Are Multiple Speed Cameras More Effective Than a Single One? Causal Analysis of the Safety Impacts of Multiple Speed Cameras

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Highlights

- Propensity score method is applied to analyze how multiple speed cameras affect road safety.
- Doubly robust estimation is conducted by using a pairwise comparison approach.
- Sites with more speed cameras perform better in reducing casualties.
- Multiple speed cameras are most effective with a radius of 200 m.

ABSTRACT

Most previous studies investigate the safety effects of a single speed camera, ignoring the potential impacts from adjacent speed cameras. The mutual influence between two or even more adjacent speed cameras is a relevant attribute worth taking into account when evaluating the safety impacts of speed cameras. This paper investigates the safety effects of two or more speed cameras observed within a specific radius which are defined as multiple speed cameras. A total of 464 speed cameras at treated sites and 3119 control sites are observed and related to road traffic accident data from 1999 to 2007. The effects of multiple speed cameras are evaluated using pairwise comparisons between treatment units with different doses based on the propensity score methods. The spatial effect of multiple speed cameras is investigated by testing various radii. There are two major findings in this study. First, sites with multiple speed cameras perform better in reducing the absolute number of road accidents than those with a single camera. Second, speed camera sites are found to be most effective with a radius of 200 m. For a radius of 200 m and 300 m, the reduction in the personal injury collisions by multiple speed cameras are 21.4% and 13.2% more than a single camera. Our results also suggest that multiple speed cameras are effective within a small radius (200 m and 300 m).

Keywords: Multiple speed cameras; Road safety; Propensity score; Doubly robust estimation

1 INTRODUCTION

There were 1792 people killed on Britain's roads in 2016, which was the highest number on record since 2011 (Saarinen, 2018). At the same time, the number of serious injuries came to 24,101 in 2016. In order to tackle this road safety problem, the UK government has implemented a number of safety measures, such as speed limit enforcement cameras. Speed cameras have been worldwide adopted as a prominent road safety strategy.

Although most studies show that the installation of speed cameras has significantly improved the safety level near camera sites (Christie et al., 2003; Li et al., 2013; Montella et al., 2015; Mountain et al., 2005), there is still debate about the effectiveness of speed cameras, especially in relation to their costs (Lawson, 2011). There were 2838 speed cameras installed on Britain's roads from 1991 till 2017 (BBC News, 2017), with wide variation in the density of speed cameras across different areas One question raised here is that whether sites with multiple speed cameras are more effective in reducing road casualties than those with a single one. In other words, is it beneficial for road safety to cluster speed camera interventions?

This paper investigates the safety effects of multiple fixed speed cameras using the propensity score (PS) method to make pairwise comparisons between treatment units with different doses. Compared to the traditional matching approach, the PS method enables matching to be reduced to a single dimension, providing a solution to the problem of similarity in the empirical Bayes methods (Li et al., 2013; Rosenbaum and Rubin, 1983; Sasidharan and Donnell, 2013). Moreover, the PS methods can control for the RTM and confounding factors, which cannot be fully addressed by the conventional before-after or cross-sectional studies. In addition, this study employ circle based approaches to identify the spatial area over which speed cameras are effective.

The paper is organized as follows. Section 2 reviews relevant literature in the field. The PS method and data used in this study are introduced in Section 3 and 4. Results are presented in section 5, followed by the discussions and conclusions in the final section.

2 LITERATURE REVIEW

A number of studies have been conducted to investigate the impacts of speed cameras on road safety (Carnis and Blais, 2013; Christie et al., 2003; De Pauw et al., 2014a,b; Gains et al., 2004; Graham et al., 2019; Høye, 2015; Li et al., 2013; Li and Graham, 2016; Montella et al., 2015; Mountain et al., 2005), which show that the implementation of speed cameras has significantly reduced the vehicle speed and the number of accidents near camera sites. Furthermore, previous studies have largely focused on the effects in the immediate area of the camera site itself whereas only a few of them have investigated the spatial distribution of effects over from the cameras (Christie et al., 2003; De Pauw et al., 2014b; Høye, 2015; Kaygisiz and Sümer, 2019; Li et al., 2013; Carnis, 2010). For example, works done by Cameron and Newstead (2003) regarding the Queensland speed camera program dealt with the spatial effect or halo effect. Their results showed that the deterrent effect evolves with the distance from the location of the camera. Besides, a study by De Pauw et al. (2014b) shows that the reduction of severe crashes is 27%

within 250 m from the camera, while the reduction is 23% for 250 to 500 m.

Despite that most previous studies have shown significant safety impacts of speed cameras, it remains unclear that whether sites with multiple speed cameras are more effective in reducing road casualties than those with a single one. It can be speculated that driving behavior may differ in locations with multiple speed cameras from those with a single isolated camera. For example, at a site with single camera, drivers would slow down ahead of a camera and speeding up once they are clear of it, which is known as “kangaroo effect” (Elvik, 1997; Thomas et al., 2008). And it is also possible that drivers may choose alternative routes to avoid single speed camera (Mountain et al., 2005). To the best of the authors’ knowledge, the safety effects of multiple speed cameras have never been formally studied. Most previous studies have focused on the effects of a single speed camera on road safety (e.g., Christie et al., 2003; Goldenbeld and van Schagen, 2005; Høye, 2015; Li and Graham, 2016; Montella et al., 2015; Shin et al., 2009), which have ignored potential impacts from adjacent speed cameras which could be important when studying the safety impacts of speed cameras. In addition, some studies have investigated the dose-response relationship between the number of speed cameras and traffic fatalities and injuries (e.g., Blais and Carnis, 2015; Carnis and Blais, 2013). However, these studies are based on descriptive statistics or incorporate parameters, estimating the growing effect of speed camera programs as the number of devices increases.

