doi:10.1093/bjc/azaa067 BRIT. J. CRIMINOL. (2021) **61**, 364–388
Advance Access publication 16 October 2020

MEASURING THE DARK FIGURE OF CRIME IN GEOGRAPHIC AREAS: SMALL AREA ESTIMATION FROM THE CRIME SURVEY FOR ENGLAND AND WALES

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For decades, criminologists have been aware of the severe consequences of the dark figure of police records for crime prevention strategies. Crime surveys are developed to address the limitations of police statistics as crime data sources, and estimates produced from surveys can mitigate biases in police data. This paper produces small area estimates of crimes unknown to the police at local and neighbourhood levels from the Crime Survey for England and Wales to explore the geographical inequality of the dark figure of crime. The dark figure of crime is larger not only in small cities that are deprived but also in wealthy municipalities. The dark figure is also larger in suburban, low-housing neighbourhoods with large concentrations of unqualified citizens, immigrants and non-Asian minorities.

Key Words: crime mapping, crime reporting, divergence, neighbourhood, spatial statistics

Introduction

For decades, criminologists have been aware of the severe consequences that the dark figure of crime has for designing and evaluating crime prevention policies and, by extension, for citizens' everyday lives. In 1977, Skogan stated that the dark figure of crime 'limits the deterrent capability of the criminal justice system, contributes to the misallocation of police resources, renders victims ineligible for public and private benefits, affects insurance costs, and helps shape the police role in society' (Skogan 1977: 41). These risks have been exacerbated by the generalization of the use of crime mapping techniques, the adoption of place-based policing and the more recent focus on predictive policing (Brantingham 2018). Geocoded police-recorded crimes constitute the basis for all of these. Yet, certain social groups are more likely to report crimes to the police than others, and police forces are more effective in recording crimes in certain areas (Baumer 2002; Hart and Rennison 2003; Goudriaan *et al.* 2006). The dark figure of police statistics is thus likely to be unequally distributed across geographic areas. This fact has remained as something to be borne in mind and stated as a limitation in many crime mapping studies, but little has been done to account for the geographical inequality of the dark figure of crime. This paper produces small area estimates of the dark figure of crime in England and Wales to serve as basis for future research

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aiming to correct for measurement error in crime data by combining police records with survey-based estimates.

Crime reporting rates are larger for female victims than males, and elderly citizens are more likely to report crimes than young people (Hart and Rennison 2003; Tarling and Morris 2010). There are also contextual factors that explain why the dark figure of crime may be larger in certain geographic areas. Victims from suburban areas report crimes less frequently than urban and rural residents (Hart and Rennison 2003; Langton *et al.* 2012), and the neighbourhoods' economic disadvantage, concentration of immigrants and social cohesion affect crime reporting rates (Goudriaan *et al.* 2006; Xie and Lauritsen 2012; Berg *et al.* 2013; Xie and Baumer 2019). The dark figure of crime also varies between crime types (Gove *et al.* 1985; Tarling and Morris 2010).

Although, nowadays, it is well known that police records are more reliable in some areas than others, most crime mapping methodologies geocode offences known to the police and examine their patterns. Advanced techniques are applied to produce crime maps at small spatial scales to enable targeted policing strategies (Weisburd *et al.* 2012), while potential sources of error arising from the dark figure of crime are usually left touched upon as a limitation or area for future work. Victimization surveys were developed to address the limitations of police statistics as crime data sources (Skogan 1977), and estimates produced from crime surveys can be used to mitigate the sources of measurement error in police data.

However, surveys have their own methodological issues, and measurement error may arise from victims' non-recall, overestimation or underestimation of situations. Moreover, surveys have limitations to produce crime estimates at the increasingly smaller focus of the criminology of place (Weisburd *et al.* 2012). Most surveys are designed to record representative samples for large geographical areas, and direct estimates of target parameters are unreliable for most small unplanned areas. This paper makes use of model-based small area estimation (SAE) to produce small area estimates of the dark figure of crime. SAE uses available survey data and auxiliary information to produce reliable estimates of parameters of interest for unplanned areas for which direct estimates are not precise enough (Rao and Molina 2015). In this study, we produce estimates of crimes unknown to the police from the Crime Survey for England and Wales (CSEW), which can then be used to complement existing police statistics.

The Crime Mapping and the Dark Figure of Crime section introduces the implications of the dark figure of crime for crime analysis. The Factors Affecting the Geography of the Dark Figure of Crime section discusses the contextual conditions that affect the dark figure of crime. The Data and Methods section presents data and methods. The SAE of Crimes Unknown to the Police section shows model results and estimates. The Discussion and Conclusions section presents conclusions.

Crime Mapping and the Dark Figure of Crime

Police records are the main source of data used for crime mapping. However, the likelihood of crimes to be missing in police statistics is related to social conditions unequally distributed across areas (e.g. economically deprived areas and concentration of minorities). The dark figure of police statistics is likely to be larger in some places than others, and crime maps produced from police records may show an unreliable representation of crime. Producing estimates of the dark figure of crime from survey data may help mitigate the measurement error in police statistics.

Some argue that maps produced from police records and surveys show similar results and assume that police-recorded crimes show true crime levels (Gove *et al.* 1985). In 1979, Mawby compared police records with other data sources (victimization surveys and self-report studies) in nine areas of Sheffield and concluded that all data showed similar results (Mawby 1979). Bottoms and Wiles (1997) argue that such results must not be overstated and cannot be overgeneralized. They argue that these findings cannot be used to establish a working presumption that police statistics are always valid indicators of crime. Bottoms *et al.* (1987) conducted a similar study in seven areas of Sheffield and concluded that police data may provide valid crime rates for comparisons across areas with similar housing types and within the same police force jurisdiction. However, police records underestimated crime rates in high-rise areas, and authors warned that caution is necessary when comparing statistics across police forces.

Others show evidence that residents from certain areas are more likely to report crimes to the police than others. Goudriaan *et al.* (2004) argue that victims of property crimes are more likely to report in countries where police forces are perceived to be competent. Xie (2014) analysed crime reporting trends in large American metropolitan areas and observed that there was a national trend towards higher reporting rates, which was shown in several cities but not in New York. Victims from suburban areas report crimes less often than urban and rural citizens (Hart and Rennison 2003; Langton *et al.* 2012), and residents from deprived neighbourhoods are less likely to report certain crime types (Goudriaan *et al.* 2006; Slocum *et al.* 2010; Xie and Lauritsen 2012; Berg *et al.* 2013). Baumer (2002) shows that citizens living in deprived neighbourhoods, but also those living in wealthy areas, are less likely to inform the police. Although public reporting is not the unique pathway through which the police become aware of crimes (police can witness crimes, observe cues of crimes and be informed by private law enforcers, and offenders may surrender), it is arguably the main source of data for most crime types and has large impacts on crime rates (Mawby 1979; Brantingham 2018).

Maps produced from police statistics may not show accurate visualizations of the geography of crime, and it should always be checked whether other variables are conditioning crime records in geographic areas. Surveys provide key information to complement police statistics.

Factors Affecting the Geography of the Dark Figure of Crime

Researchers have found several contextual conditions affecting the dark figure of crime. Factors can be aggregated in variables that affect victims' reporting rates, unequal police surveillance across areas and differences in counting rules. In England and Wales, the latter was scrutinized and all 43 police forces follow common counting rules (i.e. Home Office Counting Rules for Recorded Crime, National Crime Recording Standard). Thus, we focus on the other factors. We note, however, that a 2014 inspection into police statistics reported a series of practices that need improvement to increase police records' comparability (HMIC 2014).

Economically deprived areas tend to suffer from lower reporting rates than middle-class neighbourhoods (Goudriaan *et al.* 2006; Slocum *et al.* 2010; Xie and Lauritsen

2012; Berg *et al.* 2013). Social identities in disadvantaged areas may develop legal cynicism that reduces public cooperation with police services and, in certain areas, 'call the police, or even to cooperate with them, may also be deviant' (Black 2010: 106). Berg *et al.* (2013) argue that normative constraints on crime reporting may not exist in middle-class areas where antipolice views play a less important role. Baumer (2002) shows that socio-economic disadvantage affects the likelihood of crime reporting in the case of crime indices dominated by simple assaults, but it does not affect reporting rates for serious crimes (e.g. robbery and aggravated assault). Moreover, while victims of simple assault living in disadvantaged neighbourhoods were less likely to report crimes to the police than elsewhere, the lowest reporting rates were found in the wealthiest areas. Baumer (2002) argues that deprived and wealthy areas are characterized by high levels of social cohesion that help residents cope with minor crimes without the need to contact the police (including taking the matter into own hands). Thus, the relationship between neighbourhood disadvantage and crime reporting would be curvilinear.

