SMALL AREA ESTIMATION IN CRIMINOLOGICAL RESEARCH

Theory, methods, and applications

A thesis submitted to the University of Manchester for the degree of Doctor of Philosophy in Criminology in the Faculty of Humanities

2019

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Word count – 54,481 words (excluding bibliography, table of contents and initial pages)

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ABSTRACT

Criminological research is moving towards the study of small geographic areas. Crime and crime perceptions are influenced by environmental features and contextual conditions that are more common in some places than others, and therefore these are unequally distributed in space. By visualising criminological phenomena with maps at small area level, researchers are able to examine their immediate environmental explanations, and police forces can design targeted strategies to reduce crime and increase public safety. The two main sources of data for mapping crime are police records and surveys, and crime perceptions are mainly recorded by surveys. Although police-recorded crimes can be used for crime mapping, these suffer from a high risk of bias arising from victims' underreporting. Victimisation surveys record information about unreported crimes, fear of crime and attitudes towards policing. However, surveys tend to be designed to record representative samples for large geographies, and small areas suffer from small sample sizes. Small samples do not allow for direct estimates of adequate precision. In order to produce reliable small area estimates of survey-recorded crime and perceptions about crime, small area estimation techniques introduce models to borrow strength across related areas. Small area estimators can incorporate spatially and temporally correlated random effects to increase the estimates' reliability. The primary goal of this thesis is to bridge the gap between criminology and small area estimation, by providing a framework of theory, simulation experiments and applications for the use of small area estimation in criminological research. This is an alternative format thesis (by publications) including four papers framed between an introduction, literature review and conclusions.

The first chapters present a discussion about the move in criminology towards the study of micro places, as well as an introduction to the small area estimation methods used in this dissertation (i.e. Empirical Best Linear Unbiased Predictor (EBLUP) based on Fay-Herriot model, Spatial EBLUP (SEBLUP), Rao-Yu model and Spatial-temporal EBLUP). The first paper provides a simulational assessment of the SEBLUP under different scenarios of number of areas and spatial autocorrelation, and produces estimates of confidence in policing at a ward level in London. The second paper produces estimates of worry about crime –burglary and violence– at a regional level in Europe and examines its predictors. The third paper produces estimates of perceived neighbourhood disorder in Manchester. The fourth paper presents estimates of crimes unknown to police –a measure of dark figure of crime– at neighbourhood and local level in England and Wales.

Substantive and methodological theory and exemplar studies are integrated to show the utility of applying small area estimation to analyse some topics of interest in criminology. By expanding the body of research using small area estimation in criminological research, these methods may become a core tool for crime analysts and geographic criminologists.

DECLARATION

No portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

COPYRIGHT STATEMENT

DEDICATION

To my grandparents:
[*Pels meus avis*]:

Aurora Gil Teodoro
Celestina Guirado Díaz
José María Buil Toledo
Segundo Gil Gómez

ACKNOWLEDGMENTS

Some would describe the PhD as a three-year mud run in which you are expected to learn all skills needed to survive a forthcoming lifelong obstacle race: the academic career. This mud run, however, would be uncompleted without the support along the way of my supervisors, colleagues, family and friends.

First, I would like to express my deepest gratitude to my supervisors, Juanjo Medina and Natalie Shlomo. I am aware of how fortunate I have been to be guided by such experienced and competent supervisors. For three years, I have experienced every supervision meeting as a unique –and challenging– opportunity to engage with and learn from two world-leading experts in the main areas of my dissertation: quantitative criminology and small area estimation. I also want to thank my examiners, Jonathan Jackson and Simon Peters, for their support and advice.

I am very thankful to Emily Buehler and Angelo Moretti for their continuous help and motivation when conducting my research, and to Jackie Boardman and the PGR Office for their commitment to support doctoral students and foster a welcoming environment in the School of Social Sciences. I owe my gratitude to my colleagues in Williamson Building for being always supportive and friendly: Reka Solymosi, Jon Davies, Elizabeth Cook, Sebastian Acevedo, William Floodgate, Max Dyck and Elena Zharikova, among many others. I have also greatly benefited from the support provided by my colleagues in the Spanish Society of Criminological Research: Fernando Miró, José E. Medina, Francisco J. Castro, Nuria Rodríguez, Asier Moneva, Ana B. Gómez, Francesc Guillén and Jose Pina – to mention a few of them.

I want to thank my friends and family for their love and caring, especially my mum, dad and sister. My grandparents and my uncles have always been a fundamental pillar at all moments in my life. I am eternally grateful to my friends in my home town, Rubí (Barcelona), for their affection without expecting anything in return: Eric, Carlos, Sergio, Carlos, Cristina, Esther and others.

Last but not least, I owe the greatest gratitude to Yongyu. Thank you for being my friend, colleague, partner of adventures and companion, but above all thank you for your love. You are awesome.