Most previous studies used route based methods, while circle methods are rarely studied. Christie et al. (2003) compared the route and circle methods for evaluating the effectiveness of speed cameras. Although there are a few drawbacks of the circle methods, it also has some advantages over the routes methods. First, it is possible that speed cameras may cause accidents migration to alternative routes (Mountain et al., 2005), which is a critical issue in the route based analysis especially when the traffic flow data for the before and after periods are unavailable. Second, the crash locations recorded by the police can be imprecise, which may lead to underestimations of the camera effects in routes analysis (e.g., Abay, 2015; Amoros et al., 2006; Watson et al., 2015). However, such imprecision would not have substantially affected the circles analyses (Christie et al., 2003). Finally, the route based method only investigates the local effect of a particular camera site, while the circle method can estimate the generalized effect of speed cameras in an entire police force area. In this study, we investigate the safety effects of speed cameras within circular areas with various radii.

Several approaches have been applied in previous road safety evaluation studies (Christie et al., 2003; Gu et al., 2019; Guo et al., 2018; Hauer et al., 2002; Li et al., 2017; Martínez-Ruíza et al., 2019; Wood and Donnell, 2017; Xu et al., 2018;). Before and after study with control groups is one of the most commonly used methods to estimate the impacts of speed cameras on speed and the number of accidents (De Pauw et al., 2014a; Bar-Gera et al., 2017). However, the traditional before-after method usually suffers from the regression to the mean (RTM) effect. The empirical Bayes (EB) method has been widely used over the last decades, which can account for the RTM (Elvik et al., 2017; Hauer et al., 2002; Høye, 2015; Wood and Donnell, 2017). However, the performance of the EB approach can be adversely affected if the similarity issue is not properly addressed. Thus, an alternative method to the EB approach, the PS method, are proposed as a solution to this problem of similarity in recent studies to estimate the impact of road safety countermeasures (e.g. Li et al, 2019; Sasidharan and Donnell, 2013; Wood et al., 2015a, b).

PS methods are based on the rule that the control or reference group should have similar characteristics with the treated ones. Propensity scores can be constructed as a scalar value, which summarizes a potentially high-dimensional covariate vector accounting for the probability that a unit is assigned to the treatment (Rosenbaum and Rubin, 1983). The PS methods have been widely applied in numerous sociology, epidemiology and economic studies (e.g., Chattopadhyay et al., 2016; Kowaleski-Jones et al., 2018; Shahidi et al., 2019). Over recent decades, the PS methods have also been used to estimate the impact of road safety measures as well (e.g., Hou et al., 2019; Li et al., 2013; Sasidharan and Donnell, 2013; Wood et al., 2015a, b). For example, Wood et al. (2015b) investigated the safety effect of four lane widths (9, 10, 11, and 12 ft.). In their study, the comparisons of different lane widths are performed respectively via the PS methods.

3 METHOD

3.1 PS methods with multiple treatment levels

The PS methods are based on the idea that the control group should have similar characteristics with the treated ones. We first introduce the potential outcomes framework with multiple treatment levels. Each unit (i.e. speed camera site) is assigned one of $J+1$ possible treatment levels (i.e. number of cameras), where j=0, 1, ..., J corresponding to $J+1$ treatment conditions and T_i denotes the treatment level of unit i. The treatment indicator $d_{ij}=1$ if unit i receives the j level treatment and $d_{ij}=0$ otherwise, where i = 1, …, N, and N denotes the total number of units. Referring to the potential outcome framework of Rubin (1974), Y_i denotes the observed outcomes (i.e. observed accidents) and Y_{ij} are the potential outcomes (i.e.

the potential accidents without speed camera in the site). Thus, the observed outcome is given by:

$$Y_i = \sum_{j=0}^{J} d_{ij}(T_i) Y_{ij} \tag{1}$$

Therefore, the individual-level treatment effect φ_i corresponding to treatment level u versus v ($u \neq v$) for unit i can be written:

$$\varphi_i = Y_{iu} - Y_{iv} \tag{2}$$

Accordingly, in practice, the population average treatment effect on the treated φ_{ATT} is given by the difference in the means of two potential outcomes, which can be written:

$$\varphi_{ATT} = E[Y_{iu} - Y_{iv}] = \lambda_u - \lambda_v \tag{3}$$

where λ_u and λ_v denote the averages of the observed outcomes for the treatment groups U and V respectively.

Three crucial assumptions need to be satisfied to ensure the validity of the PS method (Rosenbaum and Rubin, 1983). The first assumption is stable unit treatment value assumption (SUTVA), which defines the treatment assigned to a unit have no impact on the outcomes of others. The second is conditional independence assumption (CIA), which states that the potential outcomes are independent of the treatment status after controlling for covariates $\boldsymbol{X}$. The last is common support condition (CSC), which is also known as the overlap condition, ensuring the probability of being treated and untreated is positive for the units with the same $\boldsymbol{X}$ values.

