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ORIGINAL PAPER

Absence of Street Lighting May Prevent Vehicle Crime, but Spatial and Temporal Displacement Remains a Concern

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Abstract

Objectives This paper estimates the effect of changes in street lighting at night on levels of crime at street-level. Analyses investigate spatial and temporal displacement of crime into adjacent streets.

Methods Offense data (burglaries, robberies, theft *of* and theft *from* vehicles, and violent crime) were obtained from Thames Valley Police, UK. Street lighting data (switching lights off at midnight, dimming, and white light) were obtained from local authorities. Monthly counts of crime at street-level were analyzed using a conditional fixed-effects Poisson regression model, adjusting for seasonal and temporal variation. Two sets of models analyzed: (1) changes in night-time crimes adjusting for changes in day-time crimes and (2) changes in crimes at all times of the day.

Results Switching lights off at midnight was strongly associated with a reduction in night-time theft from vehicles relative to daytime (rate ratio RR 0.56; 0.41–0.78). Adjusted for changes in daytime, night-time theft from vehicles increased (RR 1.55; 1.14–2.11) in adjacent roads where street lighting remained unchanged.

Conclusion Theft from vehicle offenses reduced in streets where street lighting was switched off at midnight but may have been displaced to better-lit adjacent streets. Relative to daytime, night-time theft from vehicle offenses reduced in streets with dimming while theft from vehicles at all times of the day increased, thus suggesting temporal displacement. These findings suggest that the absence of street lighting may prevent theft from vehicles, but there is a danger of offenses being temporally or spatially displaced.

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Introduction

Research has increasingly moved from a focus on offenders to studying the micro-places at which crimes occur (Weisburd et al. 2012). This focus has led to the development of a number of place-based interventions which draw from situational crime prevention (SCP) (Clarke 1997) to block opportunities for crime by making offending more risky and less rewarding at particular locations (Eck and Guerette 2012). SCP is predicated on manipulating environmental features of places which encourage or facilitate crime occurrence, rather than seeking to alter the propensity to offend. One environmental condition that has long been thought associated with crime is lighting levels (Painter and Farrington 1997).

This paper focuses on how changes to street lighting at places might influence crime. Unlike previous evaluations of this type of intervention, analyses are conducted at the street segment level, which allows for a sensitive test of how changes to street lighting might affect crime on the focal street segments, and the extent to which changes might spill over to street segments nearby. We use a quasi-experimental method, namely a controlled interrupted time series analysis, an essential approach for addressing causality when Randomized Controlled Trials are not possible (Nagin and Weisburd 2013). In what follows, we start by summarizing what is known about the impact of street lighting on crime. We then discuss some of the challenges associated with the evaluation of place-based interventions. In the next section we present our analytic strategy, in the form of the data used to test the hypotheses and the model specification. We conclude with a discussion of our findings and suggestions for future work.

Street Lighting

Academic interest in the relationship between street lighting and crime began in the 1960s in North America amid a backdrop of escalating crime rates. Initially, studies concerned with the crime reduction effect of improved street lighting showed promising effects (Wright et al. 1974), but poor study designs, as revealed by Tien and colleagues' review (1979), predominated, and the evidence was equivocal.

Renewed interest in the impact of street lighting on crime emerged in the late 1980s in the United Kingdom (UK). Small-scale pilot projects in London that studied the effects of improved street lighting showed a positive effect on crime, disorder and fear of crime and pedestrian use of streets (see Painter 1994). However, research from another area of London around the same time showed no effects (Atkins et al. 1991). Key discussion points from these early studies centered around measurement of crime issues (i.e., self-reported victimization versus police-recorded crime) and whether it could be accurately judged which crime types might be affected by changes in street lighting. Displacement effects, whereby crime is deflected from one location, time or target to another, and the inverse—diffusion of benefit effects—whereby the benefits of an intervention extend beyond the treatment group, were coming to the fore in later study designs exploring the effects of improved street lighting on crime (Painter and Farrington 1999).

Systematic review evidence produced by Welsh and Farrington (2008) found that improvements in street lighting could reduce crime. Across the 13 studies they reviewed, both violent and property crime was seen to reduce by around 21 per cent compared to areas that did not receive improved street lighting. The review identified that effects are likely to be magnified if the previous street lighting provision was particularly poor. In addition, moderator analysis in the review found that street lighting improvements were associated with greater reductions in the UK than the US, and that property crime reduced more than violent crime in treatment areas. The review was not able to systematically examine geographical displacement or the diffusion of benefits to nearby locations, and findings from individual studies on this issue were mixed.

Overcoming previous methodological weaknesses in the evidence base, Chalfin et al. (2021) have produced experimental evidence of the benefits of increased lighting on serious crime in New York. These scholars randomly allocated the provision of temporary light towers, with more luminosity than regular streetlights, across 80 public housing developments that had been identified as having a high crime rate. The 40 treatment developments were not adjacent to the 40 control developments, which helped to protect against spillover effects that threatened the internal validity of earlier studies. Chalfin et al. estimated that serious outdoor night-time crimes reduced by around a third in the treatment area, when spillover effects were accounted for. There was, however, little evidence that displacement occurred. They note that the intervention had a weaker effect on less serious crimes, such as theft and public order offenses.

At least four mechanisms have been proposed by which *improved* street lighting may reduce crime (Chalfin et al. 2021; Welsh and Farrington 2008). The first hinges on deterrence; that street lighting discourages offenders because it threatens their ability to avoid being seen by witnesses and detected by police. The second relates to what Chalfin et al. (2021) call the 'incapacitation' mechanism—that street lighting assists law enforcement to apprehend offenders. Chalfin and colleagues' (2021) tests of these two mechanisms found that general deterrence was the better explanation in their study area, as arrests declined at the same rate as did crime.

The third mechanism is that street lighting improves visibility at night, making people feel safer, which increases the use of streets at night. Increased usage can plausibly increase the supply of 'informal guardianship' on streets and hence the (perceived) risks to potential offenders of being recognized or caught. Of course, as Chalfin et al. (2021) point out, this might also increase the number of potential victims in an area which could make crime more likely.

The fourth mechanism concerns 'community cohesion', which has been argued to be associated with crime risk (Sampson et al. 1997 call this 'collective efficacy'). According to this perspective, local government funding in neighborhood infrastructure, such as improved street lighting, may be perceived by residents as signaling an investment in their community, which has the potential to increase community pride, cohesion and informal social control. According to the first three mechanisms, where street lighting is improved, relative to the day-time, the risk of crime would be expected to reduce during the hours of darkness. According to the fourth mechanism, any changes in the risk of crime would be expected to be similar regardless of the time of day. Consequently, the rate of crime at night would be expected to follow the same trend as that during the day.

In Welsh and Farrington's (2008) review, none of the reviewed studies directly examined the mechanisms through which improvements to street lighting might impact upon crime (e.g., none examined whether improved street lighting influenced the on-street population at night). Nor did they examine if and how *reduced* street lighting might influence crime risk. However, for the sample of studies where relevant data were collected, these tended to suggest that crime reduced during both the day and night, suggesting that changes to guardianship at night alone were less likely to have caused the changes observed.