Research examining the effect of social cohesion on victims' willingness to report crimes to the police show contrasting results. Some argue that areas characterized by high social cohesion are those where reporting rates are lower due to residents' higher social resources to cope with crime through social mechanisms alternative to the police (Baumer 2002). As discussed by Black (2010: 7), 'a citizen is more likely to call the police if he has no one else to help him'. However, Jackson *et al.* (2013) argue that high collective efficacy measures, defined as shared values and willingness to act to achieve collective goods, are associated to more cooperation with the police. Goudriaan *et al.* (2006) also show that larger social cohesion measures are related to an increased likelihood of reporting crimes to the police. According to these results, the more cohesive a neighbourhood is, the greater the cooperation with the police.

Residents living in suburban areas are less likely to report crimes to the police than citizens from urban and rural contexts (Hart and Rennison 2003; Langton *et al.* 2012). Xie and Baumer (2019) show that crime reporting rates are lower in non-traditional destinations with high concentrations of immigrants, and they argue that this might be due to the poor police effectiveness in assisting immigrant victims and the small social support for immigrants. Moreover, certain demographic characteristics are related to an increased likelihood of victims' reporting to the police (Hart and Rennison 2003; Tarling and Morris 2010). Areas characterized by larger proportions of these groups may have larger crime reporting rates. For example, reporting rates may be larger in ageing areas but also in neighbourhoods with more married residents. Ethnicity and crime reporting are not always related (Skogan 1977).

Berg *et al.* (2013) found that the most important contextual factor to explain the victims' likelihood to report crimes to the police is the area crime rate: those who live in areas with high levels of crime are less likely to notify the police. Other research shows no significant effects of crime rates on citizens' cooperation with police services, while perceived disorder reduces calls for police services (Jackson *et al.* 2013).

The public perceptions about police services, which vary between neighbourhoods, are known to be good predictors of crime reporting rates (Xie 2014). Jackson *et al.* (2013) show that perceptions of police legitimacy and trust in police fairness are the most important predictors of citizens' willingness to cooperate with the police. Citizens' perceptions of police legitimacy are related to their contact with the police, but these are also explained by social identities shaped by neighbourhood conditions (Bradford 2014).

Finally, policing strategies may affect the proportion of crimes known to the police, both through affecting the victims' willingness to report and the police probability to witness incidents. Braga (2007) reveals that place-based policing strategies reduce calls for services in treatment places relative to control areas. Schnebly (2008) shows that police notification is higher in cities with more police officers trained in community-oriented policing, but victims are less likely to call the police in cities with more community-oriented officers. Research analysing the effect of stop and search on crime reporting shows conflicting results: '[t]he presence of police undertaking stop and searches may increase the opportunity for victims to report crimes, as well as increasing so-called discovery crimes. But stop and searches, if poorly handled, may discourage cooperation in the short and long term, and possibly reduce reporting rates' (McCandless *et al.* 2016: 37). Targeting stop and search practices on selected areas might increase crime figures. However, overpolicing areas and targeting stop and search practices in specific locations may also alienate residents from the police and decrease the willingness to cooperate with the police (Jackson *et al.* 2013).

Previous research about contextual predictors of the dark figure of crime is necessary when selecting area-level covariates in SAE. We will examine available data about these variables to produce estimates of crimes unknown to the police.

Data and Methods

First, we present the survey used to produce estimates of crimes unknown to the police. Second, we introduce SAE methods. Third, optimal covariates are selected to estimate SAE models. Fourth, we apply different SAE approaches and select the approach with the highest performance with respect to the reliability and goodness-of-fit criteria to analyse and map the dark figure of crime.

Data

The CSEW is used to produce small area estimates of crimes unknown to the police. It is an annual victimization survey conducted since 1982. The sampling design consists of a multistage stratified random sample by which a sole randomly selected adult (aged 16 and over) from a randomly selected household is asked about instances where the respondent (household in some cases) had been a victim of a crime in the last 12 months. The questionnaire includes questions about perceived safety and perceptions about the police among others. The main part of the questionnaire is completed face-to-face in participants' houses, but some questions (alcohol and drugs use and domestic abuse) are administered with computer-assisted personal interviewing. Some modules are asked to a sample of 10-to-15-year-old respondents, but these are not used here. A special licence to the survey's secure access was needed to obtain information about respondents' low-level geographies (Office for National Statistics 2018). Survey series from 2011–12 to 2016–17 are used in this research. Respondents' sample sizes are $n = 46,031$ in 2011–12, $n = 34,880$ in 2012–13, $n = 35,371$ in 2013–14, $n = 33,350$ in 2014–15, $n = 35,324$ in 2015–16 and $n = 35,420$ in 2016–17.

Participants are asked about their personal victimization for a list of crimes, which range from misdemeanour-type offences (e.g. theft and criminal damage) to major felonies (e.g. sexual assault and burglary). In case of a positive answer, respondents are asked about the details of each victimization, with a cap of five incidents per person. Although this cap allows cross-sectional comparisons, it reduces information in an arbitrary way and is being reviewed by survey administrators. This is not expected to have a large impact in our analyses since only 2.1 per cent of victims registered by the CSEW reported more than five crimes in 2011–12, 2.1 per cent in 2012–13, 1.7 per cent in 2013–14, 1.7 per cent in 2014–15, 1.0 per cent in 2015–16 and 1.5 per cent in 2016–17.

In this research, we analyse recorded crimes. Sample sizes of recorded crimes are $n = 14,758$ in 2011–12, $n = 10,296$ in 2012–13, $n = 9,282$ in 2013–14, $n = 8,259$ in 2014–15, $n = 10,594$ in 2015–16 and $n = 11,352$ in 2016–17. Each victim of each crime is asked 'Did the police come to know about the matter?', which is used to estimate the percentage of crimes unknown to the police. At a national level, the percentage of crimes unknown to the police remains stable around 60 per cent (Figure 1).

Among those who answer that the police know about the incident, the most common pathway through which the police become aware of offences is by the victim's report (around 64 per cent of crimes), followed by a report by another person (around 32 per cent), which appears to decrease slightly over time. The percentage of crimes known to the police by another way (the police were there or found out by another way) is small (Table 1). The dark figure of crime appears to be quite stable at a national level. Nevertheless, based on this information, we cannot rule out the possibility that the proportion of crimes known to police varies across years in certain areas but not others and, hence, we need small area estimates.

Table 2 shows the percentage of crimes unknown to the police by victims' characteristics, their relationship to offenders and crime types. The dark figure of crime tends to be lower among female victims, persons living in low-income households, unemployed or economically inactive victims and married respondents. These differences are statistically significant in some years but not others. The percentage of crimes unknown to the police by victims' ethnicity and age show inconsistent results across years due to small samples in certain categories. The percentage of unknown crimes is larger when the offender is a stranger. The crime type which is most likely to be known to the police is theft of motor vehicle, but a small dark figure is also observed for burglary. The

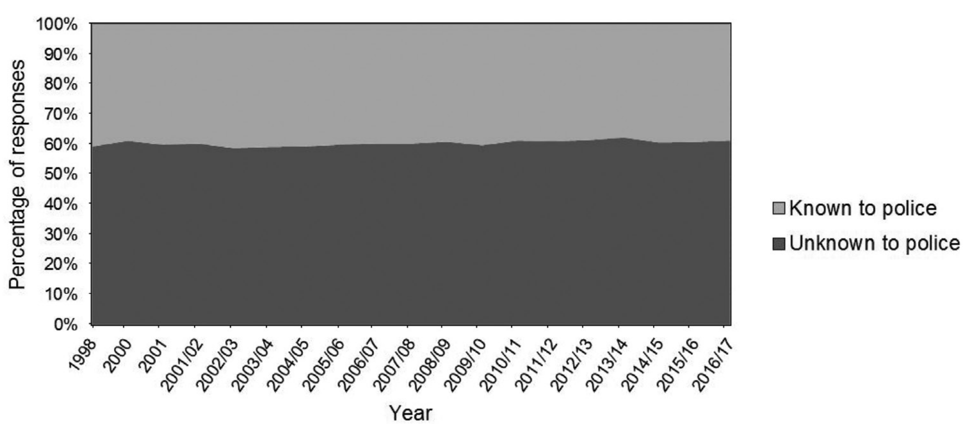

Figure 1. Percentage of crimes known and unknown to the police (unweighted). Source: CSEW.