Several PS based methods can be used to estimate the effects of treatment, such as regression-adjusted estimators, inverse-probability weighted (IPW) estimators, matching estimators, and doubly robust (DR) estimators. Recent studies have shown that the DR methods can provide an additional level of robustness and model both the probability of treatment and the outcome simultaneously within the same framework, providing the investigator two opportunities to derive consistent treatment effects (Funk et al., 2011; Robins et al., 1995). Besides, the DR estimator can maintain asymptotically unbiased estimates when only one of the two models is correctly specified. For more details, please refer to the works by Lunceford and Davidian (2004) and Graham et al. (2015).

3.2 Estimating the safety effects of speed cameras using the PS methods

The PS method has been widely used for the binary treatment framework. The procedure for estimation of treatment effects using PS method can be illustrated as follow.

The first step is to estimate the propensity scores. The propensity score indicates the probability of an observation having multiple speed cameras. So the propensity scores range from 0 to 1. For a binary treatment variable, logit and probit models are usually preferred to a linear probability model. And logit and probit models usually produce similar results (Smith, 1997), the choice is not critical. In this paper, a binary logit model is used to estimate the propensity score:

$$P(d_{ij} = 1|X) = \frac{\exp(\alpha + \beta X)}{1 + \exp(\alpha + \beta X)} \tag{5}$$

where P is the propensity score for each observation, $\boldsymbol{X}$ is the vector of covariates, α is the intercept, and β is the vector of parameters to be estimated.

The second step is to select a matching algorithm. A number of matching algorithms have been discussed in previous studies, including nearest neighbor matching, K-nearest neighbor matching, kernel and local linear matching, caliper and radius matching, mahalanobis matching and genetic matching (e.g., Heinrich et al., 2010; Wood and Donnell, 2016). There is no theoretical guidance on how to choose the most appropriate algorithm for matching. Given a large sample, the result from different algorithms should be similar and therefore the choice is not critical. It is suggested to use multiple matching algorithms for more credible results (please refer to Heinrich et al., 2010 for detailed discussion).

The third step is to estimate the treatment effects. Once treatment units have identified matches from the untreated group, the treatment effect can be estimated by taking differences in the outcomes between treated units and their matches. A number of programs are available. The program used in this study is **psmatch2** in STATA developed by Leuven and Sianesi (2003).

In summary, the procedures for using the PS method to evaluate safety effects of multiple speed cameras can be illustrated as following steps.

(1) The data for different types of speed camera sites, such as accidents record and site information, is collected and constructed in a single data set.

(2) Covariates are selected to be included in the logit model to estimate the propensity score.

(3) The distributions of propensity scores are compared between different types of speed camera sites to check the overlap condition. If the condition is not satisfied, then covariates included in the PS model need to be re-selected. In our study, multiple matching algorithms are applied to increase the credibility of the PS method.

(4) A balancing test is conducted to test whether different types of speed camera sites are statistically similar after matching. If significant differences are found, the logit model is re-specified and the process is repeated from the beginning.

(5) The safety effects of multiple speed cameras can be evaluated by taking differences in outcomes between different types of camera sites.

(6) DR estimation is applied to increase our confidence in the estimation results.

4 DATA

4.1 Sample size

Due to the data availability, 464 speed cameras, which measure speed in both directions, are selected from ten following English administrative districts, including Cheshire, Dorset, Hertfordshire, Lancashire, Leicester, London, Manchester, Merseyside, Sussex and West midlands. "Handbook of Rules and Guidance for the National Safety Camera Programme for England and Wales" defines the rules and guidelines that the partnerships are required to follow (DfT, 2006). Fixed and mobile cameras are both used in Britain and some of them are hidden. However, because the data on mobile cameras were limited and the installation time of mobile speed cameras was unavailable, the mobile cameras were not taken into consideration in this study. Figure 1 shows an example of speed camera clusters in London and these speed cameras were all installed between 2002 and 2004, which shows great diversity in the density of speed cameras across different areas.

Since the criteria for selecting camera sites and the safety effects may change over time (DfT, 2004 & 2006; Høye, 2015), it is necessary to limit our study to a short period. In addition, as suggested by previous studies (Gains et al., 2004; Høye, 2015; Li and Graham, 2016; Mountain et al., 2005), three-year data before and after the installation of all speed camera sites are usually required. Since speed cameras were installed at different time, if the study period covers too many years, it would be difficult to define the before and after periods for each camera site. Therefore, only speed cameras installed between 2002 and 2004 are chosen.

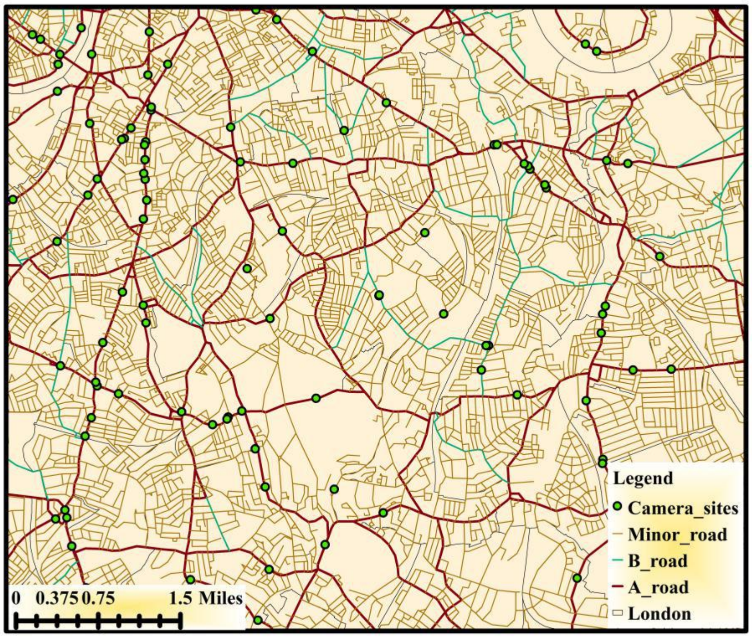

Fig. 1. An example of speed camera clusters in London.