Until recently research has overwhelmingly focused on the effects of *improved* street lighting. In other fields, improved street lighting has been criticized for producing light pollution which adversely affects the sleep of animals and humans, and for the increased energy it requires (Schuler et al. 2018). In the UK, cuts in public spending led some local authorities to reduce their provision of street lighting at night, causing public concerns about safety and crime risk (see Perkins et al. 2015). If improvements to street lighting do in fact prevent crime, then reducing street lighting might be expected to increase it. A national evaluation conducted in the UK examined the effects of *reductions* to street lighting on crime (Steinbach et al. 2015). The changes to street lighting observed included part-night lighting—whereby lights are switched off after midnight, dimming—whereby lighting remains on all night but levels of illumination are reduced, and the replacement of (yellow) sodium lighting with white lighting. Steinbach and colleagues' study found no evidence that *reductions* in street lighting at night were associated with increases in crime. Additionally, there was evidence to suggest that for some types of offending, crime was reduced following the dimming of lights, or the introduction of white lights. However, due to the data available in that study the authors were only able to examine changes in crime at the area level due to the spatial precision of the open source crime data (see Tompson et al. 2014), and hence the analyses may have been insensitive to the precise pattern of changes observed along the particular street segments targeted and those adjacent to them. Moreover, in Steinbach et al.'s study the authors only considered total counts of crime and were unable to distinguish changes in crime at night—when any direct effects of changes to street lighting on visibility would be observed—and during the day.

As noted above, on the face of it, if we invert the mechanisms proposed thus far in the literature then removing or decreasing streetlight would be expected to increase crime. This may come about as darkness can diminish the effectiveness of guardianship on the street by influencing would-be guardians' capacity to see and their willingness to intervene (see Tompson and Bowers 2013). It might also afford offenders with a cloak of anonymity which can be 'deindividuating' (Rotton and Kelly 1985). Such variables may play into an offender's cost–benefit calculation by dampening the perception of risk (Cornish and Clarke 1986). However, reducing street lighting may simultaneously increase the costs of searching for a target (Chalfin et al. 2021), as the lack of visibility renders this a harder task for some types of crime, particularly perhaps for property crime. As Arvate et al. (2018: 1051) note, "lighting illuminates objects (i.e., objects of value)". Thus, reduced street lighting may increase uncertainty about the risk, effort and benefits associated with exploiting identified crime opportunities and thereby deter offenders from engaging in crime.

Alternatively, if street lighting is not simply reduced, but changed through the introduction of (say) energy-efficient white light, just like increases in street lighting, this may signal a commitment to environmental sustainability to residents and in turn catalyze social action. Such action might translate into greater informal social control and have a beneficial impact on both neighborhoods and crime. Other possibilities also exist.

Challenges in the Evaluation of Place-Based Interventions

The place-based nature of situational crime prevention (SCP) strategies, such as street lighting, often render them unsuitable for conducting randomized control trials (RCTs) (see Eck 2017). As such 'high-quality' impact evaluation studies in SCP, so determined by internal validity as measured by the Maryland Scale (Sherman et al. 1997), are less common than in other fields. A key challenge associated with the evaluation of place-based interventions concerns the use of data for appropriate geographic units of analysis (Weisburd et al. 2009). Depending on the study, small units such as street segments, addresses or buildings may be theoretically and methodologically appropriate (Weisburd et al. 2012). However, empirical evaluations of interventions are often driven by data availability rather than theory. So, the effects of interventions at the micro-level of place are expected to be observed at this level. Yet for many such interventions there exists a lack of evaluation research that is conducted using data geocoded to this unit of analysis. Instead, evaluations tend to focus on changes observed at the area level.

In the case of street lighting evaluations, this is appropriate if the intervention covers an entire area. However, in the event that (for example) improvements to lighting are limited to particular streets, analyses conducted at the area level may lead to errors of inference, or conservative estimates of the effect of intervention. A related issue, that is important for the evaluation of place-based interventions, including street lighting, concerns the adequate measurement of potential side-effects. Perhaps the most commonly raised issue is the spatial displacement of crime from the location(s) of intervention to those nearby (for a discussion, see Johnson et al. 2014). The assumption is that by simply blocking opportunities for offending, offenders' motivations will be unaffected and they will simply choose to target alternative locations nearby (e.g., see Eck 1993; Clarke and Eck 2005). As is now increasingly recognized in the literature (Barr and Pease 1990; Bowers and Johnson 2003; Hesseling 1994), the displacement of crime is far from an inevitable outcome of successful crime prevention interventions. Moreover, Clarke and Weisburd (1994) outline clear theoretical reasons (see also, Cornish and Clarke 1986) as to why crime might not be expected to displace, but rather for the benefits of intervention to diffuse spatially (or otherwise). In doing so, they articulate two mechanisms in particular: deterrence and discouragement. Both mechanisms are informed by the rational choice perspective of offender decision making (Cornish and Clarke 1986), which assumes that offenders consider (however briefly) the costs and benefits of committing a specific offense when deciding whether to offend or not. It is argued that offenders who are aware of an intervention are unlikely to have complete and accurate information about the area of implementation, and as such may perceive coverage to be more extensive than it in fact is. This may create the perception that offending is associated with an increased risk of detection (deterrence), or that the effort involved now exceeds the perceived benefits of offending (discouragement), or both. In support of this, systematic review evidence (Bowers et al. 2011; Braga et al. 2014) suggests that place-based interventions can be associated with a *diffusion of benefits* whereby the risk of crime not only decreases in the area of intervention but also nearby.

Detecting evidence of spatial displacement or a diffusion of crime prevention benefits can, however, be difficult, particularly as study designs employed to measure the direct effects of interventions are not necessarily conducive to measuring displacement or a diffusion of benefits (Weisburd et al. 2006). Other methodological problems include the selection of an appropriate size and location of the displacement catchment areas into which crime might be displaced or benefits diffused, and how to account for any potential overlap in these areas (Weisburd and Mazerolle 1995; Weisburd et al. 2006).

Where appropriate data exist, the analysis of geographical displacement is relatively straightforward with the weighted displacement quotient devised by Bowers and Johnson (2003). This analytic technique requires crime data to be collected for the treatment area, a buffer zone area and a control area. This has been widely employed by scholars seeking to determine the effects of area-based interventions using pre-post quasi-experimental designs.

The Current Study

Local authorities across England and Wales, and in many other countries, are reducing the amount of street lighting at night to save energy costs and reduce carbon emissions (Steinbach et al. 2015). In the current study we estimate the effects of changes to street lighting for a case study area for which detailed street lighting and police recorded crime data were available. This enabled us to examine changes at the street segment level for both those streets along which changes to street lighting were implemented, those adjacent to them, and to contrast changes for hours of daylight and darkness. We employ a quasi-experimental method and use a controlled interrupted time series statistical framework to estimate parameters. To recapitulate, part-night lighting is where lights are switched off after midnight, dimming is where lighting remains on all night, but levels of illumination are reduced and white lighting is where (yellow) sodium lighting is replaced.