Table 1 *Descriptive statistics of how the police come to know about crimes (unweighted)*

		2011–12	2012–13	2013–14	2014–15	2015–16	2016–17
Police told by respondent	*f*	3,445	2,352	2,147	1,935	2,004	1,902
	%	63.2	63.2	65.0	63.4	64.0	65.5
Police told by another person	*f*	1,759	1,214	1,032	974	978	872
	%	32.3	32.6	31.2	31.9	31.3	30.0
Police were there	*f*	127	79	65	65	84	58
	%	2.3	2.1	2.0	2.1	2.7	2.0
Police found out by another way	*f*	121	76	60	77	65	70
	%	2.2	2.0	1.8	2.5	2.1	2.4
Total		5,452	3,721	3,304	3,051	3,131	2,902

Source: CSEW.

largest proportions of crimes unknown to the police are observed for robbery, criminal damage and threat/intimidation. Differences based on the victim's relationship to the offender and the crime type are statistically significant in all editions.

Table 3 shows descriptive analyses of the percentage of crimes unknown to the police by respondents' area of residence. Crimes suffered by victims from rural areas are generally more likely to be known to the police than those in urban areas. The dark figure tends to be larger among respondents living in inner parts of cities. These differences are only statistically significant in some years and after merging all years. When comparing the dark figure of crime by deciles of the Indices of Multiple Deprivation, we observe that the dark figure of crime tends to be larger in the least deprived areas, but this is inconsistent across years and is only statistically significant in some years. The Index of Multiple Deprivation classifies small areas in England and Wales by their relative deprivation. It is constructed from seven domains (income, employment, education, health, crime, barriers to housing and services and living environment), and it is generally used as a measure of multidimensional deprivation.

Small area estimates are produced for local authority districts (LADs) and middle layer super output areas (MSOAs). LADs represent local governments and MSOAs are small areas designed to improve the reporting of statistical information. LADs have an average of 168,000 citizens according to estimates from 2016: a maximum of 1,128,077 in Birmingham and a minimum of 2,331 in the Isles of Scilly. Greater London has 33 LADs. Each MSOA contains between 5,000 and 15,000 residents (on average, 7,200), and between 2,000 and 6,000 households. There are 7,201 MSOAs and 348 LADs in England and Wales. Producing estimates at smaller geographical scales would allow for more precise spatial analyses of the dark figure of crime. However, the main area-level SAE techniques require that the assumption of normal distribution of the direct estimates is met at the target spatial scale. Such an assumption is only met when aggregating CSEW victimization data at the LAD level or at the MSOA level after merging more than five editions together, while data aggregates at smaller scales suffer from zero-inflated data and distributions skewed towards zero. New SAE methods are being developed in agricultural research to deal with zero-inflated data and skewed distributions (Dreassi *et al.* 2014), but further research is needed before these can be applied in criminology. Instead, the aggregation of data in LADs and MSOAs allows for using extensively researched methods within social science research.

TABLE 2 *Descriptive statistics of crimes unknown to the police by victim's characteristics, relationship to offender and crime type (unweighted)*

		2011–12	2012–13	2013–14	2014–15	2015–16	2016–17	2011–17
Total	*F*	8,874	6,205	5,669	4,868	5,038	4,753	35,407
	%	61.0%	61.5%	62.3%	60.6%	60.8%	61.3%	61.2%
Gender								
Male		62.2%	62.6%	63.5%	61.6%	62.1%	62.3%	62.4%
Female		59.9%	60.5%	61.1%	59.7%	59.8%	60.4%	60.2%
χ^2test		7.2**	4.4*	5.4*	3.0+	4.2*	2.9+	27.6***
Ethnicity								
White		60.8%	61.5%	62.3%	60.7%	60.5%	61.1%	61.2%
Black		61.9%	62.9%	58.8%	53.8%	68.4%	63.5%	61.7%
Asian		63.3%	60.0%	61.6%	61.0%	59.4%	60.2%	61.1%
Other		61.9%	62.9%	67.6%	64.1%	68.0%	67.0%	65.0%
χ^2test		2.2	1.0	3.8	5.6	11.6**	3.8	8.1*
Age								
16–29		62.5%	63.6%	63.7%	63.1%	59.3%	59.5%	62.2%
30–49		60.2%	60.2%	61.6%	59.5%	59.4%	61.1%	60.3%
50–64		62.2%	62.3%	61.7%	60.6%	65.1%	62.9%	62.4%
65 or older		58.7%	59.9%	63.2%	59.7%	59.8%	61.4%	60.3%
χ^2test		10.5*	9.3*	3.3	6.5+	20.7***	4.3	24.4***
Marital status								
Never married		62.8%	62.7%	62.0%	61.7%	60.4%	61.0%	61.9%
Married		60.2%	60.8%	61.6%	59.6%	61.4%	61.8%	60.8%
Other		59.2%	60.2%	64.1%	60.8%	60.8%	60.8%	60.8%
χ^2test		13.2**	4.8+	3.8	2.8	0.7	0.7	6.9*
Employment status								
Employed		62.0%	62.6%	62.9%	61.4%	61.6%	62.0%	62.1%
Unemployed		61.6%	59.2%	62.8%	61.3%	64.6%	57.0%	61.1%
Economically inactive		59.0%	59.4%	60.9%	58.8%	59.1%	60.3%	59.5%
χ^2test		11.8**	9.9**	3.1	4.5	6.3*	4.0	33.5***
Household income								
Under £20,000		60.0%	59.8%	62.0%	61.3%	59.7%	60.3%	60.4%
£20,000–£49,999		63.0%	63.6%	62.9%	61.2%	61.9%	61.2%	62.4%
£50,000 or over		61.7%	62.2%	63.3%	58.6%	62.7%	63.0%	61.9%
χ^2test		10.0**	11.1**	1.0	3.5	4.8+	2.9	17.7***

Table 2 *Continued*

		2011–12	2012–13	2013–14	2014–15	2015–16	2016–17	2011–17
Total	*F*	8,874	6,205	5,669	4,868	5,038	4,753	35,407
	%	61.0%	61.5%	62.3%	60.6%	60.8%	61.3%	61.2%
Relationship to offender								
Knew well		50.9%	52.5%	50.8%	50.5%	49.0%	49.4%	50.6%
Casual		49.7%	53.2%	52.2%	47.8%	51.7%	51.4%	51.0%
Stranger		63.3%	63.5%	64.7%	63.2%	63.3%	63.9%	63.6%
χ^2test		148.4***	71.0***	99.0***	96.7***	89.8***	95.3***	592.4***
Crime								
Violent/sexual offences		53.7%	53.5%	51.9%	48.8%	44.9%	53.7%	51.4%
Robbery/theft		61.7%	62.1%	65.4%	63.1%	64.6%	63.6%	63.2%
Burglary		27.7%	26.7%	26.2%	32.3%	32.5%	27.3%	28.6%
Theft of motor vehicle		7.3%	8.1%	5.9%	12.6%	5.0%	7.1%	7.5%
Theft of cycle		53.7%	56.0%	52.9%	50.2%	48.8%	48.4%	52.2%
Criminal damage		66.8%	66.8%	68.4%	67.9%	68.4%	67.7%	67.5%
Threat/ intimidation		59.3%	63.8%	63.7%	59.1%	61.0%	61.8%	61.5%
χ^2test		665.4***	460.9***	504.2***	339.3***	449.6***	385.3***	2,748.9***

Source: CSEW.

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.10$.

TABLE 3 *Descriptive statistics of crimes unknown to the police by areas (unweighted)*

	2011–12	2012–13	2013–14	2014–15	2015–16	2016–17	2011–17
Rural or urban							
Urban	61.3%	61.8%	62.3%	60.8%	60.8%	61.9%	61.5%
Rural	59.7%	59.8%	62.4%	59.5%	60.7%	58.1%	60.1%
χ^2test	2.2	2.3	0.1	0.8	0.0	5.9*	7.0**
Inner city or not							
Inner city	62.9%	61.9%	60.0%	64.5%	62.5%	64.3%	62.6%
Not inner city	60.8%	61.4%	62.6%	60.2%	60.6%	60.9%	61.1%
χ^2test	2.4	0.1	2.7	5.7*	1.2	3.5+	5.1*
Index of Multiple Deprivation 2010–2015 (England)							
30% most deprived	60.9%	60.4%	61.7%	62.2%	59.5%	60.8%	60.9%
40% between most and least deprived	61.3%	61.6%	63.3%	60.4%	61.3%	60.8%	61.6%
30% least deprived	62.1%	62.9%	62.2%	57.8%	59.6%	63.0%	61.4%
χ^2test	1.2	3.5	1.8	9.1*	5.6+	2.6	2.0
Index of Multiple Deprivation 2008/2011/2014 (Wales)							
30% most deprived	52.5%	58.2%	56.3%	59.5%	60.3%	53.9%	56.5%
40% between most and least deprived	59.3%	63.3%	62.7%	65.5%	65.7%	63.6%	63.0%
30% least deprived	59.5%	64.3%	64.0%	64.8%	65.3%	65.8%	63.2%
χ^2test	4.9+	2.1	3.2	2.1	1.8	6.2*	18.5***

Source: CSEW.
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.10$.