4.2 Covariates

In this study, a site is a circular area and the site length corresponds to the radius of the area. Several studies have been conducted to explore the most effective monitoring length for speed cameras (e.g., Gains et al., 2004; Li et al., 2013). In this paper, in order to investigate the effect area of speed cameras, circles approaches are applied. The effective area is investigated by using different radii to the camera sites, including 200, 300, 400, 500, 600, and 1000 m.

The covariates included in the PS model should be based on the criterion that they affect both treatment and outcome, not on their statistical significance (Rubin and Thomas, 1996; Sasidharan and Donnell, 2013). According to the UK guidelines for selecting camera sites (Gains et al., 2005), and previous studies on speed cameras and road safety (Li and Graham, 2016; Mountain et al., 2005; Wang and Huang, 2016), the following covariates are included in the PS model:

(1) FSCs: the number of fatal and serious collisions occurred within a circular zone around the site in baseline years (3 years before the installation of speed cameras).

(2) PICs: the number of personal injury collisions occurred within a circular zone around the site in baseline years.

(3) AADT: the annual average daily traffic within a circular zone around the site.

(4) Road length: the total road length within a circular zone around the site.

(5) Intersections per km: the number of intersections per km within a circular zone around the site.

Although the selection of the speed camera sites is primarily based on accident history (DfT, 2006), there are also secondary criteria, such as the 85^{th} percentile speed and percentages of vehicles over the speed limit, which are normally unavailable. As discussed in previous studies (Gains et al., 2004; Mountain et al., 2005), however, the national average mean speed and percentages of speeding are similar for the untreated sites and camera sites with the speed limit of 30 mph and 40 mph, which are the focus groups in this study. It is reasonable to assume that there is no significant difference in the speed distribution between the treated and control groups and the exclusion of the speed data will not affect the accuracy of estimation results. In addition, it is also difficult to identify the road class and speed limit when using the circle method. Thus, these factors are also not considered.

It is suggested that a sufficient number of control group candidates should be included to guarantee the matching quality (Kurth et al., 2006; Peikes et al., 2008). Therefore, a total of 3119 potential control sites were chosen randomly within ten districts mentioned above. These sites had no speed cameras before 2008 and are at least 2 km away from any camera sites. For the control sites, the study periods are defined as the same as those of the proximate treated sites.

Safety impacts of different numbers of speed cameras are evaluated in a circular area. Every camera has its own circle and circles are drawn around all speed cameras. The circles are combined if they overlap. Figure 2 shows three types of speed camera sites, which are defined based on the number of speed cameras within a circular zone:

(1) Single speed camera: there is no other speed camera within a specific radius of a speed camera.

(2) A site with two speed cameras: there is one other speed camera within a specific radius of a speed camera.

(3) A site with multiple speed cameras: there are more than one other speed cameras within a specific radius of a speed camera.

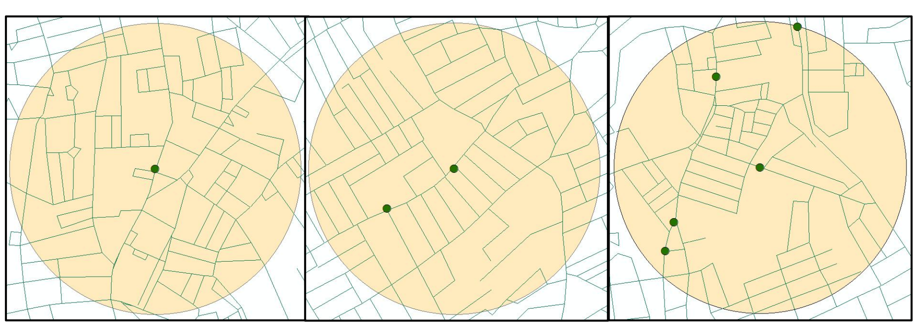

Fig. 2. Three types of speed camera sites.

Table 1 shows different speed camera sites with radii of 200, 300, 400, 500, 600, and 1000 m. The numbers of the treated and control sites are also shown in the table. However, the number of sites with three or more speed cameras is too small when the radii are 200, 300, 400, and 500 m. Thus, only the sites with a radius of 600 m and 1000 m are used to estimate the effect of multiple speed cameras.

Table 1

The number of treatment and control group for different radii.

Radius	Number of speed camera	Number of treatment group	Number of control group
200 m	1	413	2631
	2	50	479
300 m	1	384	2790
	2	76	639
400 m	1	346	2821
	2	100	828
500 m	1	312	3119
	2	111	910
600 m	1	282	2940
	2	105	1043
	3 or more	76	635
1000 m	1	199	2239
	2	110	1087
	3 or more	154	1287

5 RESULTS

5.1 Estimating the propensity scores

We first estimate the propensity scores for all the treated and untreated units using a logit model. The results in Table 2 show that the covariates included in the PS model are all essential in predicting the probability of being chosen as the camera sites. However, Westreich et al. (2011) suggested that the main purpose of the PS method is not to predict the treatment assignment, but to balance the covariates so that the confoundedness can be controlled for.

Table 2

Results of the PS model.