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LIST OF ABBREVIATIONS

AIC	Akaike Information Criterion
AR	Autoregressive
ARB	Absolute Relative Bias
ARE	Absolute Relative Error
ASS	Absolute Standard Score
BCS	British Crime Survey
BIC	Bayesian Information Criterion
BJS	Bureau of Justice Statistics
BLUP	Best Linear Unbiased Predictor
BME	Black and Minority Ethnic
cAIC	Conditional Akaike Information Criterion
CAPI	Computer Assisted Personal Interviewing
CASI	Computer Assisted Self Interviewing
CDRC	Consumer Data Research Centre
CFA	Confirmatory Factor Analysis
CO	Combinational Optimisation
CPTED	Crime Prevention Through Environmental Design
CSEW	Crime Survey for England and Wales
CV	Coefficient of Variation
EB	Empirical Bayes
EBLUP	Empirical Best Linear Unbiased Predictor
EIMD	English Index of Multiple Deprivation
ESPC	Catalan Crime Victimisation Survey
ESRC	Economic and Social Research Council
ESS	European Social Survey
EUROSTAT	European Union Open Data Portal
EVAMB	Barcelona Metropolitan Area Victimisation Survey
FH	Fay-Herriot model
GMP	Greater Manchester Police
GREGWT	Generalised Regression Reweighting
HB	Hierarchical Bayes
HMICFRS	Her Majesty's Inspectorate of Constabulary and Fire & Rescue Services
HT	Horvitz-Thompson estimator
ICVS	International Crime Victims Survey
IERMB	Barcelona Institute of Regional and Metropolitan Studies

IPF	Iterative Proportional Fitting
LAD	Local Authority District
ML	Maximum Likelihood
MOPAC	Mayor's Office for Policing and Crime
MPSPAS	Metropolitan Police Service Public Attitudes Survey
MRTS	Manchester Resident Telephone Survey
MSE	Mean Squared Error
MSOA	Middle Super Output Area
MTMM	Multitrait-Multimethod Matrix
NCVS	National Crime Victimization Survey
NUTS	Nomenclature of Territorial Units for Statistics
OA	Output Area
ONS	Office for National Statistics
PAF	Postcode Address File
PFA	Police Force Area
RD	Relative Difference
REML	Restricted Maximum Likelihood
RMSE	Root Mean Squared Error
RMSEA	Root Mean Squared Error of Approximation
RMSR	Root Mean Squared of the Residuals
RRMSE	Relative Root Mean Squared Error
SAE	Small Area Estimation
SAR	Simultaneous Autoregressive process
SBLUP	Spatial Best Linear Unbiased Predictor
SE	Standard Error
SEBLUP	Spatial Empirical Best Linear Unbiased Predictor
SRSWR	Simple Random Sampling With Replacement
SSO	Systematic Social Observation
STEBLUP	Spatial-temporal Empirical Best Linear Unbiased Predictor
TLI	Tucker-Lewis Index
UK	United Kingdom
UNODC	United Nations Office on Drugs and Crime
US	United States

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CHAPTER 1 - Introduction

Criminological research and evidence-based criminal policy are progressively drifting towards the study of small geographic areas to explain and develop strategies to tackle crime and disorder, reduce public worries about crime, and improve perceptions about the criminal justice system. Crime is known to be concentrated in micro places (Weisburd et al., 2012; Weisburd, 2015), emotional responses to fear of crime tend to arise from environmental cues (Doran and Burgess, 2012; Solymosi et al., 2015), and public perceptions about police work vary between small geographic areas and are associated to neighbourhood conditions (Bradford, 2014; Jackson et al., 2013). These are not only topics of major interest for contemporary criminological research, but also have very large effects on local communities and citizens' well-being. Precise maps of their distribution at small geographical scales are thus needed to allow for better theoretical explanations and more efficient evidence-based policies. However, crime maps produced solely from police-recorded offences are incomplete and crimes known to police are likely to be affected by selection biases and measurement errors (O'Brien, 1996). Victimisation surveys provide essential information to account for crimes unknown to police (Skogan, 1977) and are the main source of data to analyse emotions about crime and perceptions about policing. Nevertheless, samples recorded by available surveys are not large enough to allow for direct estimates of adequate precision at small geographical levels. Refined model-based small area estimation techniques (henceforth, SAE) may be used to increase the reliability of small area estimates of parameters of criminological interest produced from survey data.

The next paragraphs present the motivation for conducting spatial analyses of crimes (known and unknown to police), emotions about crime and perceptions about police work at low geographical scales, as well as an introduction to the limitations of available datasets for producing valid maps at small area level. The use of SAE is then introduced as a potential solution to allow for reliable small area estimates of many parameters of criminological interest.