Part-night lighting and dimming reduce the amount of light on intervention streets (albeit the former in totality and the latter partially). If visibility is the primary mechanism linking street lighting to crime, we hypothesize that night-time crime rates (for most crime types, but particularly so for property crime) will increase on streets with part-night lighting and dimming. This is due to darkness providing a better cover for committing crime, since potential guardians are less likely to be available and capable of witnessing the crime. As the introduction of white light does not substantially change the luminescence of streetlights, we do not expect to see a change in night-time crime rates on streets receiving the white light intervention. In keeping with the extant empirical evidence on street lighting and crime displacement, we hypothesize that the lighting interventions will not change night-time crime on adjacent streets.

Crime rates may also change in response to a perception of decreased local government funding in neighbourhood infrastructure through an indirect effect on community cohesion. If this mechanism drives the association between lighting and crime, we hypothesize that part-night lighting, dimming, and white light interventions (which all represent a decrease in government spending) will be associated with increases in total numbers of crime during all hours of the day. We also hypothesize that lighting interventions should not change levels of crime on adjacent streets within this context.

Methodology

Street Lighting Data

Street lighting data were obtained for the (UK) Thames Valley Policing area from the local authorities in Oxfordshire, Reading, West Berkshire and Wokingham from April 2004 to September 2013 (July 2013 in Wokingham). These data detailed all lighting changes implemented by these councils which included switching off lights between midnight and 6am (hereafter referred to as ‘part-night’ lighting, or PNL), dimming (whereby the lights remained on all night, but their illumination was reduced), and the replacement of orange sodium lamps with white lights. It also detailed the month and year that changes were implemented (which ranged from before the study period began to September 2013), the month and year any changes that were reversed (if, say, lights went from being dimmed back to full power), and the geographic coordinates of the lighting columns at which changes were implemented. The data were held in a secure environment, and a Geographical Information System was used to link the data to Ordnance Survey (OS) street network data. In what follows, and in keeping with prior research (e.g. Johnson and Bowers 2010; Weisburd et al. 2012), the street network was divided into street segments, which were defined as any section of road that connected two or more intersections. For intervention street segments (at which changes were implemented), dummy coding was used to indicate what type of change occurred, and the months over which the change applied.

In total, the data related to 33,804 street segments. Of these, 815 (2.4%) had lights switched off at midnight (PNL) at some point during the study period, 1315 (3.9%) had lights dimmed, and 958 (2.8%) had orange lights replaced with white lights.

Police Recorded Crime Data

Police recorded crime data were obtained from Thames Valley Police (TVP) for April 2004 to September 2013, thereby providing time series data for a ten-year period after changes to street lighting commenced. Data were acquired for the offenses of residential burglary, robbery, vehicle crime and violence, since these were the offenses that would be most expected to be affected by changes to street lighting. Vehicle crimes were disaggregated into theft *of* vehicles and theft *from* vehicles since these two variants of vehicle crime have shown to have different trends over time due to the timing of the introduction of security features (Farrell and Brown 2016).

The data included the type of offense, date, time and location at which each offense occurred. The exact hour an offense occurred was known for 39% of offenses. Civil twilight times were obtained for each day of the year, and crimes that occurred after evening civil twilight but before morning civil twilight were classified as occurring at night. All other crimes were classified as having occurred during the day. Among those offenses where the hour was not known, in two thirds of cases the earliest and latest times were both within either day or night-time hours. In the other third of cases[1] the earliest and latest times spanned day and night, so the midpoint of the time period was used. Whilst an imperfect estimation of the precise time of offenses, the midpoint of the time period was used as this has been found to be a better approximation of peak offense times than earliest or latest times (see Ashby and Bowers 2013).

Over the ten-year period April 2004 to September 2013 in Thames Valley (July 2013 in Wokingham), there were 283,275 crimes, of which 91,970 were violent offenses (57% occurred at night); 89,752 were residential burglaries (60% occurred at night[2]), 57,918 were theft from vehicle crimes (64% occurred at night) and 20,967 were theft of vehicle crimes (70% occurred at night), and 22,668 were robberies (52% occurred at night). In what follows, the unit of analysis for the dependent variable is the street segment month, and hence the crime data were aggregated to monthly counts for each street segment.

[1] Which amounted to 21% of offenses in our data.

[2] This figure may seem high but is consistent with findings from the Crime Survey of England and Wales (e.g., ONS, 2017) which suggests that about 60% of residential burglaries take place during the evening or overnight (6 pm and 6 am).

Controlled Interrupted Time Series Model

Controlled interrupted time series models are increasingly used in policy research to evaluate the impact of community interventions (Biglan et al. 2000), in particular to analyze 'natural experiments' where the researcher has no control over the randomization of intervention implementation (Kontopantelis et al. 2015). A key advantage of this design for analyzing changes to street lighting over a traditional controlled before/after design is that it can make full use of over ten years of longitudinal data and use pre-intervention trends in crime on both intervention and non-intervention streets to estimate the counterfactual, rather than relying on a comparison of a single-pre- and single-post-intervention point (or means) in the intervention and control groups (Bernal et al. 2018).

When selecting streetlights for part-night lighting in our study areas, the local authorities used exemption criteria to determine which lights should *not* be operated part-night (Wokingham Borough Council, n.d.):

- Lights at major road junctions /roundabouts.
- Lights in town centers where there is CCTV, high security businesses like banks, and/or lots of people at night, for example, near nightclubs and train stations.
- Lights in areas where streetlights are needed to reduce road accidents.
- Lights in areas where there could be an increase in crime through reduced lighting such as near pubs and specific residential areas.

So, given these criteria, we may be reasonably confident that the lighting changes were made in *all* eligible streets and were not made in response to crime or because of a decline in crime. The lighting changes may thus be treated as an exogenous shock to the neighborhood and may be legitimately analyzed as a natural experiment.

Our model uses monthly time series of crimes across all street segments in Thames Valley (including both those with and without any changes to lighting) to establish an underlying trend, which is 'interrupted' by any changes to street lighting on street segments. Hypothetically, if changes to street lighting had not occurred, the underlying trend on intervention street segments would be similar to those on non-intervention streets (the counterfactual scenario). Because both intervention and non-intervention street segments are included in the analysis, model coefficients indicate the change in crimes over and above any underlying trend in crimes on all street segments in Thames Valley.

Controls, in this analysis, are therefore any street without a particular lighting intervention (for example, dimming) at a point in time. The purpose of controls in this analysis is to exclude time-varying confounders, in particular co-interventions or other events occurring around the time of the intervention (such as other austerity measures), as any impact of these on crime would be unpredictable based on modelling pre-intervention trends. As the intervention was implemented on street segments at different points in time, street segments that at some point would become intervention streets are used in estimations of the underlying trend up until the point at which they become intervention streets.

