year, denoted \(Q_B\)), before mean speed (in mph, denoted \(V_B\) as before) and binary variables for each of the three scheme types.

The initial model is fitted without the error term (Model 2) in order to obtain a covariate function via the usual model selection procedures in S-PLUS. The fitting functions come from the MASS library (Venables and Ripley, 1997) namely glm.nb and stepAIC, a forward and backward selection procedure based on the Akaike Information Criterion. Up to two-way interactions of variables were permitted. The model selected from stepAIC is then tidied up by removing terms not significant at the 5% level.

The final model estimates are shown in Table 2 and give estimates of treatment effect defined as:

Urban sites without vertical deflections:

\[
\frac{Y}{M_A} = \frac{26.3}{(V_B)^{0.59}}
\]

Urban sites with vertical deflections:

\[
\frac{Y}{M_A} = \frac{18.0}{(V_B)^{0.99}}
\]
The residual plots from the initial fits appear to show that the model fits the data reasonably well without the term for variation around the offset (Fig. 4). The residual mean square error of this model is 3.2, indicating that it is nearly as adequate in modelling after accidents as when the observed after mean speed is available.

The results from the WinBUGs fit with the variation around the offset are extremely similar (see Table 2) with the reduced intercept reflecting the smaller coefficient for before mean speed so that the fitted values are similar: the size of the reduction in mean speed is fairly consistent for all values of before mean speed so that the after mean speed is dependent on the before mean speed. For schemes with vertical deflections, however, the after mean speed is largely independent of the before mean speed. This may well explain why the ratio of before to after mean speeds was not significant for vertical deflections in modelling after accidents (see Models 3(i)-(iv), Table 1).

All of the variables selected had credibility intervals that did not span 0, hence none of the selected variables appear to lose significance after adding the random effect.

In addition to predictive models of treatment effect, it may also be of interest to model how different site and scheme variables can predict the after mean speed at sites so that the impact on speed can be predicted prior to scheme implementation. Fig. 5 shows the relationship between before and after speeds for the three scheme types. It is interesting to note that, for cameras and schemes with horizontal deflections, the speed reduction in mean speed is fairly consistent for all values of before mean speed so that the after mean speed is independent of the before mean speed. This may well explain why the ratio of before to after mean speeds was not significant for vertical deflections in modelling after accidents (see Models 3(i)-(iv), Table 1).

It was assumed that after speeds were normally distributed and hence an ordinary least squares model was employed. Possible covariates were the same as those tested for modelling after accidents by before variables. The model estimates are shown in Table 3 and are summarised as:

Possible covariates were the same as those tested for modelling after accidents by before variables. The model estimates are shown in Table 3 and are summarised as:

Table 2: Estimates of coefficients for models of accidents by before site variables

<table>
<thead>
<tr>
<th>Model</th>
<th>Model parameter</th>
<th>MLE/mean of posterior distribution</th>
<th>Standard error/standard deviation of posterior distribution</th>
<th>95% confidence interval/95% credibility interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLE (S-PLUS)</td>
<td>Intercept</td>
<td>3.27</td>
<td>1.31</td>
<td>(0.70, 5.84)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Vertical</td>
<td>0.00</td>
<td>(−0.73, −0.25)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Village</td>
<td>0.60</td>
<td>(−0.60, −0.15)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>J × village</td>
<td>0.06</td>
<td>(−1.02, −0.17)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>K</td>
<td>9.6</td>
<td>(4.06, 15.08)</td>
</tr>
<tr>
<td>BAYESIAN MODEL (BUGS)</td>
<td>Intercept</td>
<td>2.92</td>
<td>0.80</td>
<td>(1.52, 4.55)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Vertical</td>
<td>0.00</td>
<td>(−1.37, −0.00)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Village</td>
<td>0.00</td>
<td>(−0.62, −0.13)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>J × village</td>
<td>0.06</td>
<td>(0.01, 0.11)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>K</td>
<td>15.6</td>
<td>(7.3, 31.5)</td>
</tr>
</tbody>
</table>

$V_B$ is the before mean speed. Vertical = schemes with vertical deflections with or without horizontal features. Village is the coefficient for villages in the binary variable for urban vs. village sites. $J ×$ village is the interaction term for number of minor junctions across the scheme and village sites (i.e. the coefficient of number of minor junctions for village sites only). $K$ is the estimate of the shape parameter for the negative binomial distribution.
Village sites without vertical deflections:
\[ V_{Ai} = 10.72 + 0.57 V_{Bi} \]

Village sites with vertical deflections, verticals:
\[ V_{Ai} = 27.71 - 0.11 V_{Bi} \]

This model has residual standard error of 3.2 and \( R^2 = 0.58 \).

6. Discussion

As noted in the introduction, it has been suggested that a progressive relationship exists between reductions in accidents and mean speed: a 5% reduction in accidents for each 1mph reduction in mean speed is widely quoted. The results presented here suggest that in fact the relationship between accident changes and speed changes is complex and is dependent on the nature of the speed management scheme.