In the second half of the 1980s, several researchers focused their attention on examining the geographic concentration of crime. In 1988, Pierce et al. (1988) found that only 2.6% of addresses in the city of Boston produced 50% of all crime calls to police services. One year later, Sherman et al. (1989) published the results of a similar study conducted in Minneapolis with almost identical conclusions: 3.5% of all addresses produced 50% of the annual crime calls to the police. Since then, multiple researchers have looked at the spatial concentration of crime in places and found similar results. In 2004, Weisburd et al. (2004) looked into the geographical distribution of crime statistics in Seattle over short periods of time between 1989 and 2002, and concluded that micro places with high concentrations of crime are stable over time. In this context, 'micro places' refer to microgeographic units of analysis such as addresses, street segments or clusters of these units (Weisburd et al., 2009). Thus, some argue that today there is enough evidence to state that there is a law of crime concentration in places: "for a defined measure of crime at a specific microgeographic unit, the concentration of crime will fall within a narrow bandwidth of percentages for a defined cumulative proportion of crime" (Weisburd, 2015:138). Moreover, intelligence-led policing strategies that focus their actions on places with high concentrations of crimes tend to be successful in cutting down crime and antisocial behaviour (Braga et al., 2012, 2014; Weisburd, 2018).

In order to map crime rates at a detailed geographical scale and examine their micro-level distribution patterns, police-recorded crimes are the most used source of data. While police records allow for advanced statistical analyses and are used to design targeted evidence-based urban policies, police-recorded crimes are known to suffer from missing data and the 'dark figure of crime' is likely to be larger in some areas than others (Brantingham, 2018; Maltz and Targonski, 2003; O'Brien, 1996; Xie and Baumer, 2019). The 'dark figure of crime' refers to all crimes not registered in the statistics of whatever agency is the source of the data being used (Biderman and Reiss, 1967). Cross-national comparisons of police statistics are conditioned by counting rules defined by legal, substantive and statistical factors that affect each country in a different way (Aebi, 2010; Kitsuse and Cicourel, 1963). At a lower level, victims from suburban areas are less likely to report crimes to police than urban and rural residents (Hart and Rennison, 2003; Langton et al., 2012), and the neighbourhood conditions such as economic disadvantage, concentration of immigrants, crime rates and social cohesion may affect the victims' crime reporting rates in some neighbourhoods more than others (Baumer, 2002; Berg et al., 2013; Goudriaan et al., 2006; Xie and Baumer, 2019). Therefore, novel statistical techniques are needed to account for crimes unknown to police in order to develop micro-level crime maps of increased precision. Surveys provide essential information to investigate crimes known and unknown to police and may be used to produce maps of crime with increased validity.

The emotional reactions of fear and worry about crime are affected by the characteristics of the immediate environment and the conditions of local areas, and therefore these are more common in some areas than others. Fear of crime episodes are more frequent under certain situational and social organisation circumstances (Castro-Toledo et al., 2017), and this is the reason why Solymosi et al. (2015) argue that there is a need to "consider fear of crime events at the smallest possible scale to be able to un-erroneously associate them spatially with elements of the environment" (Solymosi et al., 2015:198). Certain community characteristics and social processes, such as neighbourhood disorder, residential instability and racial composition, are used to explain the unequal geographical distribution of worry about crime at a neighbourhood level (Brunton-Smith et al., 2014; Brunton-Smith and Jackson, 2012; Brunton-Smith and Sturgis, 2011). At a larger geographical scale, there is a large amount of evidence about the effect of the countries' social and economic issues on the citizens' anxiety-producing concerns about crime (Hummelsheim et al., 2011; Vauclair and Bratanova, 2017; Vieno et al., 2013; Visser et al., 2013). However, these macro-level conditions are known to vary also between the regions in each country and thus are likely to be reflected unequally in the regional distribution of emotions about crime. Maps of fear and worry about crime at a neighbourhood and regional level are needed to better understand their explanatory mechanisms at the different scales and design targeted policies for their reduction.

Similarly, perceptions about police work are influenced by neighbourhood conditions that affect some communities more than others (Jackson et al., 2013; Sampson and Bartusch, 1998). As a result, public perceptions about policing vary between neighbourhoods and small areas (Williams et al., 2019). Some neighbourhood conditions that have been used to explain the distribution of the citizens' perceptions about police services are the economic deprivation, unemployment, residential mobility and concentration of minorities (Bradford et al., 2017; Dai and Johnson, 2009; Jackson et al., 2013; Kwak and McNeeley, 2017; Sampson and Bartusch, 1998; Wu et al., 2009). Improving the public perceptions about police forces in geographic areas is needed to encourage citizens to cooperate with police services and to enhance the residents' sense of belonging in local areas (Loader, 2006). This is the reason why government inspections into police forces assess the efforts made by the police to increase its public confidence and legitimacy (HMICFRS, 2017).