We note that our estimates are produced for area victimization rates rather than area offence rates. The former measures offences committed against a population who lives in an area, regardless where incidents happened, while the latter measures the crimes that happen in each area. This may complicate efforts to compare our estimates with police records. We could mitigate this limitation by selecting only offences that take place within respondents' area of residence (i.e. 74.0 per cent in 2011–12, 73.7 per cent in 2012–12, 72.4 per cent in 2013–14, 72.9 per cent in 2014–15, 71.8 per cent in 2015–16 and 73.2 per cent in 2016–17), but this will reduce the sample size of crimes leading to more sparse data and non-normality of the direct estimates. In order to ensure that our estimates are not largely affected by this shortcoming, we also compute estimates of crimes unknown to the police after selecting only crimes that take place in the persons' area of residence and compare these with estimates of the dark figure of crime produced from all crimes, but only the latter are reliable enough to be analysed in this research.

To produce estimates at the LAD level, we explore the use of SAE techniques based on spatial, temporal and spatial–temporal models and select the method that produces the highest performance with respect to reliability and goodness-of-fit criteria to present the analysis. To produce estimates at the MSOA level, all six CSEW editions are merged together (2011–17) to increase effective sample sizes of crimes and meet the assumption of normal distribution of direct estimates, and non-temporal models are used. Thus, estimates are produced at the LAD level for six time periods (2011–12, 2012–13, 2013–14, 2014–15, 2015–16 and 2016–17) and at the MSOA level for all editions together (2011–17). The main limitation of producing one estimate for combined years 2011–17 per MSOA is that such estimates may hide variability across years. At the LAD level, average sample sizes of crimes in areas are 41.8 in 2011–12 (min = 0 and max = 235), 29.0 in 2012–13 (min = 0 and max = 137), 26.1 in 2013–14 (min = 0 and max = 133), 23.3 in 2014–15 (min = 0 and max = 117), 23.8 in 2015–16 (min = 0 and max = 160) and 22.3 in 2016–17 (min = 0 and max = 139). At the MSOA level, after merging all editions, the average sample size per area is 8.0 (min = 0 and max = 53) and 544 out of 7,201 areas have zero sample sizes.

SAE methods

We explore the use of different SAE methods to produce estimates of crimes unknown to the police for area victimization rates. The highest performing SAE method (in terms of reliability of estimates and goodness-of-fit of models) will be utilized to explain and map the dark figure of crime in the SAE of Crimes Unknown to the Police section. At the LAD level, we explore the use of six methods (based on direct estimators and traditional, spatial, temporal and spatial–temporal model-based approaches), but only the approach with the best results is applied to analyse the dark figure of crime. At the MSOA level, since we merged all survey editions into a single data set, we only explore the use of non-temporal approaches (i.e. traditional and spatial model-based SAE) and select the highest performing approach. Below, we discuss all SAE approaches explored in this research. See Rao and Molina (2015) for more details of the SAE approaches.

First, direct estimates are produced based on the Horvitz and Thompson (1952) estimator, which uses survey data and survey weights to obtain design-unbiased estimates of the percentage of crimes unknown to the police. Direct estimates are computed as follows:

$$\widehat{\overline{Y}}_d = \widehat{N}_d^{-1} \sum\nolimits_{j \in sd} w_{dj} Y_{dj} \tag{1}$$

where w_{dj} is the adjusted individual weight for unit/crime j in area d, Y_{dj} is the value of crime reporting for unit/crime j in area d and N_d is approximated as the sum of adjusted individual weights in area d (estimated number of individuals who were victims of crime). We adjusted individual weights by dividing original weights by the number of crimes per respondent. Original individual weights are provided by survey administrators and computed by calibrating the proportion of respondents by regions, age and sex to such proportion in the population (Office for National Statistics 2017). Direct estimates are design unbiased but suffer from high variance in areas with small sample sizes. Therefore, model-based approaches are needed.

Second, regression-based synthetic estimates are produced by fitting a linear regression with the direct estimates as dependent variable and relevant area-level auxiliary information as covariates and computing regression-based predictions (synthetic estimates). Synthetic estimates can be produced for all areas, including those with zero sample sizes. However, these are not based on a direct measurement of the variable in each area and may be subject to bias due to model misspecification (Rao and Molina 2015). Due to their high risk of bias, synthetic estimates are only used for areas with zero and one sample sizes, while composite estimates based on linear combinations of direct and synthetic estimates are used for areas with at least two units/crimes.

Third, the area-level empirical best linear unbiased predictor (EBLUP) obtains an optimal combination of direct and synthetic estimates in each area (Fay and Herriot 1979). The EBLUP gives more weight to the direct estimate when its sampling variance is small, while more weight is given to the synthetic estimate when the direct estimate's variance is larger. The EBLUP reduces the variance of direct estimates and the risk of bias of synthetic estimates by producing optimal combinations of these in each area.

Fourth, the Rao–Yu model (Rao and Yu 1994) is an extension of the area-level EBLUP for cross-sectional data. It adds temporally autocorrelated random effects to the EBLUP and estimates borrow strength over time. The Rao–Yu model tends to provide better estimates than the EBLUP when the between-time variation relative to sampling variation is small and there is high correlation in the variable of interest over time.

Fifth, the spatial EBLUP (SEBLUP) adds spatially autocorrelated random effects to the EBLUP and borrows strength from neighbouring areas (Pratesi and Salvati 2008). It tends to improve estimates when the outcome measure has medium/high levels of spatial autocorrelation (i.e. when values cluster together in neighbouring areas). The proximity matrix used to borrow strength across neighbouring areas follows a 'Queen continuity' approximation, which defines as neighbours all polygons that share at least one vertex.

Sixth, the spatial–temporal EBLUP (STEBLUP) is an extension of the EBLUP that accounts for both temporally and spatially autocorrelated random effects (Marhuenda *et al.* 2013). It is expected to improve our estimates when the variable of interest is stable across time and shows spatial clustering.

In SAE, every estimate needs to be accompanied by its measure of uncertainty. This allows examining which method produces the most reliable estimates and which estimates are less reliable. A parametric bootstrap approach is used to compute the relative root mean squared errors (RRMSEs) of model-based estimates (González-Manteiga *et al.* 2008; Marhuenda *et al.* 2013). Smaller RRMSEs indicate more reliable estimates. RRMSEs lower than 25 per cent in areas are regarded as reliable, while RRMSEs ranging from 25 to 50 per cent in areas can be used with caution, and RRMSEs larger than 50 per cent are unreliable. The measure of uncertainty of direct estimates is the coefficient of variation, which corresponds to the RRMSEs for direct estimators. Small area estimates and RRMSEs are computed in R with 'sae' (Molina and Marhuenda 2015) and 'sae2' (Fay and Diallo 2015) packages.

Covariates selection

Area-level covariates are needed to fit SAE models and produce estimates. Existing literature and preliminary data analyses (Tables 2 and 3) are used to select potential covariates associated to our outcome measure. In order to fit the temporal SAE models for the LAD level, only covariates with available information for all years between 2011 and 2017 are included. These are selected from reliable sources, such as the Office for National Statistics (ONS) and the Consumer Data Research Centre (CDRC). An optimal set of LAD-level covariates for SAE models across years is selected following a step-forward variable selection procedure as suggested by Brakel and Buelens (2014) and described below. The selected covariates are used to estimate models for SAE. Thus, in this section, we are not discussing which SAE approach is preferred to produce estimates but which is the optimal set of area-level covariates to fit SAE models across years. Selected covariates will then be used to estimate different modelling approaches and select the SAE method that produces the best results. The same covariates and additional cross-sectional covariates recorded by UK Census are used at the MSOA level.