Statistical Model

To control for confounding due to differences in roads (not) chosen for lighting reduction, we analyzed street segment counts as a 'panel', conditional on the total counts on each street segment: a conditional Poisson model (Armstrong et al. 2014). As such, factors that are constant over time (e.g., the availability of on-street parking or the number of residences on a street) were controlled for and contributed no information to the analysis.[3] We adjusted for seasonal variations and temporal trends using step functions (indicators) for calendar month and year.[4] All street lighting interventions (part-night lighting, dimming, and white light) were entered into the same model to avoid mutual confounding.[5]

We focus our attention on two sets of outcome measures: night-time crimes and all crimes (i.e., regardless of the time of day) to examine mechanisms associated with visibility and community cohesion. If visibility is the key mechanism linking street lighting to crime, changes in street-lighting would only be expected to have a direct impact at night. However, to guard against bias due to changes concurrent with lighting interventions that impact on the overall (i.e., day and night) crime rates, our model also estimated the change in day-time crimes rates associated with interventions and, as a refined measure of change in outcome rates following each intervention, the ratio between the night-time and day-time changes. Our models on night-crime outcomes can be expressed as: (expression (3) from Armstrong et al. 2014):

$$E\left(Y_{i,s}\right) = \mu_{i,s} = \exp\{\alpha_s + \boldsymbol{\beta}^{\boldsymbol{T}}\boldsymbol{x_i}\} \tag{1}$$

where $Y \sim$ Poisson (μ_i, conditional on total crimes in segment $Y_{.,s} = \sum_i Y_{i,s}$).

Where $\mathbf{x_i}$ is a column vector of explanatory variables, and β a column vector of their coefficients. T indicates transpose[6]; $i = 1\ldots\mathrm{I}$ is the study month (months elapsed since the start of the study in April 2004); $s = 1\ldots\mathrm{S}$ is the street segment; $\mathrm{Y}_{\mathrm{i,s}}$ is the number of crimes in month i on road segment s.

The parameters α_s, which allow for variation in rates across street segments, are not estimated but are 'conditioned out' by conditioning on the sum of events $Y_{.,s} = \sum_i Y_{i,s}$ in each road segment. This model is equivalent to a multinomial model. This and other technical aspects of the model are discussed in Armstrong 2014 and the references cited therein. The Stata code used to run the analyses is provided in the Supplementary Appendix A.

The vector $\mathbf{x_i}$ of explanatory variables has the following components (sub-vectors of x):

Potentially confounding variables

- $\mathbf{x_{month}}$ Indicator variables for calendar month (1–12) to control for seasonal patterns and month duration;
- $\mathbf{x_{year}}$ Indicator variables for calendar year (2004 to 2013) to control for time trends.

To allow adjustment for patterns of day-time crimes

[3] It is possible that these types of factors may lead to differential effects of the intervention on crime. For instance, part-night lighting may have a larger effect on crime in densely populated streets compared to those with few residences. However, as these factors are constant over time, they cannot confound the temporal trend estimated by the controlled interrupted time series analysis. Unfortunately, data on vehicle presence was not available to test differential effects of changes to street-lighting.

[4] Exploratory analyses showed that more parsimonious models provided a poorer fit to the data (assessed using Akaike's Information Criterion).

[5] A correlation matrix of the three lighting intervention variables produced correlations < .5 which, taken with the absence of large standard errors, was interpreted to mean that multicollinearity, though present, was acceptable.

[6] The expression $\boldsymbol{\beta}^{\boldsymbol{T}}\boldsymbol{x}_i$ can alternatively be expressed: $\sum_j \beta_j x_{i,j}$ where j indicates the specific explanatory variable component.

- $\mathbf{x_{night}}$ An indicator variable for night-time crime (1 for night-time; 0 for day-time);
- $\mathbf{x_{month*night}}$, $\mathbf{x_{year*night}}$ Interaction of the night-time indicator with each potentially confounding variable (above) to allow different seasonal patterns and time trends for night-time and day-time crimes.

Variables of interest

- $\mathbf{x_{pn}}$,$\mathbf{x_{dim}}$,$\mathbf{x_{white}}$ Indicator variables for each lighting intervention:, part-night lighting, dimming, and white light (0 before intervention; 1 after intervention);
- $\mathbf{x_{pn*night}}$, $\mathbf{x_{dim*night}}$, $\mathbf{x_{white*night}}$ Interaction of these with the night-time indicator; the coefficients of these variables estimate change in the night-time crimes rate following the intervention adjusting for any changes observed in the day-time crimes rate.

We ran models separately for each of the crime types. Residual variance greater than that expected (i.e., 'over dispersion') in the Poisson statistical distribution was allowed for in standard errors using a scale factor estimated from the Pearson chi-squared statistic divided by the degrees of freedom of the residuals. Tests of over-dispersion for the models of different crime outcomes ranged from 1.07 to 1.13, indicating slight over-dispersion. We allowed for this by using the quasi-Poisson variant of the conditional Poisson model. As we adjusted for over-dispersion, we did not feel it necessary to run zero-inflated models, which produce results that are less intuitive to interpret.

To explore the community cohesion mechanism linking street lighting to crime we ran a second set of models examining changes in total crimes (day and night-time). Models are similar to those with night-crimes as the outcome, but there is no indicator variable for night-time crime, and no interactions between night-crime and lighting intervention variables. We conducted sensitivity analyses using 1) just the data where the crime was recorded as definitely falling within the day-time or night-time period, and 2) with one, two and three month time lags to account for a delay in offenders being aware of the lighting changes and subsequently responding to them. Only results of the sensitivity analysis that materially change the results are reported.

We additionally examined potential displacement effects of the intervention. It was not possible to use the weighted displacement quotient here as this requires simple before and after measures and the approach is typically used to examine changes at the area level. This contrasts with the current study in which we exploit time series data for a large number of small spatial units. The same principles were, however, employed. In particular, we examined how crime changed in the street segments adjacent to those in which lighting regimes changed (equivalent to using a buffer zone for the weighted displacement approach). To do this, we used the same regression framework described above but modelled changes on the adjacent street segments. This enabled us to estimate the extent to which changes that occurred on these (adjacent) street segments were coincident with the timing of changes to street lighting. In addition to examining the changes observed on the adjacent street segments alone, we repeated the analysis for these street segments and those on which lighting actually changed (the focal street segments). The aim of so doing was to enable us to estimate net changes to the local network of street segments to see if, overall, changes on the focal street segments were (for example) cancelled out by those that occurred on those nearby.