Crime-related perceptions and emotions (i.e. worry about crime, perceptions of disorder, perceptions about police services and related constructs) are mainly recorded by social and victimisation surveys, such as the Crime Survey for England and Wales (CSEW) and the National Crime Victimization Survey (NCVS) in the US. Surveys are also needed to account for the dark figure of crime when producing crime maps. However, victimisation surveys are usually designed to allow for precise direct estimates of target parameters only for large geographical scales (e.g. states, regions, counties), while small geographic areas are unplanned domains and suffer from small (and zero) sample sizes that do not allow producing direct estimates of adequate precision. In this context, 'unplanned domains' refer to areas that were not identified at the sampling design stage (i.e. areas in which sample sizes cannot be controlled and where direct estimates are likely to be imprecise).

Model-based SAE techniques may be used in criminological research to produce reliable small area estimates of crime rates, emotions about crime and perceptions about the police, among other variables of criminological interest. SAE is the term used to refer to those techniques designed to produce reliable estimates of characteristics of interest (e.g. means, totals) for areas or domains for which only small or no samples are available (Pfeffermann, 2013; Rao and Molina, 2015). SAE may be of great value for the study of small areas in criminological research: to estimate the geographical distribution of crimes known and unknown to police and to produce detailed maps of crime-related perceptions and emotions. This is the reason why, in 2008, the US Panel to Review the Programs of the Bureau of Justice Statistics (BJS) recommended the use of model-based SAE to produce subnational estimates of crime rates: "BJS should investigate the use of modelling NCVS data to construct and disseminate subnational estimates of crime and victimization rates"

(Groves and Cork, 2008:8). This work was started by Robert E. Fay and colleagues at the BJS to produce estimates of victimisation rates for states and large counties in the US (Fay and Diallo, 2012, 2015a; Fay and Li, 2011; Fay et al., 2013). The need for the incorporation of SAE to increase the reliability of subnational crime estimates has also been acknowledged by other governmental agencies for official statistics, such as the Australian Bureau of Statistics (Tanton et al., 2001), Statistics Netherlands (Buelens and Benschop, 2009) and the Italian National Institute of Statistics (D'Alò et al., 2012). In the UK, the Government Statistical Service and the Office for National Statistics (ONS) have incorporated the use of SAE to produce estimates of income, health, housing affordability, unemployment and deprivation, but −to the extent of my knowledge− these agencies have not yet applied model-based SAE to criminological data.

Although SAE techniques have shown to be a very valuable tool to map social issues recorded by surveys, such as poverty and unemployment (e.g. Molina and Rao, 2010; Moretti, 2018; Pratesi, 2016), and there is a clear need for their use in criminology, there has not been yet a detailed, unified examination of their applicability to analyse criminological data. Moreover, SAE techniques have been rarely applied in criminological research, and these may provide essential information to develop theoretical explanations of the effect of space on crime and crime perceptions. This doctoral dissertation aims to bridge this gap between criminological research and SAE techniques, by providing a novel framework of theory, simulation experiments and applications for the use of SAE to examine social phenomena of criminological interest. If proven valuable, SAE techniques may turn into a common methodology in criminological research and become a core tool to design intelligence-led criminal policy and policing strategies.

The main area-level SAE techniques will be examined, such as the Empirical Best Linear Unbiased Predictor (EBLUP) based on the Fay-Herriot (FH) model (Fay and Herriot, 1979) and the temporal Rao-Yu estimator (Rao and Yu, 1994). However, this thesis will particularly focus on introducing, evaluating and applying those SAE techniques that account for the implicit spatial dimension and the typically high spatial autocorrelation of criminological phenomena (Petrucci et al., 2005). The spatial autocorrelation parameter measures the correlation of a variable with itself across neighbouring areas. Therefore, a large spatial autocorrelation means that spatially neighbouring areas have similar values (i.e. high values of a variable in one area are surrounded by high values, and low values are surrounded by low values), while a spatial autocorrelation parameter close to zero represents a spatially random phenomenon. Many social issues of interest for criminological research are known to be geographically aggregated and neighbouring areas tend to have more similar values than non-contiguous geographies (Elffers, 2003; Townsley, 2009). This is typically the case of crime rates (Anselin et al., 2000; Baller et al., 2001), emotions about crime (Brunton-Smith and Jackson, 2012) and signs of neighbourhood disorder (Mooney et al., 2018), amongst others. A new wave of SAE techniques incorporate the spatial autocorrelation parameter into SAE methods, and these methods have shown to improve the small area estimates' reliability when the variable's spatial autocorrelation parameter is medium or high, as tends to be the case in criminological studies. Particular attention will be given to the Spatial EBLUP (SEBLUP; Pratesi and Salvati, 2008; Salvati, 2004) and the Spatial-temporal EBLUP (STEBLUP; Marhuenda et al., 2013), which have shown promising results in applied studies looking into the geographical distribution of poverty and unemployment.