	Coef.	S.E.	z	P>z	[95% Conf. Interval]	
PICs in baseline years	-0.019	(0.004)	-4.64	0.000	-0.027	-0.011
FSCs in baseline years	0.131	(0.027)	4.79	0.000	0.078	0.185
The number of intersection per km	0.325	(0.068)	4.79	0.000	0.192	0.458
Road length	1.82E-04	(4.22E-05)	4.32	0.000	9.95E-05	0.000
AADT in baseline years	-1.19E-05	(5.72E-06)	-2.07	0.038	-2.31E-05	0.000
Constant	-6.335	(0.510)	-12.42	0.000	-7.335	-5.336

5.2 Tests of matching quality

We then examine the validity of the PS method through two approaches, one of which is a visual inspection of the propensity score distributions for both the treatment and control groups. Figure 3 shows an example of the distributions of the propensity scores in percentage, which indicates sufficient overlapping of the distributions. In addition, the total number of speed cameras involved in the estimation is 464, and the ratio of the number of control candidates to the treated ones ranges from 6:1 to over 10:1. The common support condition is well satisfied in this study.

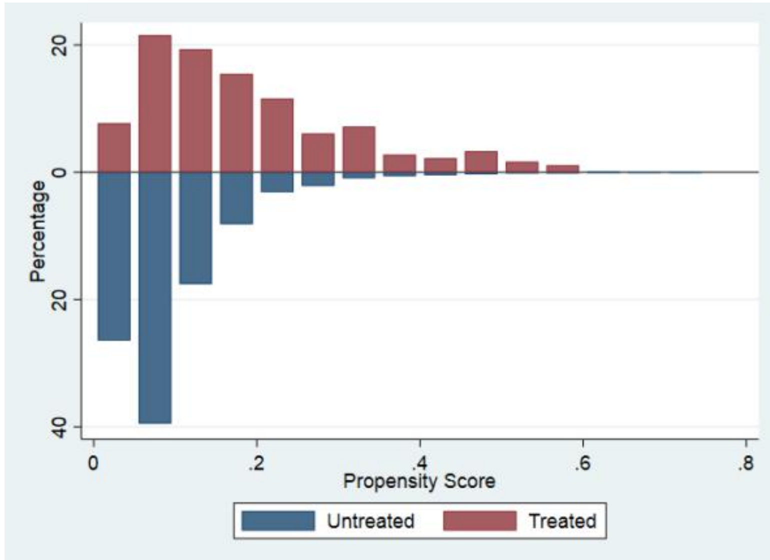

Fig. 3. Propensity score distribution.

A balance test is also performed to check the validity of conditional independence assumption. Theoretically there should be no significant differences in the covariates means between the treated and control groups after matching. Table 3 shows an example of the *t*-test of the differences in covariates means before and after matching. Significant differences are observed for all covariates before matching, indicating that the characteristics of the treated and control units are not similar if the traditional before-after control methods are used. In contrast, all covariates are well balanced between the treated and matched control groups after matching.

Table 3

Balance test between groups (k = 5 nearest neighbors matching).

Covariate	Sample	Mean			%reduced	t-test	
		Treated	Control	%bias	|bias|	t	p>|t|
PICs in baseline years	Unmatched	39.705	22.734	59.6		5.42	0.000
	Matched	38.312	36.766	5.4	90.9	0.31	0.758
FSCs in baseline years	Unmatched	6.1667	3.5614	57.2		5.19	0.000
	Matched	5.8571	5.5974	5.7	90	0.35	0.726
The number of intersection per km	Unmatched	6.2705	5.2484	43.8		3.53	0.000
	Matched	6.2626	6.3871	-5.3	87.8	-0.34	0.738
Road length	Unmatched	3215.8	2842.4	32.1		2.42	0.016
	Matched	3204.7	3182.9	1.9	94.2	0.12	0.903
AADT in baseline years	Unmatched	32442	29423	12.8		0.99	0.324
	Matched	32510	34529	-8.6	33.1	-0.49	0.626

5.3 Evaluating the safety impacts of multiple speed cameras

In order to estimate the effects of treatments with different doses, we follow the practice by Wood et al. (2015). For example, the comparisons between one speed camera and no speed camera within a circular zone can be defined as “1:0”. The comparisons between two speed cameras and no speed camera within a circular zone is defined as “2:0”. Additionally, the comparisons between three or more speed cameras and no speed camera within a circular zone is defined as “3:0”. When performing the comparison of “1:2”, only 200 m and 300 m are selected to guarantee sufficient sample sizes of the treated and control groups. Similarly, the comparison of “3:0” are only performed for the radii of 600 m and 1000 m due to the limitation of the number of the treated sites.

Table 4 shows the effects of speed cameras on annual PICs and FSCs per km in absolute number. The safety effects of installing multiple speed cameras are estimated by taking the differences in the crash frequency between the matched observations of treated and control groups. The effects of different numbers of cameras on PICs and FSCs are presented for different radii. The estimation results based on different matching algorithms and the DR approach are very similar, which increases our confidence in the PS method. It is found that the speed cameras are most effective within 200 m radius of camera sites, where the reduction in the annual PICs per km in absolute number is 0.481 for the sites with single speed camera. The estimations are 0.219 for up to 400 m, 0.152 for up to 600 m and 0.069 for up to 1 km respectively for “1:0”. Generally, the effectiveness decreases as the radius increases, which is consistent with the traditional halo effect and the main findings of previous studies (Cameron, 2008; Christie et al., 2003; De Pauw et al., 2014b; Høye, 2015; Li et al., 2013).