Street segments were considered 'adjacent' if they were directly connected to intervention streets; that is, if they shared a common node in the street network. If lighting changes subsequently took place on an "adjacent" street, this was categorized as an adjacent street

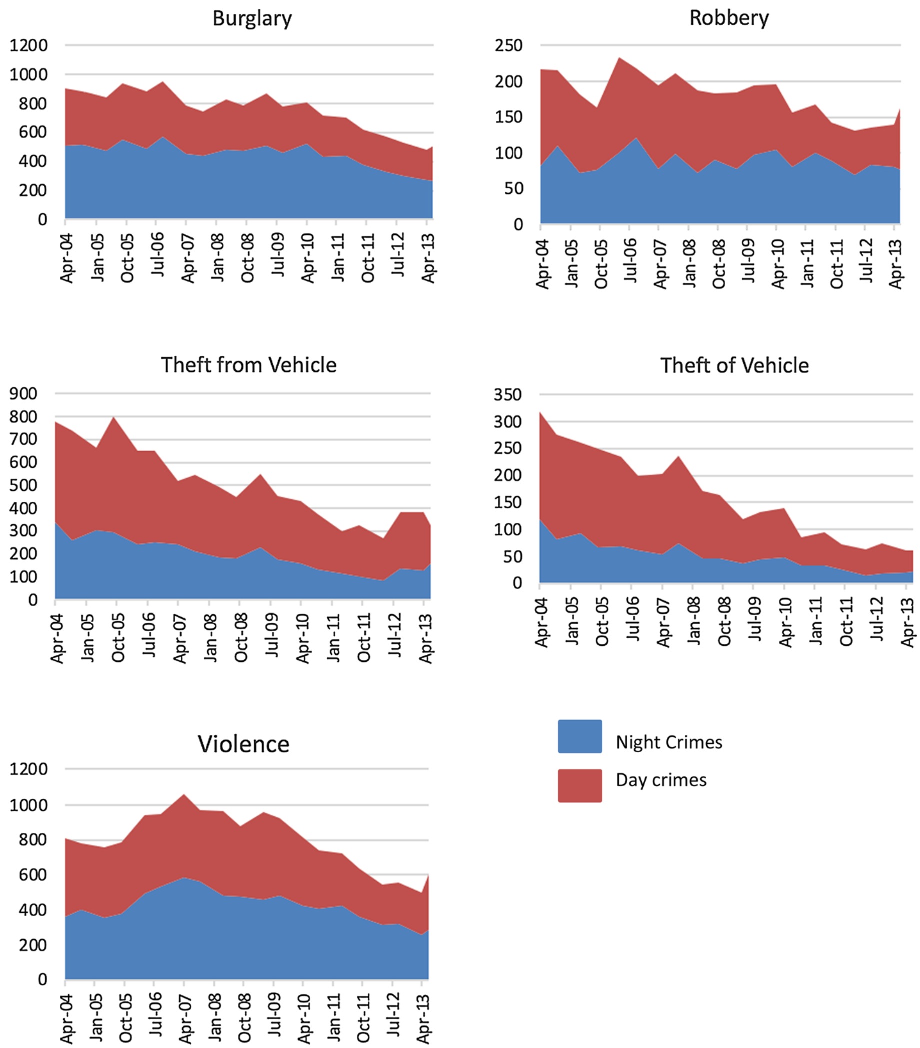

Fig. 1 Monthly trends in night-time and day-time crimes in the Thames Valley region

up until the month the lighting changes took place on that street segment. Thereafter, it was categorized as an intervention street segment.

Results

For the purposes of illustration, Fig. 1 shows the monthly volumes of crime recorded during the day and at night in the Thames Valley region. It shows that for all five types of offending, crime declined over time and that more than half of all crimes were recorded as having occurred at night.

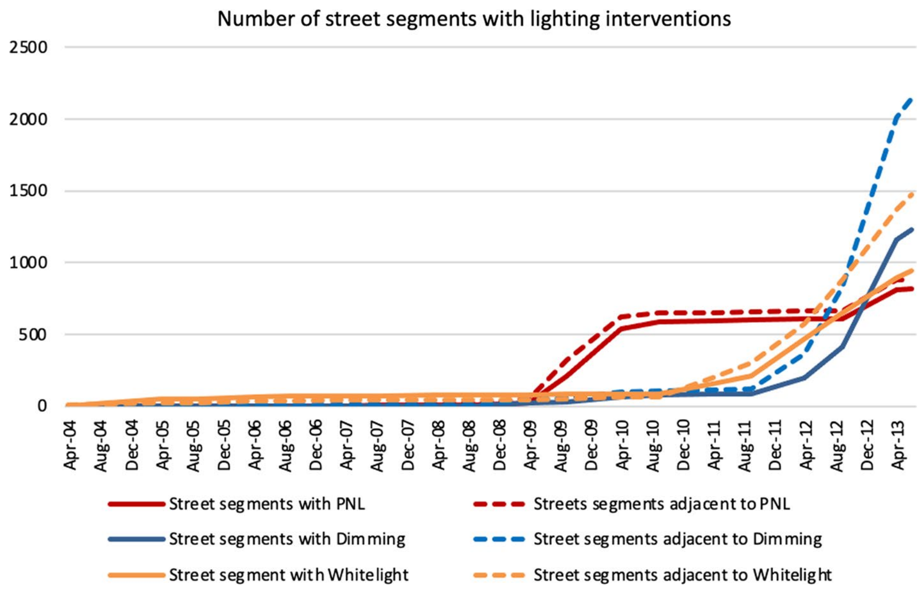

Fig. 2 Number of street segments with lighting interventions over the study period

Table 1 Night-time crime rate ratio adjusted for changes in day-time crime

Crime	PNL		p value	Dimming		p value	White light		p value
	RR	95% CI		RR	95% CI		RR	95% CI	
Burglary	0.86	0.67, 1.11	0.243	1.05	0.80, 1.38	0.741	0.82	0.62, 1.09	0.173
Robbery	1.35	0.54, 3.40	0.519	1.83	0.76, 4.42	0.177	0.59	0.26, 1.35	0.212
Theft of vehicles	0.62	0.32, 1.19	0.150	0.48	0.24, 0.95	0.036	1.62	0.73, 3.58	0.233
Theft from vehicles	0.56	0.41, 0.78	< 0.001	0.71	0.50, 1.01	0.058	0.97	0.67, 1.40	0.979
Violence	0.75	0.56, 1.02	0.068	1.01	0.78, 1.31	0.912	0.87	0.66, 1.14	0.305
Total crime	0.74	0.63, 0.87	< 0.001	0.95	0.81, 1.11	0.531	0.86	0.73, 1.02	0.076

Figure 2 shows the timing of the lighting interventions in Thames Valley. The number of streets with part-night lighting increased rapidly from mid-2009 to mid-2010 and between mid-2012 and mid-2013. White light increased steadily from late-2010, while the number of street segments with dimming increased rapidly from late-2011. The numbers of streets adjacent to streets with lighting intervention increased in line with each intervention. Over the whole study period, 2.75% of streets (n = 930) were adjacent to streets with PNL, 7.03% of streets (n = 2375) were adjacent to streets with dimming and 4.84% of streets (n = 1637) were adjacent to white light streets.