Regarding potential covariates in the SAE models, estimates on area percentages of males/females, average age, unemployment, house prices, income, population density and urban/rural classification are provided by the ONS. Three categories are used to classify areas based on the urban/rural classification: urban conurbations, urban cities/towns (henceforth small urban areas) and rural areas. Urban conurbations classify large cities with large population density and urban morphology. These mainly include urban areas of Birmingham, Leeds, Liverpool, London, Manchester, Newcastle, Nottingham and Sheffield. Most urban areas outside these cities are classified as 'small urban areas', while the rest of areas are defined as rural. The absolute standard score (ASS) of the area's income is computed to obtain the distance between the area's income and the average income to analyse the curvilinear relation between income and crimes unknown to the police. It is calculated as $ASS\left(x_d\right) = \left|\frac{x_d - \bar{x}}{s}\right|$, where x_d is the average income in area d, $\bar{x}$ is the average income across all areas and s is the standard deviation (SD) across areas. Estimates of ethnic groups and population churn are provided by CDRC under a user agreement for safeguarded data. Police-recorded crimes and stop and search data are provided by Home Office. Crime rates are calculated as police-recorded incidents divided by the population times 100. Stop and search data is only published since 2015 and cannot be used to model temporal data. The Census 2011 provides additional data that may be used to fit cross-sectional models at the MSOA level for the combined survey editions, such as the workday population, language skills, marital status, country of birth, social grade and education level. We did not find reliable sources of data to measure social cohesion, perceptions about police services and policing strategies. In order to analyse the effect of these measures, previous studies use area-level aggregates of data obtained from surveys (Sampson and Groves 1989), but this practise is not advised in SAE, since area-level survey aggregates suffer from errors of measurement that are likely to affect the reliability of model-based estimates. Similarly, in Table 2, we observed some variables recorded in the survey that are associated with the dark figure of crime, but area-level aggregates of survey data may suffer from unreliability and cannot be directly used as covariates in our area-level models.

As mentioned, for the variable selection procedure, Brakel and Buelens (2014) proposed a method to identify optimal sets of covariates when analysing data across years. They conclude that the best method consists of selecting covariates through a step-forward variable selection procedure in each survey edition and averaging the optimization criteria across years. The preferred selection criterion is the conditional Akaike information criterion (cAIC). The option with the best averaged cAIC will be used to estimate the area-level SAE models according to the different approaches presented in the SAE methods section, which will allow selecting the SAE approach that produces the best results. We select the following covariates: ASS of income, percentage employed, percentage whites, percentage Asians, mean house price, percentage males, crime rate and two dummy measures for conurbations and small urban areas (Model 4 in Table 4).

Table 4 *Averaged cAIC across years for four models with best optimization criteria (LAD level)*

	Model 1	Model 2	Model 3	Model 4
Males (%)		x	x	x
Mean age	x		x	
Employed (%)		x		x
Mean house price		x	x	x
Population density				
Mean income		x		
ASS income	x		x	x
Conurbation				x
Small urban	x	x	x	x
Rural				
Whites (%)	x	x	x	x
Blacks (%)				
Asians (%)	x	x		x
Others ethnic groups (%)	x			
Population churn				
Crime rate	x	x		x
Averaged cAIC	2,835.89	2,835.87	2,834.37	2,834.01

At the MSOA level, the same covariates are averaged across years to estimate the cross-sectional models, and additional covariates are included to increase the model's explanatory capacity: percentage without qualifications, percentage with higher/intermediate occupations, percentage born in the United Kingdom and workday population density. The latter are recorded by Census 2011 and could not be used to fit the temporal models at the LAD level.

In order to gain understanding about the effect of each covariate on the dark figure of crime, all covariates are rescaled by subtracting the covariate's mean from each value and dividing it by two SDs (Gelman and Hill 2007). By rescaling covariates, we obtain standardized model coefficients not affected by the covariates' natural scales without affecting the estimates, estimates' RRMSEs and other SAE parameters.

Selecting the highest performing approach for SAE

Various SAE approaches mentioned in the SAE methods section are examined to produce estimates of crimes unknown to the police, and we select the method with the highest performance to explain and map the dark figure of crime for area victimization rates. Both cross-sectional and temporal models are examined to estimate the dark figure at the LAD level over survey editions, but only cross-sectional approaches are examined to model crimes unknown to the police at the MSOA scale for the combined survey editions. We select the method that produces estimates with the smallest RRMSE.

Table 5 shows estimates' averaged RRMSE for all SAE methods. Direct estimates have the largest RRMSEs. At the LAD level, the STEBLUP produces the most reliable estimates for four survey editions out of six, while Rao–Yu estimates are slightly more reliable in 2013–14 and 2016–17. The inclusion of temporal and spatial random effects provides a slight improvement in estimates' reliability. The SEBLUP produces the most reliable estimates at the MSOA level.

At the LAD level, 1,548 out of 2,055 (75.3 per cent) direct estimates have RRMSEs larger than 25 per cent, while this number is reduced to 48.7 per cent EBLUPs, 41.3 per

Table 5 $\overline{RRMSE}\%$ *of small area estimates*

		Direct	EBLUP	SEBLUP	Rao–Yu	STEBLUP
$\overline{RRMSE}\%$	LADs 2011–12	30.61	21.77	21.54	21.34	21.26
	LADs 2012–13	34.58	24.28	24.03	23.55	23.37
	LADs 2013–14	35.23	24.95	24.95	24.33	24.36
	LADs 2014–15	38.93	27.08	26.79	26.14	25.93
	LADs 2015–16	37.53	26.24	25.96	25.58	25.33
	LADs 2016–17	38.21	26.78	26.50	26.33	26.34
	MSOAs 2011–17	57.77	37.76	36.08		

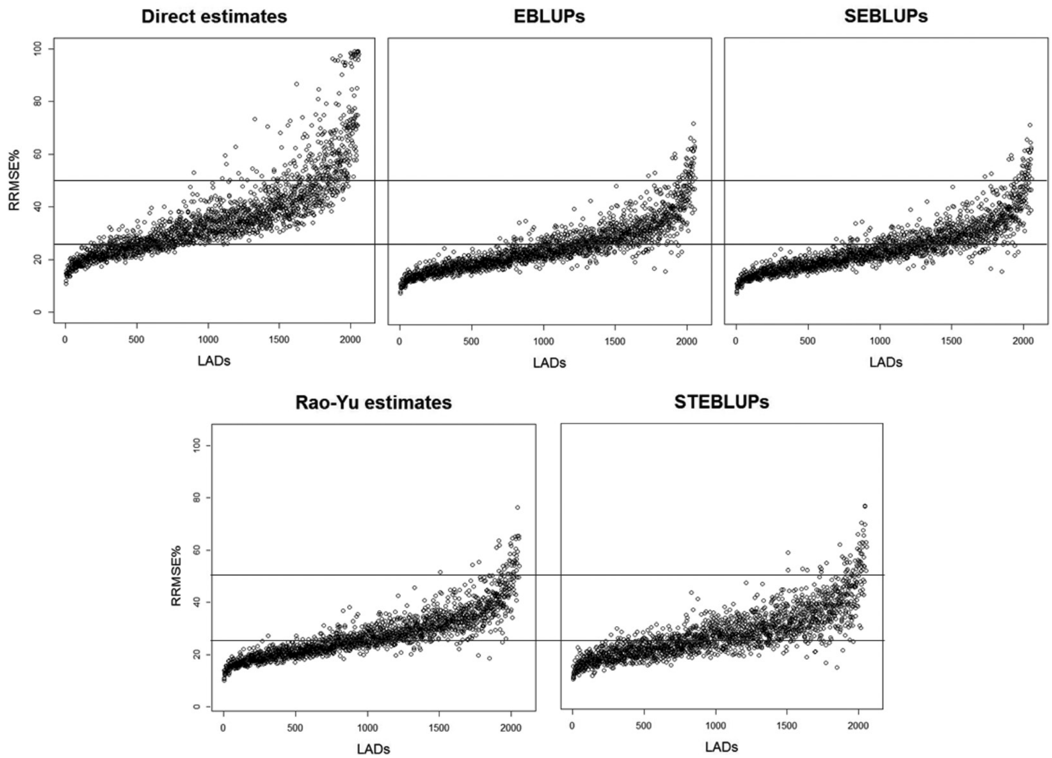

Figure 2. RRMSE% of estimates produced for LADs (ordered by sample size).

cent SEBLUPs, 39.9 per cent Rao–Yu estimates and 38.2 per cent STEBLUPs (Figure 2). The percentage of estimates with RRMSEs larger than 50 per cent is reduced from 14.5 per cent direct estimates to 3.2 per cent EBLUPs, 2.2 per cent SEBLUPs, 1.5 per cent Rao–Yu estimates and 1.4 per cent STEBLUPs.