It is also found that the effectiveness increases as the number of speed cameras increases. The reduction in annual PICs per km in absolute number ranges from 0.069 to 0.481 for “1:0”, while the annual reduction per km for “2:0” ranges from 0.094 to 1.362. Similarly, the reductions in the annual PICs per km in absolute number are 0.152 for “1:0”, 0.155 for “2:0” and 0.371 for “3:0” respectively when the radius is 600 m. When the radius is 1000 m, however, the estimated results are only partly significant at the 10% level for the “1:0” group, while the treatment effects are all insignificant for “2:0” and “3:0”. Moreover, we also compare the safety impacts of one speed camera with two cameras directly. The results from Table 4 show that the sites with two speed cameras are more effective in reducing road accidents compared to those with single speed camera.

Table 5 shows the average effects of speed cameras on annual PICs per km in percentages.

Similarly, the results suggest that, comparing to 400, 500, 600, and 1000 m, when the radius is 200 m, the speed cameras are most effective (14.97% for “1:0” and 34.63% for “2:0”). As for “2:1”, average effects on the annual PICs is 21.44% for 200 m and 13.23% for 300 m, suggesting that the sites with two speed cameras are more effective than those with one camera with small radii of 200 m and 300 m. However, for “3:0”, effects on the annual PICs is 9.94% for 600 m and 1.84% for 1000 m, indicating that sites with three or more speed cameras are less effective with radii over 500 m.. Meanwhile, for 400, 500, 600, and 1000 m, the safety effectiveness of two or more speed cameras are not larger than the sites with one camera. The results indicate that the sites with multiple speed cameras are more effective in reducing road accidents with a radius of 300 m. Our results are partly consistent with the findings by Christie et al. (2003).

Table 4

Average effects of speed cameras on annual PICs/FSCs per km in absolute number.

	200 m		300 m		400 m		500 m		600 m		1000 m	
	Effects	T-stat	Effects	T-stat	Effects	T-stat	Effects	T-stat	Effects	T-stat	Effects	T-stat
	Average effects on annual PICs per km in absolute number											
	1:0											
Unmatched	-0.781	-9.52	-0.467	-7.69	-0.286	-5.66	-0.208	-4.66	-0.173	-4.00	-0.067	-1.64
K-nearest Neighbors Matching (K = 1)	-0.439	-2.87	-0.381	-3.96	-0.210	-3.11	-0.220	-3.80	-0.171	-2.79	-0.073	-1.44
K-nearest Neighbors Matching (K = 5)	-0.443	-3.77	-0.339	-4.09	-0.214	-3.56	-0.155	-3.14	-0.124	-2.62	-0.064	-1.51
Kernel Matching (Bandwidth = 0.05)	-0.524	-4.74	-0.332	-4.36	-0.228	-4.10	-0.174	-3.79	-0.151	-3.46	-0.069	-1.73
Radius Matching (Caliper = 0.05)	-0.541	-4.90	-0.350	-4.61	-0.236	-4.24	-0.180	-3.93	-0.157	-3.61	-0.074	-1.87
Doubly robust	-0.456	-3.47	-0.325	-4.01	-0.205	-2.98	-0.178	-3.23	-0.157	-3.55	-0.065	-1.79
Average Effect	-0.481		-0.344		-0.219		-0.181		-0.152		-0.069	
	2:0											
Unmatched	-1.646	-5.90	-1.392	-9.45	-0.853	-8.61	-0.396	-4.13	-0.205	-2.45	-0.190	-2.79
K-nearest Neighbors Matching (K = 1)	-1.342	-2.64	-1.001	-3.57	-0.514	-2.73	-0.300	-2.03	-0.124	-1.05	-0.101	-1.56
K-nearest Neighbors Matching (K = 5)	-1.252	-3.08	-1.002	-3.80	-0.562	-3.31	-0.242	-2.14	-0.177	-1.99	-0.082	-1.03
Kernel Matching (Bandwidth = 0.05)	-1.453	-3.88	-1.096	-4.29	-0.518	-3.15	-0.225	-2.21	-0.156	-1.97	-0.091	-1.34
Radius Matching (Caliper = 0.05)	-1.505	-4.03	-1.129	-4.40	-0.532	-3.23	-0.233	-2.30	-0.171	-2.16	-0.105	-1.59
Doubly robust	-1.259	-3.16	-0.963	-3.27	-0.511	-2.79	-0.225	-1.95	-0.146	-1.97	-0.094	-1.64
Average Effect	-1.362		-1.038		-0.527		-0.245		-0.155		-0.094	
	2:1								3:0			
Unmatched	-1.114	-3.38	-0.883	-4.60					-0.713	-6.39	-0.396	-7.37
K-nearest Neighbors Matching (K = 1)	-0.475	-1.09	-0.763	-2.47					-0.454	-2.04	-0.068	-0.59
K-nearest Neighbors Matching (K = 5)	-0.701	-1.70	-0.529	-2.00					-0.390	-2.15	0.006	0.07
Kernel Matching (Bandwidth = 0.05)	-0.783	-2.06	-0.563	-2.19					-0.331	-1.96	0.031	0.38
Radius Matching (Caliper = 0.05)	-0.829	-2.19	-0.576	-2.27					-0.342	-2.03	0.026	0.03
Doubly robust	-0.679	-2.02	-0.573	-2.02					-0.339	-1.93	-0.007	-0.06
Average Effect	-0.693		-0.601						-0.371		-0.002	

Table 4 (continued)

Average effects of speed cameras on annual PICs/FSCs per km in absolute number.