Thus, this thesis aims at investigating into the following questions:

RQ1: To what extent can existing SAE techniques be used for producing valid maps of criminological parameters?

RQ2: To what extent are SAE techniques that incorporate the spatial autocorrelation parameter preferred to produce estimates of criminological data?

RQ3: Which topics of criminological interest may be analysed by using existing SAE techniques?

RQ4: To what extent can existing SAE techniques be used for advancing theoretical explanations of criminological parameters?

1.1 Chapter summary

Following this introduction, Chapter 2 presents an in-depth discussion about the need for mapping criminological phenomena at small geographical scales, and reviews the main opportunities and limitations for producing micro-level maps of variables of criminological interest from available data sources (mainly police statistics and sample surveys). The sampling designs of the social and victimisation surveys used in this thesis are then presented to motivate the use of SAE in criminology.

Then, Chapter 3 presents the main SAE techniques used in this dissertation and discusses previous applications of SAE to estimate parameters of interest for criminological research.

Four substantive areas of criminological interest in which the use of SAE may be beneficial are identified, and the following chapters present four case studies shaped as research papers. More specifically, SAE is used to produce small area estimates of confidence in police work, worry about crime, perceived neighbourhood disorder and the dark figure of crime. Each paper presents its substantive literature review, research questions or hypotheses, data and methods, discussion and conclusions. Chapter 4 discusses the outline of papers, and presents their abstracts and a detailed explanation of the original contribution of the doctoral candidate to each article.

Chapter 5 presents the first paper, which is titled *"Applying the Spatial EBLUP to place-based policing. Simulation study and application to confidence in police work"*. This article has been accepted for publication, pending minor corrections, in *Applied Spatial Analysis and Policy*. Although different studies have analysed the performance of the main SAE techniques under different spatial conditions, there is a lack of evidence about the combined effect of the number of areas under study and the spatial autocorrelation parameter on the SEBLUP's relative performance. Given that this method has a large potential to analyse confidence in police work and other variables of criminological interest, and both the number of areas and the spatial autocorrelation tend to have large effects on model-based estimates, a simulation assessment is considered necessary to gain evidence about this technique. Therefore, a simulation study is designed to assess the performance of the SEBLUP, in terms of the bias and Mean Squared Error (MSE), under different scenarios of number of areas and spatial autocorrelation. Further, the first application of the SEBLUP to criminological data is presented. Small area estimates of confidence in police work are produced at a ward level in Greater London to show the applicability of this method for designing place-based policing interventions.

Data from the Metropolitan Police Service Public Attitudes Survey (MPSPAS) 2012 are used in this paper.

The second paper, which is titled *"Worry about crime in Europe: A model-based small area estimation from the European Social Survey"* (published in *European Journal of Criminology*), is presented in Chapter 6. This paper applies the SEBLUP to produce estimates of worry about burglary at home and worry about violent crime at a regional level in Europe from European Social Survey (ESS) 5 (2010/2011) data. A map of the regional distribution of worry about crime in Europe is presented, and the social and economic conditions that explain the regional levels of worry about crime are examined. This study shows the potential of the SEBLUP to study and produce maps of emotions about crime. It also shows that SAE may be used to produce estimates at large spatial scales when sample sizes are not large enough to produce precise direct estimates.

Chapter 7 presents the third case study, which is titled *"The geographies of perceived neighbourhood disorder. A small area estimation approach"* and has been published in *Applied Geography*. In this case, the SEBLUP is used to produce small area estimates of a latent score of perceived neighbourhood disorder in the City of Manchester. Data from the Manchester Resident Telephone Survey (MRTS) 2012 are used. This paper examines the geographical distribution of perceived neighbourhood disorder in Manchester and analyses the neighbourhood conditions that affect its distribution. Moreover, this is one of the first studies that combine latent factor models and SAE techniques, and thus a novel bootstrap method is proposed and used to evaluate the small area estimates' reliability.

The fourth and last paper is presented in Chapter 8. This paper is titled *"The measurement of the dark figure of crime in geographic areas. Small area estimation based on the Crime Survey for England and Wales"* and has been submitted for review to *Criminology* journal. This paper produces small area estimates of the percentage of crimes unknown to police at a local and neighbourhood level in England and Wales based on data recorded by the CSEW. These estimates may be used in future research to produce reliable crime maps accounting for the dark figure of crime. Different SAE techniques are applied and the most reliable estimates are used to produce the first map of the dark figure of crime in the United Kingdom and elsewhere. Area-level SEBLUP, Rao-Yu and STEBLUP techniques are examined.