In the case of the estimates produced for MSOAs, whereas 99.6 per cent direct estimates suffered from RRMSEs larger than 25 per cent, this proportion is reduced to 85.9 per cent EBLUPs and 82.1 per cent SEBLUPs (Figure 3). The percentage of estimates with RRMSEs larger than 50 per cent is reduced from 60.9 per cent direct estimates to 17.9 per cent EBLUPs and 13.6 per cent SEBLUPs. Although model-based estimates have lower RRMSEs than direct estimates, their unreliability measures are large in many areas and these must be used with caution.

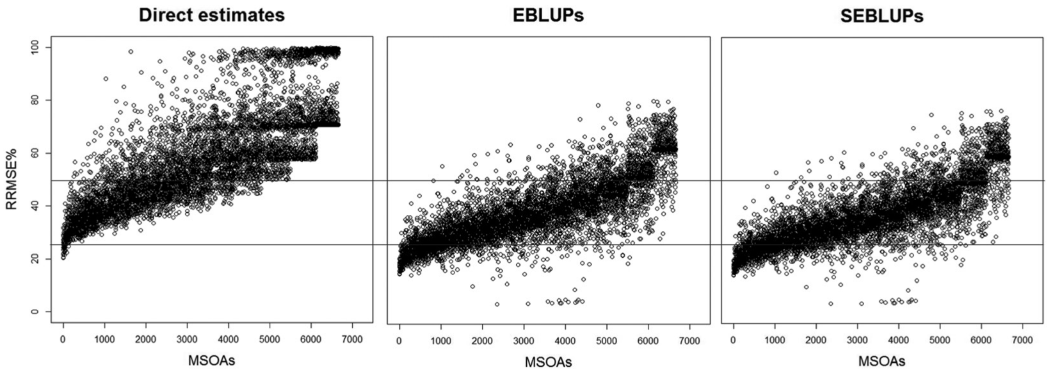

FIGURE 3. RRMSE% of estimates produced for MSOAs (ordered by sample size).

Therefore, we will use the STEBLUP approach to analyse the dark figure of crime at the LAD level, and the SEBLUP at the MSOA level. Moreover, the LAD-level STEBLUP model and the MSOA-level SEBLUP model show the best indicators of goodness-of-fit. At the LAD level, the log-likelihood indicator of the Rao–Yu model equals −8,166.6, whereas the STEBLUP model's log likelihood is −8,163.1; and the log-likelihood parameters of the models fitted at the MSOA scale are −30,562.8 for the EBLUP model and −30,560.4 for the SEBLUP model.

Additionally, in order to present further robustness checks, we also computed all estimates after selecting only those crimes that took place in the local area, and computed the Spearman's rank correlation between those and our small area estimates of crimes unknown to the police produced from all crimes. These show a very large coefficient in both cases ($\rho = 0.91,\ p < 0.001$ at the LAD level and $\rho = 0.88,\ p < 0.001$ at the MSOA level). Thus, the analytic decision of producing estimates from all crimes recorded in the CSEW, as opposed to only crimes that take place in the local area, does not have a large impact on final results.

SAE of Crimes Unknown to the Police

First, we present SAE model results to analyse the predictors of the dark figure of crime for area victimization rates. Although the main objective of SAE is to increase estimates' reliability, it provides valuable information to explain our outcome measure. Second, we map our estimates.

Explaining the dark figure of crime for area victimization rates

Table 6 shows the spatial–temporal model used to produce estimates at the LAD level across six time periods. The STEBLUP model is used to explain both the spatial and temporal variation of crimes unknown to the police, and model results do not vary across years. For instance, a large positive coefficient in one covariate indicates that areas with higher values of such variable will suffer from more crimes unknown to the police but also that years with increases in such value will tend to have a larger

TABLE 6 *STEBLUP models of crimes unknown to the police at the LAD level (standardized coefficients)*

	Beta	SE	*t*-value	*p*-value
(Intercept)	60.96	2.1	28.37	0.000
ASS income	1.558	0.8	2.04	0.031
Conurbation	0.496	1.1	0.44	0.461
Small urban	2.246	1.0	2.24	0.025
Employed (%)	−0.493	0.8	−0.58	0.459
Whites (%)	−0.374	3.3	−0.11	0.511
Asians (%)	−0.025	2.9	−0.01	0.593
Mean house price	−1.071	1.1	−0.99	0.041
Crime rate	−0.543	0.9	−0.63	0.128
Males (%)	0.514	0.8	0.64	0.517
Spatial autocorrelation	0.21			
Temporal autocorrelation	0.09			
Log likelihood	−8,171.1			
Number of areas	331			

SE, standard error.

dark figure of crime. The STEBLUP accounts for spatial ($\rho_1 = 0.21$) and temporal ($\rho_2 = 0.09$) autocorrelation parameters. Although these show relatively small scores of spatial and temporal clustering, their incorporation increases the estimates' reliability and model's explanatory capacity.

At the LAD level, three covariates show significant coefficients to explain the percentage of crimes unknown to the police. The strongest coefficient is observed for the measure of small urban areas as opposed to conurbations and rural areas. The dark figure of crime is significantly larger in small urban districts, while the measure of large conurbations shows a positive but not significant coefficient. The ASS of income has the second largest coefficient. LADs whose income is far from the average income (i.e. wealthy and deprived municipalities) have a larger percentage of crimes unknown to the police, while middle-class LADs have lower dark figures. The coefficient of mean house price shows that the percentage of crimes unknown to the police is slightly lower in expensive LADs.

Table 7 shows the results of the SEBLUP model at the MSOA level for the combined survey editions. The spatial autocorrelation parameter is $\rho_1 = 0.13$, showing that the level of spatial clustering is small.

Seven of our covariates show significant coefficients. The largest coefficient is observed for the percentage of citizens with higher/intermediate occupations: the dark figure of crime is lower in areas where more neighbours have occupations of high social grade. The second largest effect is observed for the percentage of UK-born citizens: MSOAs with more UK-born citizens have a lower dark figure. The percentages of Asians and whites in the area, as opposed to blacks and other minorities, show negative coefficients, but only the coefficient of Asians is significant. Areas with more citizens without qualifications have a larger dark figure of crime. The mean house price also shows a significant negative coefficient at the MSOA level, and the percentage of crimes unknown to the police is larger in urban neighbourhoods, which are not part of large conurbations. The ASS of income also shows a significant positive coefficient.

Table 7 *SEBLUP models of crimes unknown to the police at the MSOA level (standardized coefficients)*

	Beta	SE	*t*-value	*p*-value
(Intercept)	59.965	0.3	198.05	0.000
ASS income	1.257	0.7	1.71	0.048
Conurbation	−0.814	1.0	−0.81	0.419
Small urban	2.127	0.9	2.33	0.019
Employed (%)	−0.639	0.8	−0.81	0.420
Whites (%)	−2.747	4.4	−0.62	0.532
Asians (%)	−5.614	3.0	−1.85	0.044
Mean house price	−4.322	1.2	−3.56	0.000
Crime rate	−1.091	0.9	−1.27	0.204
Males (%)	0.616	0.7	0.84	0.401
No qualification (%)	4.453	1.7	2.63	0.008
High/int. occupations (%)	−5.989	1.9	−3.18	0.001
Born in the United Kingdom (%)	−5.666	2.4	−2.41	0.016
Workday population density	1.237	0.9	1.39	0.094
Spatial autocorrelation	0.13			
Log likelihood	−30,556.88			
Number of areas	6,657			

SE, standard error.

Mapping the dark figure of crime for area victimization rates

Figure 4 shows the wide distribution of the dark figure of crime for area victimization rates. The median percentage of crimes unknown to the police remains stable around 60 per cent, but the variation between estimates is very large. The dark figure of crime is unequally distributed across areas. The variation of the dark figure of crime is particularly large across neighbourhoods (MSOAs), which shows the need to account for crimes unknown to the police in crime mapping.

Model-based estimates of the dark figure of crime produced at the LAD level are shown in Figure 5. STEBLUP estimates are produced for 331 out of 348 municipalities, while synthetic estimates are used for areas with zero and one sample sizes. Darker shades of grey represent a larger dark figure of crime for area victimization rates, and lighter tones show lower percentages of crimes unknown to the police, according to groups defined by equal intervals. The level of spatial clustering is medium and the temporal variability is large in many districts.