	200 m		300 m		400 m		500 m		600 m		1000 m	
	Effects	T-stat	Effects	T-stat	Effects	T-stat	Effects	T-stat	Effects	T-stat	Effects	T-stat
	Average effects on annual FSCs per km in absolute number											
	1:0											
Unmatched	-0.240	-9.39	-0.171	-9.47	-0.114	-8.15	-0.088	-7.54	-0.072	-6.74	-0.037	-4.23
K-nearest Neighbors Matching (K = 1)	-0.095	-2.09	-0.093	-3.22	-0.060	-2.78	-0.058	-3.17	-0.055	-3.36	-0.017	-1.38
K-nearest Neighbors Matching (K = 5)	-0.085	-2.62	-0.087	-3.51	-0.060	-3.35	-0.051	-3.35	-0.046	-3.49	-0.016	-1.50
Kernel Matching (Bandwidth = 0.05)	-0.126	-3.64	-0.104	-4.34	-0.068	-4.08	-0.058	-4.08	-0.047	-3.77	-0.026	-2.59
Radius Matching (Caliper = 0.05)	-0.136	-3.96	-0.112	-4.70	-0.073	-4.42	-0.063	-4.40	-0.051	-4.10	-0.029	-2.94
Doubly robust	-0.102	-2.58	-0.098	-3.87	-0.063	-3.93	-0.054	-3.11	0.048	2.76	0.022	2.12
Average Effect	-0.109		-0.099		-0.065		-0.057		-0.030		-0.013	
	2:0											
Unmatched	-0.482	-5.55	-0.337	-7.11	-0.199	-6.64	-0.104	-4.88	-0.054	-3.07	-0.047	-3.72
K-nearest Neighbors Matching (K = 1)	-0.425	-2.41	-0.247	-2.59	-0.132	-2.61	-0.075	-2.28	-0.065	-2.66	-0.024	-1.22
K-nearest Neighbors Matching (K = 5)	-0.358	-2.22	-0.218	-2.23	-0.149	-2.98	-0.073	-2.88	-0.049	-2.41	-0.023	-1.50
Kernel Matching (Bandwidth = 0.05)	-0.411	-2.67	-0.235	-2.58	-0.127	-2.59	-0.070	-2.90	-0.048	-2.51	-0.025	-1.75
Radius Matching (Caliper = 0.05)	-0.422	-2.84	-0.254	-2.71	-0.129	-2.67	-0.072	-3.03	-0.050	-2.63	-0.028	-1.97
Doubly robust	-0.397	-2.63	-0.219	-2.66	-0.136	-3.01	-0.065	-2.75	-0.046	-2.59	-0.017	-1.52
Average Effect	-0.403		-0.235		-0.135		-0.071		-0.052		-0.023	
	2:1								3:1			
Unmatched	-0.246	-2.19	-0.187	-2.97					-0.158	-6.88	0.078	-7.44
K-nearest Neighbors Matching (K = 1)	-0.058	-0.60	-0.187	-1.69					-0.094	-1.99	-0.026	-1.42
K-nearest Neighbors Matching (K = 5)	-0.135	-1.04	-0.125	-1.25					-0.093	-2.31	-0.014	-0.09
Kernel Matching (Bandwidth = 0.05)	-0.203	-1.56	-0.132	-1.35					-0.089	-2.27	-0.02	-1.27
Radius Matching (Caliper = 0.05)	-0.205	-1.57	-0.137	-1.39					-0.091	-2.33	-0.021	-1.31
Doubly robust	-0.167	-1.68	-0.136	-1.60					-0.107	-1.90	-0.039	-1.70
Average Effect	-0.154		-0.143						-0.095		-0.024	

Table 5 Average effects of speed cameras on annual PICs per km in percentage.