Table 1 shows the results of the regression analysis for night-time crime outcomes. For simplicity, we only show the coefficients for the interaction terms that estimate the effects

Table 2 Night-time crime on roads adjacent to roads with lighting interventions (adjusted for changes in day-time crime)

Crime	Adjacent to PNL		*p* value	Adjacent to Dimming		*p* value	Adjacent to White light		*p* value
	RR	95% CI		RR	95% CI		RR	95% CI	
Burglary	0.99	0.79, 1.24	0.931	0.99	0.80, 1.23	0.924	0.86	0.70, 1.07	0.183
Robbery	1.24	0.55, 2.78	0.610	0.78	0.48, 1.27	0.313	0.96	0.58, 1.57	0.858
Theft of	1.44	0.71, 2.90	0.311	1.09	0.57, 2.09	0.792	0.98	0.53, 1.81	0.939
Theft from	1.55	1.14, 2.11	0.005	0.98	0.75, 1.29	0.895	1.20	0.90, 1.59	0.210
Violence	1.14	0.83, 1.57	0.412	1.04	0.85, 1.26	0.715	0.74	0.61, 0.91	0.004
Total crime	1.18	1.02, 1.38	0.027	1.00	0.89, 1.13	0.992	0.87	0.77, 0.99	0.032

Table 3 Crime rate ratio (all times of day)

Crime	PNL		*p* value	Dimming		*p* value	White light		*p* value
	RR	95% CI		RR	95% CI		RR	95% CI	
Burglary	0.75	0.65, 0.85	< 0.001	1.13	0.98, 1.31	0.086	0.72	0.62, 0.83	< 0.001
Robbery	1.00	0.62, 1.59	0.988	0.62	0.40, 0.96	0.031	0.90	0.59, 1.39	0.643
Theft of vehicles	0.85	0.62, 1.18	0.338	1.00	0.72, 1.38	0.981	1.04	0.73, 1.47	0.834
Theft from vehicles	0.95	0.81, 1.10	0.488	1.27	1.07, 1.51	0.006	1.00	0.84, 1.19	0.983
Violence	0.83	0.71, 0.97	0.018	0.98	0.86, 1.12	0.746	1.05	0.92, 1.21	0.465
Total crime	0.81	0.75, 0.88	< 0.001	1.04	0.96, 1.12	0.396	0.91	0.83, 0.99	0.022

of street-lighting on crime (i.e., the night-time crime rate ratio adjusted for changes in day-time crime), but the full regression model results can be found in the Supplementary Appendix B. As this shows an exponentiated interaction term, it is a ratio (or multiplicative term) which shows how much more (or less) crime occurs on a street segment when the intervention is in place after accounting for general trends and the time-stable variation in risk across street segments. After controlling for changes in levels of crime recorded during the day, the switching off of lights at midnight (PNL) was strongly associated with a reduction in total night-time crime (rate ratio: 0.74; 95% CI: 0.63 to 0.87) and theft *from* vehicles (RR: 0.56; 0.41 to 0.78) along those streets on which it was implemented. Dimming also appeared to be associated with a reduction in theft *of* vehicles (RR: 0.48; 0.24 to 0.95), although this effect became non-significant when crimes that could not precisely be classified to day- or night-time were removed from the analysis.[7] There was no evidence that lighting changes were associated with changes to the level of violence, robbery or residential burglary.

Table 2 shows the estimated effects on night-time crime along street segments adjacent to streets with lighting interventions. The findings suggest that, adjusting for changes in

[7] Analyses available on request from the corresponding author.

Table 4 Crime rate ratio (all times of day) on roads adjacent to roads with lighting interventions

Crime	Adjacent to PNL		*p* value	Adjacent to Dimming		*p* value	Adjacent to White light		*p* value
	RR	95% CI		RR	95% CI		RR	95% CI	
Burglary	0.90	0.80, 1.01	0.077	0.99	0.88, 1.11	0.864	0.93	0.83, 1.03	0.172
Robbery	0.90	0.60, 1.37	0.635	0.94	0.73, 1.20	0.610	0.80	0.62, 1.03	0.090
Theft of	0.79	0.57, 1.10	0.168	0.79	0.59, 1.06	0.110	1.05	0.78, 1.41	0.747
Theft from	0.86	0.74, 0.99	0.040	1.10	0.97, 1.26	0.150	0.99	0.87, 1.14	0.926
Violence	0.75	0.64, 0.89	0.001	0.93	0.84, 1.02	0.131	1.07	0.96, 1.19	0.201
Total crime	0.83	0.76, 0.89	< 0.001	0.97	0.91, 1.03	0.337	0.99	0.93, 1.05	0.695

Table 5 Total impact of street lighting interventions on intervention and adjacent streets combined- All times of day

Crime	PNL		*p* value	Dimming		*p* value	White light		*p* value
	RR	95% CI		RR	95% CI		RR	95% CI	
Burglary	0.85	0.78, 0.92	< 0.001	1.03	0.95, 1.12	0.489	0.84	0.77, 0.92	< 0.001
Robbery	0.98	0.72, 1.33	0.901	0.84	0.68, 1.04	0.112	0.82	0.66, 1.02	0.070
Theft of	0.82	0.65, 1.04	0.102	0.87	0.70, 1.09	0.219	1.04	0.83, 1.31	0.726
Theft from	0.90	0.81, 1.00	0.051	1.16	1.04, 1.29	0.006	1.00	0.89, 1.11	0.935
Violence	0.79	0.70, 0.88	< 0.001	0.94	0.86, 1.01	0.108	1.07	0.98, 1.16	0.121
Total crime	0.83	0.79, 0.88	< 0.001	0.99	0.94, 1.04	0.660	0.96	0.91, 1.00	0.073

day-time crime there was an increase in night-time crime overall of about 18% (RR: 1.18; 1.02 to 1.38) for street segments adjacent to PNL. The increase was primarily driven by increases in theft *from* vehicles (RR: 1.55; 1.14 to 2.11) and this relationship was strengthened slightly in the sensitivity analysis that omitted crimes with imprecise temporal information. There was some evidence of a decrease in overall crime on streets adjacent to white light interventions (RR: 0.87; 0.77 to 0.99), which appeared to be driven by decreases in violent crimes on streets adjacent to white light interventions (RR 0.74; 0.61 to 0.91).

Table 3 shows the estimated effect of lighting interventions on crime during all times of the day. Overall, PNL was strongly associated with a reduction in total crime (rate ratio: 0.81; 95% CI: 0.75 to 0.88) and burglary (RR: 0.75; 0.65 to 0.85) along those streets on which it was implemented. There was also evidence of an association between PNL and a reduction in violent crime (RR: 0.83; 0.71 to 0.97). There was some evidence that dimming was associated with a reduction in robbery (RR: 0.62; 0.40 to 0.96). The evidence on white light suggested an association with a decrease in all crime (RR: 0.91; 0.83 to 0.99), driven by decreases in burglaries (RR: 0.72; 0.62 to 0.83).