Estimates show that the dark figure of crime has increased in 180 out of 348 LADs (51.7 per cent) between 2011 and 2017. Nine out of the ten most populated LADs show decreases in the dark figure of crime, with the only exception of Liverpool, where the observed percentage of crimes unknown to the police increased by 4.3 per cent between 2011 and 2017. Such reduction was very large in Sheffield (–15.0 per cent) and Bristol (–9.8 per cent). In Greater London, the dark figure of crime increased in 23 out of 33 LADs. The City of London is among the five Police Force Areas (PFAs) with the lowest dark figure of crime in four out of six years. Besides West Midlands Police, the other two largest police forces (Metropolitan Police Service and Greater Manchester Police) maintain the dark figure of crime stable around 58 per cent.

Figure 6 shows model-based estimates produced for MSOAs (groups defined by equal intervals). SEBLUP estimates are used in 6,657 of the 7,201 MSOAs, while synthetic estimates are used in areas with zero or one sample sizes. On average, the PFAs with the

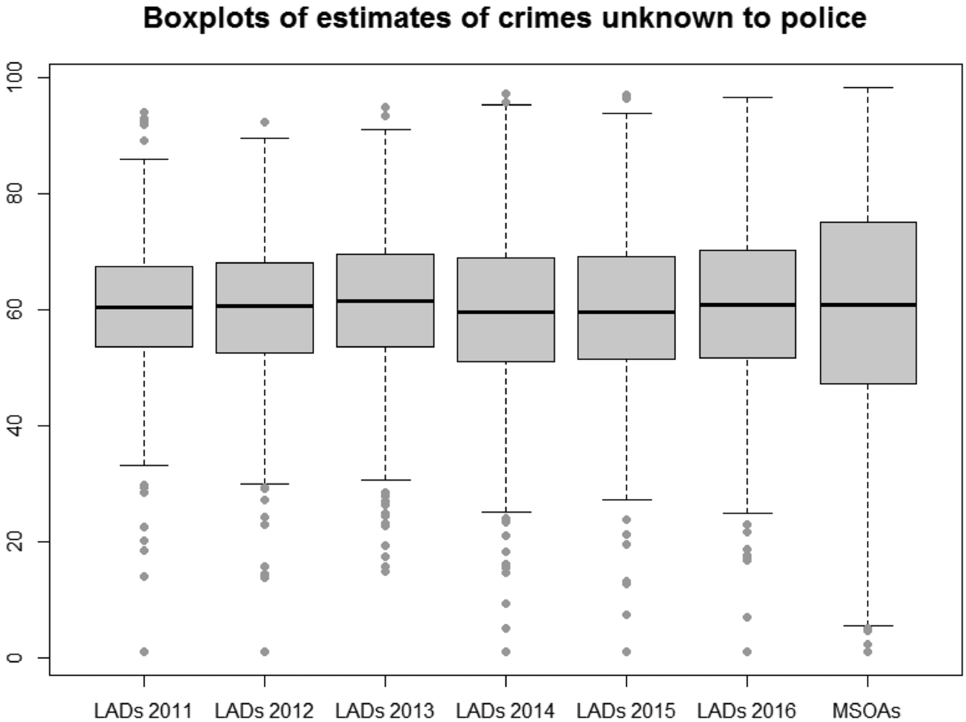

FIGURE 4. Boxplots of model-based estimates of crimes unknown to the police.

largest dark figure of crime are Sussex, Staffordshire and Hertfordshire. The PFAs with the lowest dark figures of crime are the City of London (where the police know 50 per cent of crimes), Cumbria and West Yorkshire. In Greater London, 441 of 982 MSOAs show dark figures of crime larger than 65 per cent.

Discussion and Conclusions

This research presents the first map of the dark figure of crime (for area victimization rates) in the United Kingdom and illustrates with estimates which areas may require further efforts to increase the police effectiveness to register offences. The main conclusion is that the dark figure of crime varies across neighbourhoods. Crime maps produced solely from police records may not show a valid visualization of the geography of crime, and these may be complemented by producing survey-based small area estimates of the dark figure of crime. Police records and survey-based estimates may be used as complementary sources of data to obtain more reliable representations of the geography of crime.

Moreover, although the main objective of SAE is to produce reliable estimates, our models provide a significant set of information for advancing the understanding of the dark figure of crime. At the local level, the main predictor of the dark figure of crime is the measure of small urban areas as opposed to large conurbations and rural areas. This variable is also significant at the MSOA scale, showing that the dark figure of crime is

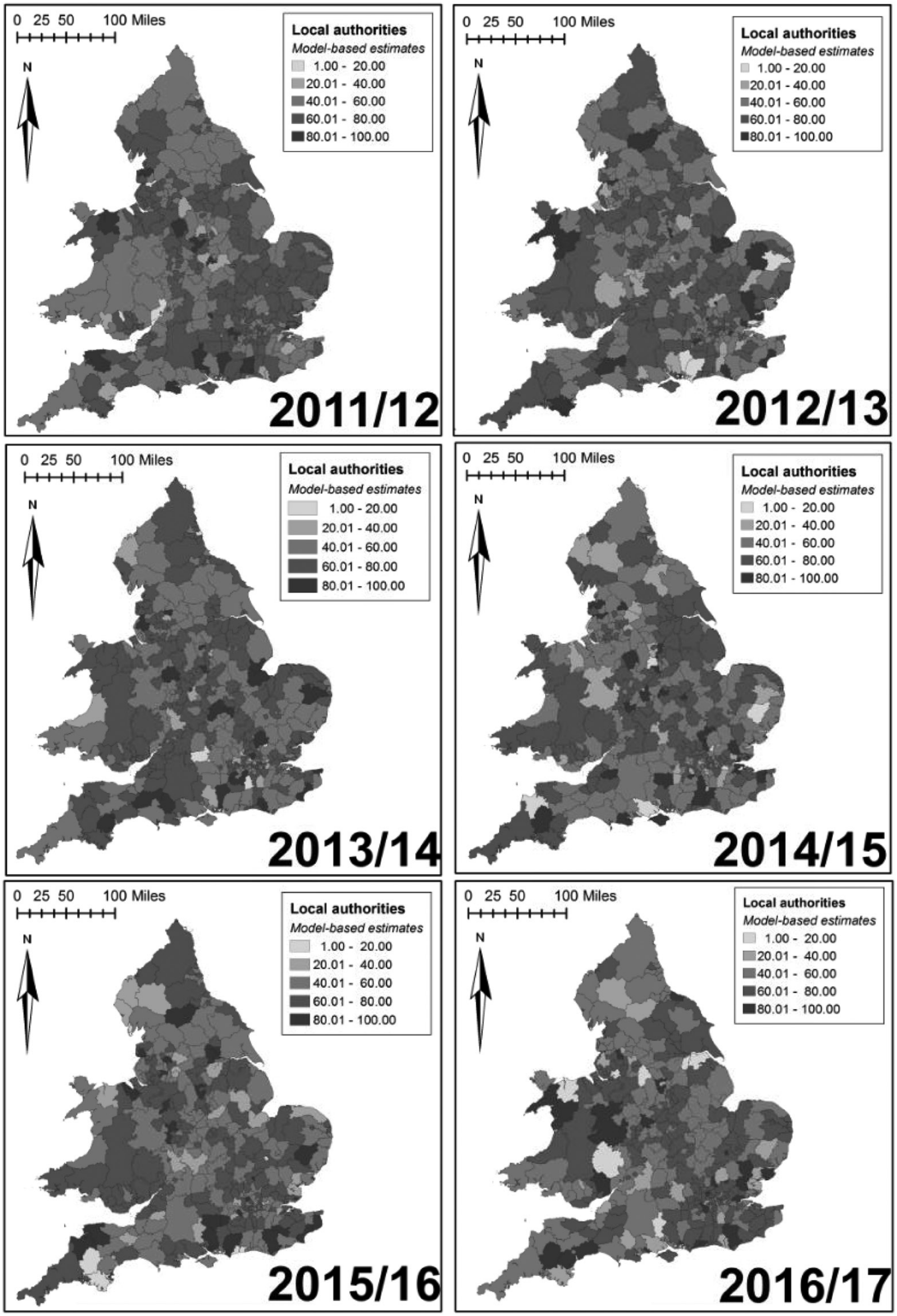

FIGURE 5. Model-based estimates of crimes unknown to the police at the LAD level.