	200 m		300 m		400 m		500 m		600 m		1000 m	
	Effects	T-stat	Effects	T-stat	Effects	T-stat	Effects	T-stat	Effects	T-stat	Effects	T-stat
	Average effects on annual PICs per km in Percentage											
	1:0											
Unmatched	-20.20	-5.46	-17.26	-3.76	-17.02	-3.73	-15.47	-3.73	-13.85	-3.22	-6.35	-1.70
K-nearest Neighbors Matching (K = 1)	-15.42	-2.77	-16.66	-2.70	-12.27	-3.63	-11.88	-2.87	-11.62	-2.56	-7.93	-1.89
K-nearest Neighbors Matching (K = 5)	-13.01	-2.78	-13.84	-3.65	-13.54	-4.02	-14.55	-4.57	-12.96	-3.98	-6.73	-2.43
Kernel Matching (Bandwidth = 0.05)	-15.05	-3.41	-13.51	-4.12	-15.31	-5.70	-13.59	-5.64	-11.89	-4.55	-5.32	-2.14
Radius Matching (Caliper = 0.05)	-15.51	-3.53	-14.00	-4.30	-15.71	-5.91	-13.88	-5.80	-12.30	-4.74	-5.79	-2.34
Doubly robust	-15.86	-3.28	-15.10	-4.37	-15.03	-5.08	-14.34	-5.23	-11.88	-3.99	-6.11	-2.18
Average Effect	-14.97		-14.62		-14.37		-13.65		-12.13		-6.38	
	2:0											
Unmatched	-36.10	-2.66	-27.17	-3.64	-19.13	-2.78	-12.77	-1.97	-8.15	-1.72	-7.35	-1.86
K-nearest Neighbors Matching (K = 1)	-30.41	-2.36	-15.03	-2.31	-11.44	-1.70	-10.93	2.00	-6.40	-2.59	-2.84	-0.88
K-nearest Neighbors Matching (K = 5)	-34.70	-3.15	-18.66	-3.65	-11.24	-3.07	-8.94	-2.58	-5.65	-1.99	-3.94	-1.83
Kernel Matching (Bandwidth = 0.05)	-35.48	-4.29	-21.63	-3.58	-11.32	-2.75	-8.55	-2.83	-6.47	-2.42	-3.77	-1.77
Radius Matching (Caliper = 0.05)	-35.82	-4.42	-22.19	-3.74	-12.01	-3.00	-8.99	-2.68	-6.77	-2.56	-4.18	-1.98
Doubly robust	-36.73	-4.61	-21.32	-3.13	-14.91	-3.25	-10.06	-2.67	-7.43	-2.62	-5.19	2.66
Average Effect	-34.63		-19.77		-12.18		-9.49		-6.54		-4.27	
	2:1								3:1			
Unmatched	-21.91	-1.92	-15.40	-2.53					-14.66	-2.06	-14.38	-3.27
K-nearest Neighbors Matching (K = 1)	-29.14	-2.01	-16.90	-2.38					-10.51	-2.04	-2.87	-1.52
K-nearest Neighbors Matching (K = 5)	-21.20	-2.60	-11.60	-2.23					-9.63	-2.64	-2.97	-1.61
Kernel Matching (Bandwidth = 0.05)	-17.80	-2.46	-12.50	-2.39					-10.63	-2.62	-0.86	-0.69
Radius Matching (Caliper = 0.05)	-18.57	-2.58	-12.75	-2.48					-10.80	-2.71	-1.17	-0.75
Doubly robust	-20.50	-2.74	-12.39	-2.62					-8.12	-1.97	-1.70	-1.70
Average Effect	-21.44		-13.23						-9.94		-1.84	

6 DISCUSSIONS AND CONCLUSIONS

As an important safety countermeasure taken by the UK government to improve road safety, the implementation of speed cameras is expected to regulate driving speed and reduce road accidents. Numerous studies have been conducted to investigate whether the introduction of speed cameras are uniformly effective in reducing traffic accidents. However, a number of issues associated with speed cameras have never been analyzed before, such as how multiple speed cameras affect road safety and under what conditions multiple speed cameras can obtain optimal effectiveness. This paper applied the PS method to address these issues. The safety effects were evaluated by using a pairwise comparison approach based on the DR estimators.

This paper has two major findings on the safety effects of different speed cameras sites. The first finding concerns the safety effects at sites with different number of speed cameras. The pairwise comparison results indicate that the sites with two or more speed cameras have greater effects in reducing the absolute number of road accidents than those with a single camera. Moreover, a direct comparison between one and two speed cameras is conducted and the results also show that circular areas with two speed cameras are more effective in decreasing the number of road accidents. However, when investigating the safety effects in percentages, it is found that multiple speed cameras are only more effective in the areas with small radii (200 m and 300 m). As for 400, 500, 600, and 1000 m, the sites with multiple speed cameras are less effective in reducing the PICs in percentages. A possible explanation is that as the radius increases, the accidents number in the baseline years also increases dramatically for sites with multiple speed cameras while the accidents reduction number remains unchanged.

The second finding relates to the radius over which the camera site is effective. Most previous studies used the route method, while the circle method has rarely been used (Li and Graham, 2016; De Pauw et al., 2014a; Høye, 2015; Christie et al., 2003). For all types of speed camera sites, the reductions in both PICs and FSCs decrease as the radius increases. For “1:0”, “2:0” and “2:1”, the speed camera sites are found to be most effective when the radius is 200 m. The effects of the speed cameras reach the peak value when the radius is 300 m. And for the sites with two speed cameras, the safety effects in percentages decrease when the radius is larger than 300 m. The results from Christie et al. (2003) suggest that camera sites had less injurious crashes than the expected numbers up to 300 m, which is partly consistent with our findings. However, it is unclear whether this relationship holds when the radius is larger than 1000 m.

In summary, this paper contributes to the literature by evaluating the effects of multiple speed cameras using causal methods. The results indicate that multiple speed cameras are more effective than a single one and the authors suggest that multiple speed cameras could be installed at high-risk locations to improve the road safety level. However, it is also worth noting that multiple speed cameras can provide better performance only in the areas with a small radius (i.e. under 500 m). Another contribution of this study relies on the fact that we apply the PS methods to assess the impact of multiple speed cameras. The PS method is able to select proper control groups to account for the effects of confounding factors, RTM and time trend, which cannot be fully addressed by the conventional methods for road safety evaluation studies. Moreover, the PS method provides a solution to the problem of similarity in the EB approach. Therefore, we suggest the PS methods can be further used in future road safety studies, more specifically, on multiple treatments and time varying effects.

There are also some limitations in this study. First, the safety effects of multiple speed cameras are not compared for both routes and circle analysis. It is required that the multiple speed cameras investigated should be those installed in the same period. However, due to the data restriction in this study, it is difficult to find sufficient observations of road sections with two or more speed cameras installed in the same time period. Second, as pointed out by Christie et al. (2003), some of the accidents may be double counted and contribute to the estimation of multiple sites when using the circles methods, which may also influence our estimation results.

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