Further work is needed to establish the reasons for this variation. It may, for example, be that part of the accident reduction defined here as being associated with a reduction in speed is actually due to other changes in driver behaviour. An engineering scheme with vertical deflections, for example, may not only reduce drivers’ speeds but may also serve to alert drivers to a potentially hazardous location leading to heightened awareness and increased caution. In addition, it must be borne in mind that measurement of speed changes at different types of speed management scheme are not nec-

<table>
<thead>
<tr>
<th>Model</th>
<th>Model parameter</th>
<th>Coefficient</th>
<th>Standard error</th>
<th>t-test</th>
</tr>
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<tr>
<td>OLS model</td>
<td>Intercept</td>
<td>-1.14</td>
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<td>p = 0.71</td>
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<td>( V_A )</td>
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<td>0.09</td>
<td>p = 0.00</td>
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<tr>
<td>Vertical</td>
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<td>5.09</td>
<td>p = 0.00</td>
<td></td>
</tr>
<tr>
<td>Village</td>
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<td>4.80</td>
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<tr>
<td>( V_B \times \text{verticals} )</td>
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<tr>
<td>( V_B \times \text{village} )</td>
<td>-0.35</td>
<td>0.15</td>
<td>p = 0.02</td>
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</tbody>
</table>

\( V_B \) is the before mean speed. Vertical = schemes with vertical deflections with or without horizontal features. Village is the coefficient for villages in the binary variable for urban vs. village sites. \( V_B \times \text{verticals} \) is the interaction term for before mean speed for sites with vertical deflections with or without horizontal features. \( V_B \times \text{village} \) is the interaction term for before mean speed across the scheme and village sites.
Fig. 5. The relationship between before and after speeds for the three scheme types.

The models suggest that, for schemes where mean speeds are reduced, schemes with horizontal features will have a greater impact on accidents than cameras for a similar reduction in mean speed. For schemes with horizontal features to be as effective in reducing accidents as those with vertical deflections a reduction in mean speed of at least 20% is needed while for cameras a reduction of over 35% would be necessary.
effect of speed management schemes on vehicle speeds. In the case of schemes with vertical deflections, although the model presented in this paper suggests that the treatment effect is independent of the change in speed, it is worth noting that the mean speed change for such schemes was 8.4 mph (Mountain et al., 2005). Our model predicts an accident reduction of 44% irrespective of the impact on speed: an average 5.2% reduction in accidents per 1 mph reduction in mean speed. For other types of speed management scheme, the models confirm that there is a progressive (although not quite linear) relationship between the percentage accident reduction and the reduction in mean speed and that larger accident reductions per 1 mph mean speed reduction are achieved on roads with lower average speeds than on roads with higher speeds. For cameras, the percentage accident reduction per 1 mph mean speed reduction, is around 4% for roads with before mean speeds in the range 30–35 mph while for schemes with horizontal features the reduction is some 7–8%. Thus, while

the commonly quoted “5% accident reduction per 1 mph speed reduction” is perhaps not an unreasonable generalisation, it must be remembered that the actual accident reduction per 1 mph speed reduction will depend on both the method of speed management and the mean speed prior to implementation.

Although, for both cameras and schemes with horizontal features, larger accident reductions are achieved per 1 mph speed reduction on roads with lower before mean speeds, the predictive models for speed change (Table 3) suggest that smaller speed reductions are also likely to be achieved on lower speed roads. Over the range of before mean speed likely to be encountered at treated sites, schemes with vertical deflections result in much larger speed reductions than other scheme types, while an urban scheme of a particular type tends to be slightly more effective in reducing speeds than a similar type of scheme in a village.

Given that, for cameras and schemes with horizontal features, lower before mean speeds are associated with larger accident reductions per 1 mph speed reduction but also smaller speed reductions, the question then arises as to whether speed management schemes are likely to be more effective in reducing accidents on low or high speed roads. The predictive models for treatment effect (Table 2) indicate that larger overall percentage accident reductions (i.e. smaller values of the treatment effect) are obtained at sites with higher before mean speeds. Schemes with vertical deflections are more effective than other scheme types in reducing accidents for all values of before mean speed.

The models also suggest that larger percentage accident reductions are obtained at sites with fewer minor junctions. On average village schemes have fewer minor junctions than urban schemes (an average of 7.5 as compared with 10.8 for the schemes in this study) and, with typical numbers of minor junctions, larger percentage accident reductions are predicted for village schemes than for urban schemes. The predicted treatment effect for schemes in villages depends on the number of minor junctions, with smaller values of the treatment effect (i.e. larger percentage accident reductions) at locations with fewer minor junctions. Since minor junctions are likely to be the location of potential points of conflict between opposing traffic streams, and hence locations where accidents are more likely and speeds more crucial, this result seems counter-intuitive. However, it is possible that the presence of minor junctions induces more cautious driver behaviour (although not necessarily lower speeds) since drivers are aware that there is more likely to be a conflict where junctions are present. The effects of speed management measures might then be expected to be less than on roads where the absence of minor junctions gives drivers a false sense of security. Further research is clearly needed. Perhaps the most important unanswered question is more generally why, for a given change in speed, some speed management schemes are much more successful in reducing accidents than others, and why a few schemes appear to actually increase accident risk.
7. Conclusions

The main conclusions that can be drawn from this analysis of the relationship between speed and accident reductions following the implementation of speed management schemes on roads subject to a 30 mph speed limit can be summarized as follows.

- For cameras and engineering schemes with horizontal features, a simple relationship between the change in mean speed and the change in accidents due to speed is available. The impact of schemes with vertical deflections on accidents is similar regardless of speed change.
- While the commonly quoted “5% accident reduction per 1 mph speed reduction” is not an unreasonable generalization, it must be borne in mind the accident reductions achieved depend on both the before mean speed and the method of speed management employed. In particular, it must be remembered that, for schemes with vertical deflections, there appears to be no progressive relationship between the percentage accident reduction and the speed reduction. For other types of scheme, larger percentage accident reductions per 1 mph speed reduction are achieved on lower speed roads, but the speed reductions tend to be smaller on lower speed roads.
- It is possible to predict both changes in speeds and accidents before treatment using the models derived from this study.
- The models indicate that speed management schemes are most effective on high-speed roads: larger mean speed reductions and overall percentage accident reductions are achieved by schemes implemented on roads with higher before mean speeds.
- For all values of mean speed, the models confirm that schemes with vertical deflections are more effective than other scheme types in terms of the reduction in mean speed and the resulting percentage accident reduction.

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References