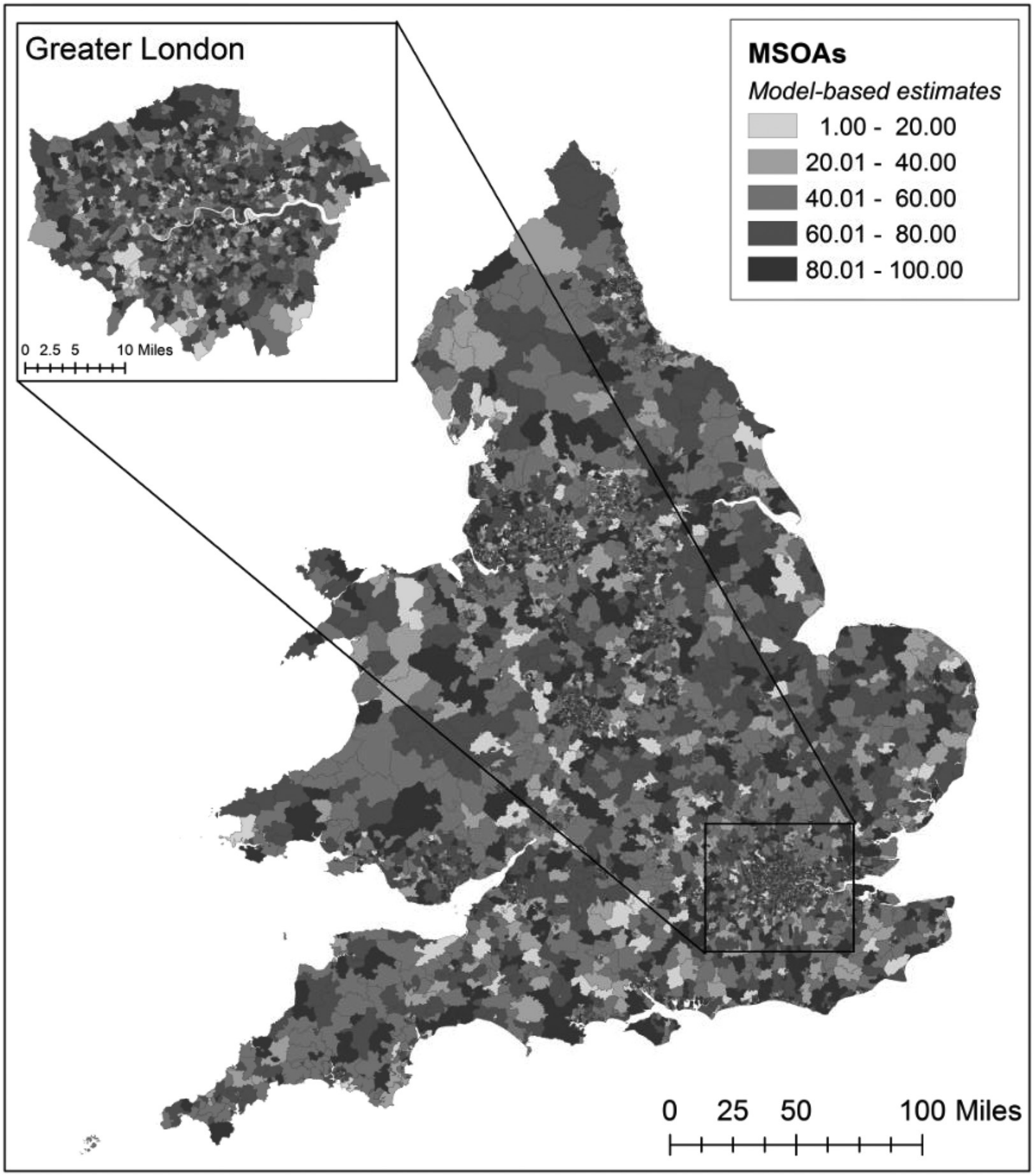

FIGURE 6. Model-based estimates of crimes unknown to the police at the MSOA level (2011–17).

larger in suburban neighbourhoods outside the main conurbations. This adds evidence to previous research (Hart and Rennison 2003; Langton *et al.* 2012). Data from the UK Community Life Survey 2016–17 show that citizens from small urban areas tend to live in those places less time than residents from rural areas and conurbations, and feelings of belonging and social harmony are the lowest in small urban areas (Department of Culture, Media and Sport 2017). One might expect that residents from areas with a low sense of community do less to maintain the security in places where they do not feel they belong (Goudriaan *et al.* 2006; Jackson *et al.* 2013). In other words, 'sense of community is expected to thrive in a socially cohesive context whereby residents would be willing to engage in activities to improve their community and to prevent crime' (Aiyer *et al.* 2015: 141). The decision to report crimes to the police (especially minor offences) tends to be driven by the residents' will to do something to keep their area safe rather than a hope or need for restoration of harm (Hart and Rennison 2003; Tarling and Morris 2010). The dark figure of crime in small urban areas may be mediated by the low perception of social harmony and feeling of belonging in those areas.

The ASS of income also explains the dark figure at the local level. Both wealthy and deprived districts suffer from more crimes unknown to the police, while crimes suffered by residents from medium-class LADs are more likely to be known to the police. Baumer (2002) showed that the relationship between the area's wealth and crime reporting is curvilinear. He argued that this is explained by the area's social cohesion, which would be larger in wealthy and deprived communities than middle-class areas and would allow residents to cope with victimization by alternative non-police ways (Black 2010). Nevertheless, research conducted in the United Kingdom and the Netherlands shows that cohesive communities tend to cooperate more with the police (Goudriaan *et al.* 2006; Jackson *et al.* 2013). Moreover, complementary analyses conducted from the CSEW 2016–17 show that the main reason for not reporting to the police among residents living in the 20 per cent most deprived neighbourhoods is the low confidence in police work (41.7 per cent believe that the police would do nothing, would not be bothered or would not be interested). Instead, the most common reason for not reporting in the 30 per cent least deprived areas is that crimes are trivial or not worth reporting (answered by 28.7 per cent who did not report). The proportion of crimes dealt by victims themselves or by other authorities is very small in both cases (smaller than 9 per cent). Therefore, while the large dark figure of crime in deprived areas is likely affected by low levels of confidence in policing (Jackson *et al.* 2013; Xie 2014), many minor crimes in wealthy areas are unreported due to their small effect on victims' lives. The mean house price also shows a negative significant relationship with the dark figure, which shows that residents from more expensive areas cooperate more with police services.

At the MSOA level, the measures of small urban areas, ASS of income and mean house price remain significant and show the same directionality, but the covariates with the major explanatory capacity are the percentage of citizens with higher/intermediate occupations, born in the United Kingdom, Asians, and without any qualification. The dark figure is smaller in areas where citizens have a higher social grade. Neighbourhoods with larger proportions of citizens with high occupations are typically expensive areas, where previous research had shown that the sense of community is larger (Stewart *et al.* 2009). Thus, residents living in high social grade areas are likely to develop proactive roles to maintain their areas safe. Xie and Baumer (2019) found that crime reporting rates are lower in neighbourhoods with a large proportion of immigrants. Our research shows that areas with larger percentages of whites and Asians, as opposed to blacks and other ethnic groups, have lower dark figures of crime, although only the proportion of Asians is significant. In the United Kingdom, Asian communities have the highest level of sense of belonging to their neighbourhoods, followed by white citizens (Department of Culture, Media and Sport 2017). Asian communities may develop more active contributions to their neighbourhoods' safety. Contrarily, other ethnic groups tend to show lower values of sense of community (Department of Culture, Media and Sport 2017) and have lower values of trust in the police (data from CSEW 2016–17). Further research should analyse the impact of perceptions about police services on different communities, as well as the composite effect of the ethnic concentration and income deprivation, since certain minorities are overrepresented in deprived areas (Xie and Lauritsen 2012; Jackson *et al.* 2013). Uneducated citizens are also overrepresented in deprived areas.

There are significant limitations to our results that need to be considered and accounted for in future research in order to offer more reliable estimates of crime:

(1) It would be more appropriate to produce estimates of the dark figure of each crime type (as opposed to aggregating crime types), but we would encounter a zero-inflated data set that requires different types of SAE methods that are still to be investigated.
(2) Our estimates produced at the MSOA level suffer from low reliability in some areas.
(3) Crime surveys have their own methodological issues and measurement error may arise from victims' non-recall, overestimation or underestimation of situations. Moreover, no information is recorded about so-called victimless crimes (drug-related offences and corporate crimes) and homicides.
(4) Our estimates show crimes unknown to the police for area victimization rates rather than area offence rates. This last limitation might complicate efforts to combine estimates of the dark figure and police records, but it can be mitigated in future research by selecting crimes that took place in the local area and applying methods to deal with zero-inflated data.

Acknowledgements

Survey data used for this research have been provided by the UK Data Service under project ID 108913; SN 7280. Data on modelled ethnicity proportions and population churn have been provided by the Consumer Data Research Centre, an ESRC Data Investment, under project ID CDRC 260, ES/L011840/1; ES/L011891/1.

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