The social conditions that explain the dark figure of crime at the different scales (i.e. neighbourhoods and local authorities) are also discussed.

Finally, Chapter 9 presents final conclusions about the use of SAE for advancing criminological research and designing evidence-informed criminal policies and policing strategies. The final chapter also presents the limitations of this dissertation and areas for future research.

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CHAPTER 2 - Small area estimation in criminological research: Motivation

2.1 Introduction

The motivation for the use of SAE in criminological research has been briefly presented in Chapter 1 and it has also been highlighted in previous governmental reports (e.g. Groves and Cork, 2008) and research papers. Moreover, there have been a few isolated applications of SAE techniques to produce maps of crime and other criminological phenomena (e.g. Fay and Diallo, 2012; van den Brakel and Buelens, 2014). This chapter, in Section 2.2, discusses in greater depth the move in criminological research and evidence-based policing towards the study of small geographic areas. A literature review examines the transition from analysing large geographies to micro places in geographic criminology. Moreover, it presents a brief review about the issue of spatial scaling in criminological research and discusses the extent to which the spatial units being investigated may affect the theoretical processes associated to the topic of interest. Then, the main methodological limitations encountered for producing maps of criminological phenomena at small area level are presented in Section 2.3. Direct estimation techniques struggle to produce valid micro-level maps of survey-recorded criminological phenomena, such as crimes unknown to police, confidence in police work, worry about crime and perceived neighbourhood disorder. This is due to the small samples recorded by surveys at small spatial scales. Available sample surveys tend to be designed to allow for reliable direct estimates only for large geographies, while small areas are unplanned domains and suffer from small and even zero sample sizes. The limitations for using the main victimisation surveys for crime mapping are then discussed in Section 2.4. These limitations are discussed in order to make a strong case for the introduction of SAE in criminological research, which is briefly summarised in Section 2.5.

Thus, this chapter has three central aims:

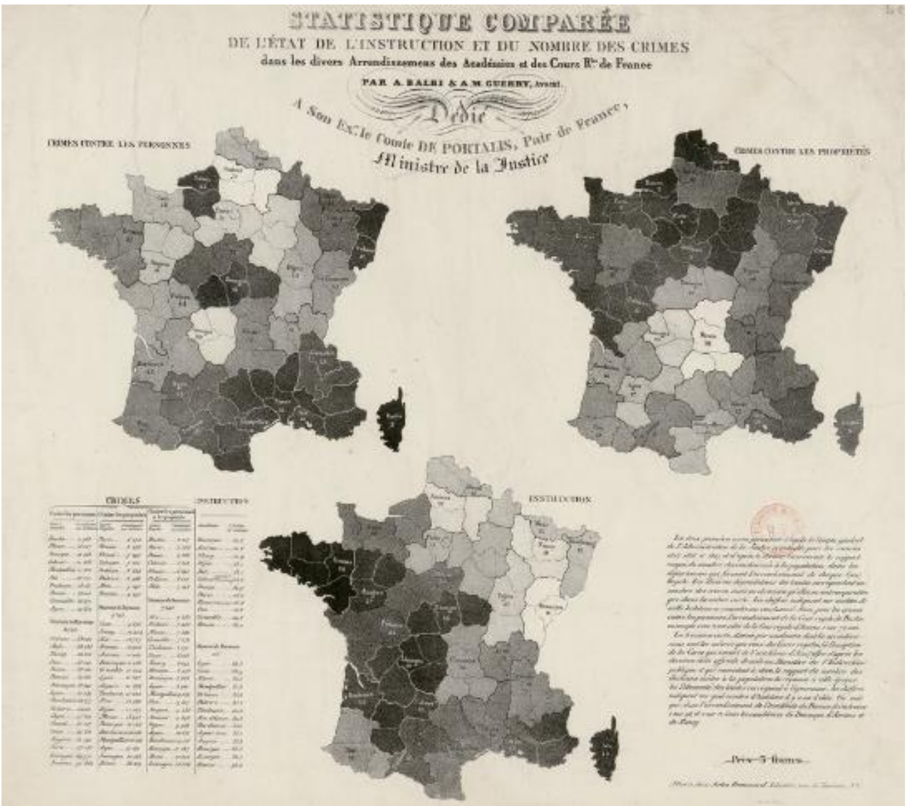
1. Discussing the need for mapping criminological phenomena at small area level.

2. Presenting the main limitations of available datasets (i.e. police records and surveys) for mapping criminological phenomena at small area level.
3. Motivating the use of SAE in criminological research.