Table 4 shows the estimated effect of lighting interventions on crime rates during all times of the day on adjacent streets. There was strong evidence of an association between PNL and reductions in total crime (RR: 0.83; 0.76 to 0.89) and violent crime (RR: 0.75; 0.64 to 0.89) on streets adjacent to the PNL intervention. There was no evidence of associations between dimming nor white light and crime on adjacent streets.

Table 5 presents the total impact of street lighting interventions with both the intervention and adjacent streets combined. This estimates the total net effect of the street lighting interventions. As can be seen from Table 5 a crime reduction effect was associated with PNL streets for total crime (RR: 0.83, CI: 0.79 to 0.88), with burglary (RR: 0.85, 0.78 to 0.92), theft from vehicles (RR: 0.90, 0.81 to 1.00) and violence (RR: 0.79, 0.70 to 0.88) contributing to this overall effect. Dimming was only associated with a net increase in theft from vehicles (RR: 1.16, 1.04 to 1.29) and streets with white light were only associated with net reductions in burglary (RR: 0.84, 0.77 to 0.92).

Discussion

The aim of the current study was to evaluate the impact on crime, at the street segment level, of changes to street lighting. In contrast to previous studies, the changes to street lighting in this study involved reducing rather than increasing lighting provision. Three different types of lighting changes were examined for five crime categories: residential burglary, robbery, vehicle crime (disaggregated into theft of vehicles and theft from vehicles) and violence.

The most interesting finding from our study suggests that, in the case of part-night lighting (PNL), after accounting for changes in crimes committed during the day, theft *from* vehicles reduced on street segments along which street lighting was switched off at midnight, but that these crimes may have been spatially displaced at night to better-lit streets nearby. This result shows a statistically significant reduction (RR 0.56; 95% CI: 0.41–0.78, $p = 0.001$) in the PNL streets, which coincides with a similarly significant increase in theft from vehicles on adjacent streets (RR 1.55; 95% CI: 1.14–2.11, $p = 0.005$). The trends for theft of vehicles are similar, albeit not statistically significant, which may be due to there being fewer of them compared with thefts from vehicles.

We can interpret this noteworthy finding through the lens of rational choice theory (Cornish and Clarke 1986). To reiterate, this perspective contends that offenders engage in a cost–benefit calculus based on imperfect knowledge. If the perceived benefits outweigh the costs the offender is tempted to go ahead with the crime commission. In the case of vehicle offenders, the benefits are the perceived rewards in the form of the vehicle itself (for transport, resale, to be used in another crime commission or to sell for parts[8]), or goods that can be stolen from the exterior or the interior of the vehicle. The costs are being witnessed committing the vehicle theft or being apprehended by the police (either at the time or later due to a witnesses' statement).

A lack of street lighting alters both sides of this calculus. In the times when PNL is switched off (after midnight) there is little chance that light from buildings will provide ambient light to the street. If this assumption holds then the streets are likely to be in near-darkness, which means that would-be offenders may find it challenging to assess target suitability (e.g., vehicles and the quality of their security—see Tilley et al. 2015). Since many contemporary vehicles have built in stereos and satellite navigation systems, offenders may be looking for other valuable goods that are left unsecured in vehicles, which may

[8] This list is not exhaustive. However temporarily depriving an owner of their vehicle – otherwise known as joy-riding – has been found to be relatively uncommon in the data period used.

prove difficult if lighting levels are low. Thus, the benefits of committing a vehicle crime in darkness are unknown or hard to estimate.

Dark conditions may also incur greater costs. A known modus operandi used by opportunistic offenders is to try car doors to see if the owner has forgotten to lock the vehicle. Unlike other modus operandi this can still be employed in darkness. However, the offender still likely requires some form of light to either start the vehicle (to drive it away) or to search the vehicle for contents to steal. Similarly, exterior fittings of vehicles,[9] such as hub caps, wheel trims or number plates all require some light to successfully remove. Artificial light introduced to the crime scene signals unusual activity to potential guardians and invites unwanted attention which the offenders may not feel comfortable risking. The costs of committing vehicle crime on unlit streets are therefore higher than elsewhere.

Farrell (2016), in his analysis of crime 'failure' rates over time, argues that the cohort of vehicle offenders in recent years is smaller than it was, but is potentially more skilled or better at making rational choices regarding vehicle crimes. It may be that the temptation to commit vehicle crime is severely dampened by conditions of darkness for these offenders and that they rationally choose to move elsewhere to fulfil their intentions.

Given this reasoning, it is perhaps unsurprising that our findings suggest that vehicle crimes may have been displaced to better-lit adjacent streets. Paraphrasing Tobler's (1970) first law of geography, 'near things are more similar than distant things', we can assume that adjacent streets are likely to share similar characteristics in terms of road width and connectivity on the network with the streets with PNL. Therefore, it is unlikely that the suitability of the targets is dramatically different on the adjacent streets, as has been seen in other study areas where vehicle crime has been displaced to neighborhoods with older vehicles with more security vulnerabilities (see Hodgkinson et al. 2016). Instead, it is plausible that offenders are using the least effort principle (Zipf 2016) and going to a proximal location to undertake their crimes.

Whilst PNL may seem to have no net-benefit with regards to theft from vehicles, Table 5 suggests that benign displacement (see Barr and Pease 1990) may be occurring. That is, fewer theft from vehicles are being displaced than would have occurred on the treatment streets had PNL not been introduced. These figures may also hide other benign displacement insofar that number plates, which are commonly stolen in theft from vehicles, are not used to facilitate further crimes. Furthermore, Farrell et al. (2015) persuasively argue that vehicle crimes are 'debut crimes' for offenders just starting out on their criminal career path. If dissuaded early into this career, it is less likely that their criminal propensity will become entrenched and result in further crimes.

When crimes committed at any time of the day were considered, we find that PNL was associated with a reduction in overall crime, burglary, and violence on both the focal streets and those adjacent. First, this suggests that the reductions in offending observed overnight were not simply displaced to the daytime. Second, it may suggest a diffusion of benefit in time rather than space. The underlying mechanism causing this is unclear. Speculatively, it is possible that reconnaissance activities of burglars are interrupted at night-time by the reduction of light, and this may reduce burglary in the daytime. As Coupe and Blake (2006) note, different types of burglars employ different target selection strategies in conditions of daylight and darkness (in different types of areas). In their study, burglaries committed in

[9] Recent figures from the UK Office of National Statistics suggest that exterior fittings are the most frequently stolen items in UK theft from vehicles – see https://www.ons.gov.uk/peoplepopulationandcommunity/crimeandjustice/articles/overviewofvehiclerelatedtheft/2017-07-20.

daylight tended to be in prosperous areas where there was cover provided by vegetation or the housing layout, whereas burglaries committed in darkness were in neighbourhoods with higher unemployment levels. Whilst they did not investigate reconnaissance activities, it is plausible that burglaries done in "up-market" locations will be more carefully planned and hence involve scoping out activities on the part of the burglar.