2.2 Geographic criminology and the criminology of place

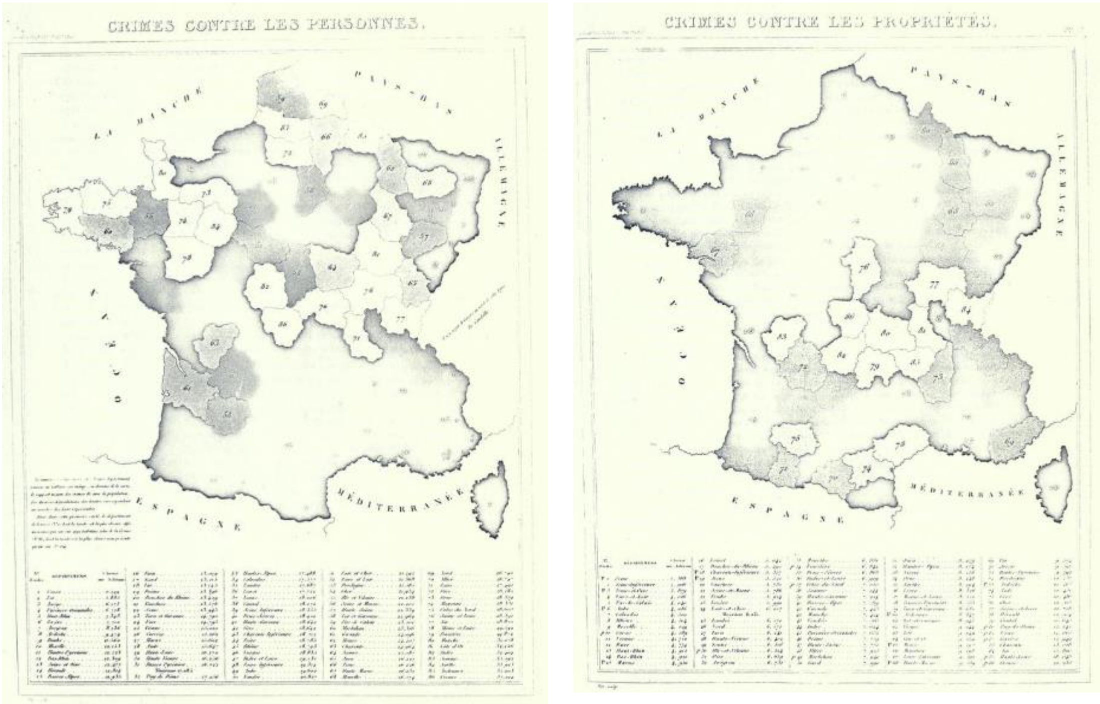
For centuries, criminological research has focused its primary attention on individuals to analyse why offenders become involved in criminal activities (Agnew, 1992; Cohen, 1955; Gottfredson and Hirschi, 1990; Hirschi, 1969; Lemert, 1967; Merton, 1938; Sutherland, 1947; Sykes and Matza, 1957). However, criminology has also been interested in the geographical distribution of crimes and the explanation about why crime rates are higher in some places than others. In the 19th Century, after the publication of the first crime statistics in France, Balbi and Guerry (1829), and then Guerry (1833), produced the first maps of crime rates at large spatial scales (see Figure 2.1 and Figure 2.2). These authors argued that regional differences in crime rates were partly explained by education levels.

Figure 2.1 Maps of personal crimes, property crimes and instructions in France (1825-1827).



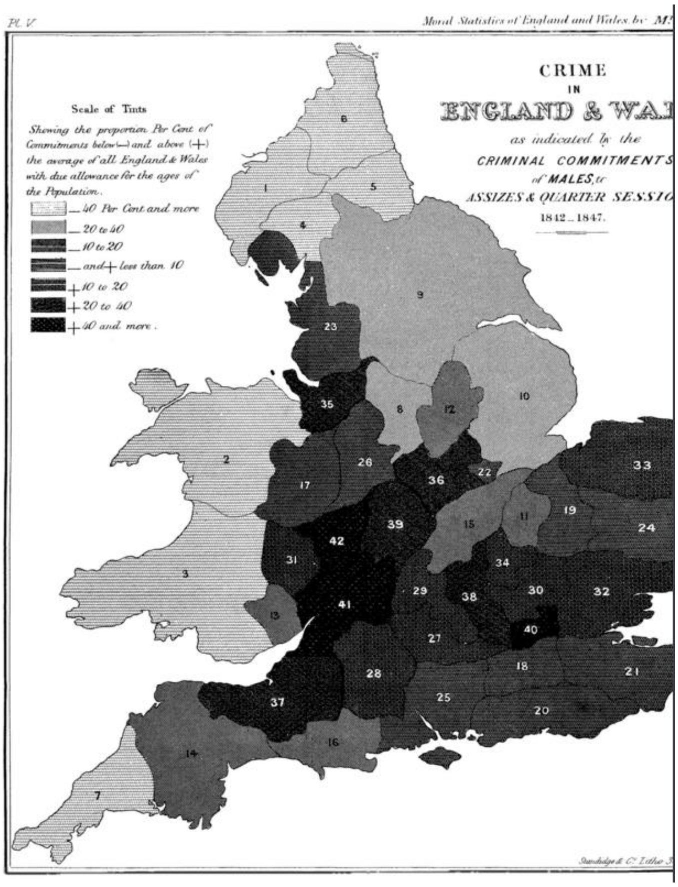
Source: Balbi and Guerry (1829:1).