However, the same explanation does not hold for violent crimes which are more likely to be undertaken without a degree of planning. The community cohesion hypothesis does not seem likely here, since on the rare occasion residents in PNL areas noticed the lighting changes, they were seen as regressive and undermined feelings of safety (Perkins et al. 2015). Instead, it may be the case that PNL may have been implemented on streets with particular characteristics (i.e., say, low vehicle traffic but moderate-high pedestrian traffic) which would alter people's walking routes and hence opportunities for interpersonal contact that might result in violent interactions. Whilst this is more likely at night-time, people's wayfaring behaviour tends to be habitualized over time, and so there could be spill over effects of changes to pedestrian behaviour into the day. It is not possible to disentangle the potential influence of any of these mechanisms in this study, but we hope future research may be able to expand our understanding of this finding.

For street segments along which lighting was dimmed, there was also evidence of a reduction in night-time vehicle crime relative to day-time crime, although the effect was less robust than for PNL and there was no evidence of spatial displacement to adjacent streets. In our study area, dimming appeared to be more geographically clustered than the other types of lighting intervention, potentially making it more difficult for offenders to easily select a nearby street to continue their intentions to commit vehicle crime. Our findings do however indicate an association between dimming and an increase in theft from vehicles occurring at all times of the day. This may suggest that dimming is more likely to temporally displace vehicle crimes to earlier in the day, rather than spatially displace offending to nearby streets. Temporal displacement is conceivably more disruptive to the offender, since it requires more effort to return at a different time, rather than to choose a different area to commit crime.

There was no evidence that white lighting was significantly associated with changes in any type of night-time crime examined here. There was some evidence of an association between changes to white light and reductions in burglary at all times of the day. Here, the mechanism of community cohesion is more plausible. Consultation with residents in treatment areas revealed that concerns regarding reducing light were intertwined with perceptions of cost-cutting (Perkins et al. 2015). So, it is conceivable that improving luminosity, as is the case with white lights, is perceived as signaling investment into the community. In turn, this can prompt feelings of community pride and cohesion and indirectly feed into enhanced informal social control in such areas.

In the recent national evaluation discussed in the introduction (Steinbach et al. 2015), recall that PNL was not found to be associated with changes in crime levels at an area level. While prima-facia those findings may seem to contradict those observed here, further consideration is warranted. For example, in the current study, the reductions of theft from vehicles observed on street segments along which there was a change to PNL were equal in magnitude to the increases observed on adjacent streets, suggesting that there would have been no net effect of intervention at the area level. The change seemed to simply have moved the problem to locations nearby. One likely reason for this is probably that as the coverage associated with the PNL intervention was limited, motivated offenders would merely have to move to adjacent locations, which would require little effort on their part and would allow them to offend in areas with which they were already familiar. It may be the case that where coverage is more extensive, such spillover effects will be less likely, since offenders would have to seek out new areas within which to offend (see Eck 1993). Future research might explore this possibility.

The current study is not without limitations. First, the findings reported here are for one (of 43) UK police force area and as such the findings may not be generalizable. However, it is worth noting that the TVP police force area covers a range of both urban and rural areas, providing data for a mix of localities, which increases external validity to some extent. Second, not all crime is reported to the police (e.g., Tarling and Morris 2010), and reporting rates vary across offense types. For example, crimes such as burglary and theft of or from vehicle tend to have high reporting rates as a police report is necessary for victims to make insurance claims. Such factors may influence the findings of studies such as this one, although it is unclear how reporting rates would be affected by the types of interventions evaluated here, or why reporting rates would be expected to vary at the street segment level.

A second issue concerns the reported and recorded time of offenses. The accuracy of such data is important in a study such as ours, since we aimed to examine if and how the risk of crime changes at particular times of the day. Unfortunately, for some crime reports (particularly those for residential burglary and vehicle crime) the exact time of an offense was unknown. In such cases, the midpoint of the earliest and latest reported time that an offense could have occurred (according to the victim) was used. Alternative approaches exist (e.g. Ratcliffe 2000), but research suggests that the approach taken here is as good as any (Ashby and Bowers 2013). The 21% of the offenses in our data that could have been misclassified to either the day- or night-time periods were removed in sensitivity analysis, and this did not demonstrably change the findings.

A third issue concerns locational accuracy. Apart from burglaries, where location data tends to be very accurate, it is also possible that there will be misclassification errors associated with the geocoding process; that is, some offenses that were linked to one street segment might actually have occurred on an adjacent or nearby street. Any bias associated with this type of error, however, is likely to be minimal as we would expect it to be constant over time and occur at similar levels for crimes committed during the day-time and at night.

A fourth issue relates to our assumption that lighting changes have an abrupt and permanent function on crime. We believe that there are good a priori reasons to expect an abrupt change. We acknowledge the possibility that effects might diminish over time since the intervention. However, few streets experienced any change before 2010 and some change types before 2012. There was thus a limited post-change timespan, such that power to detect such modification of effects would be limited.

Finally, as with most evaluation studies of crime prevention, we had no information on other crime reduction interventions that may also have been implemented during the evaluation period. It is conceivable that the police presence may increase in areas with less lighting, although given the funding cuts to police in the UK at the time of the study, it is unlikely that policing capacity would have extended to proactive patrolling unless an area was known for being a current hotspot. We did not have data to test this supposition but would encourage future research to do so.

It is also possible that our results are confounded by factors that were the basis of local authority decisions to implement street lighting changes on the selected roads. For example, for reasons of safety, PNL may have been implemented on streets with the lowest pedestrian traffic after midnight. The midnight switch-off may have deterred people from walking these streets, or parking their cars on them, which may have reduced opportunities for crime. It is though worth noting that Green et al. (2015), in their rapid appraisal of public views on street lighting changes in England and Wales, found that any changes in mobility patterns were rare, and that most people were unaffected by the reductions in lighting in their neighborhoods. It was not possible to test whether other activity occurring at street level was occurring here, but future research might seek to do so. If this explains the observed patterns, it is worth noting that if part-night lighting was implemented on relatively busier streets, the impact of intervention may well differ to the findings reported here.

The findings of this study suggest that the mechanism by which street lighting has been proposed to reduce crime—increased visibility at night—may be one that can also increase vehicle crime. This speaks to the inherent specificity in the opportunity structure of different crimes; environmental features make some types of crime more likely whilst simultaneously making other types of crime less likely. Reduced visibility at night may mean that valuables left inside cars overnight are not seen so easily, thereby reducing the temptation for would-be thieves. On unlit streets, offenders may walk past vehicles for which rewards cannot be seen, into better-lit nearby streets where rewards are more visible. This study sheds further light (pun intended) on the mechanisms through which street lighting may impact on crime and suggests that reduced street lighting may prevent theft from vehicles, but there is a danger of offenses being temporally or spatially displaced.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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