Figure 2.2 Maps of personal crimes and property crimes in France (1825-1830).



Source: Guerry (1833:38, 42).

Figure 2.3 Map of crime rates in England and Wales (1842-1847).



Source: Fletcher (1849:237).

Twenty years later, Fletcher (1849) published the first map of crimes in England and Wales (see Figure 2.3), and argued that the macro-level geographical distribution of crime was explained by the effects of the industrial depression (1842-1844), the moral influences of police services and others factors. These maps are the predecessors of geographical criminology and the empirical study of the relationship between space and crime.

In the US, the authors of the School of Chicago examined the geographical distribution of crime and delinquency in local communities. The population of Chicago grew from one to three million in only 30 years (1890-1920) due to a major migration influx of people from American rural areas and overseas, which caused social disorganisation and crime in many areas. Park et al. (1925) studied the distribution of the new human geography in the city, and Shaw (1929) observed that crime and delinquency tended to arise in areas characterised by physical deterioration, decline, large mobility of the population, and large proportions of immigrants and minorities. These authors, and in particular Shaw and McKay (1942), made use of the concentric zone map originally published in Park et al. (1925) to show that crime rates were larger in the inner city and transitional zones between the city centre and the wealthy periphery. Since then, many social scientists have examined how community conditions (e.g. poverty, ethnic concentrations, population churn, social cohesion) in different areas affect the spatial distribution of crime and delinquency (e.g. Agnew, 1992; Cloward and Ohlin, 1960; Sampson et al., 1997).

It was during the 1960s-70s of the 20th Century when the study of place became prominent in criminological research, and in particular when researchers became aware of the need to analyse small areas to obtain information about the immediate environment where crimes take place. Jacobs (1961) argued that crime tends to arise in places where there are physical barriers that prevent neighbours from interacting with each other and watching the streets. Angel argued that "physical environment can exert a direct influence on crime settings by delineating territories, reducing or increasing accessibility by the creation or elimination of boundaries and circulation networks, and by facilitating surveillance by the citizenry and the police" (Angel, 1968:15). Jeffery (1971) argued that crime could not be explained only by deprivation and subcultural theories, but rather there are environmental opportunities for crime, which can be prevented by improving urban design. Then, he coined the term Crime Prevention through Environmental Design (CPTED). Jeffery (1971) also discussed the biological determinants of criminal behaviour. Newman (1972) argued that urban architecture should promote defensible spaces to allow neighbours to see and be seen, in order to increase informal social control and crime reporting and reduce the opportunities for crimes. Mayhew et al. (1976) set the basis for the so-called situational crime prevention, which consists of redesigning urban environments to reduce opportunities for crime and manipulating the costs and benefits of offences.

Cohen and Felson published a ground-breaking article in 1979. Cohen and Felson (1979) argued that for a crime event to happen, it is necessary that suitable targets, offenders and absent capable guardians converge in the same space and time. This approach was named the routine activity model. The intersection of a victim, offender and absence of guardian in the same physical space is necessary to explain crimes; this model may be used to explain both temporal trends and specific crime events in places. Moreover, Brantingham and Brantingham (1981, 1984) examined the interaction between targets, offenders and opportunities for crime in time and space and developed the crime pattern theory, which states that crime arises in predictable locations defined by the nodes between key urban locations (e.g. work places, schools, recreational locations) where offenders and crime targets concur. Therefore, the immediate geographical location where crimes take place becomes a key element to understand opportunities for crime events.

As a consequence, several authors have proposed crime prevention strategies and evidence-based policing models that take into account the geographical distribution of crimes and incorporate the notion of micro places into policing strategies. Goldstein (1979) argued that policing models should not be reactive and incident-driven, but proactive approaches that target the underlying problems that cause crime in each location. This approach was named problem-oriented policing. Moreover, Wilson and Kelling (1982) argued that crime can be prevented by policing and tackling neighbourhood disorder when and where it arises (i.e. broken windows approach). This second approach led to controversial zero tolerance strategies implemented by law enforcement agencies in US and elsewhere (Skogan, 1990; Taylor, 2001). Critics of the broken windows approach express concern over the non-discretionary, aggressive policing practices associated with zero tolerance and its negative implications for relationships between police and urban communities.

Many criminologists and crime analysts argue today that the study of crime and place needs to be conducted at a small geographical level, and push criminological research to examine small spatial scales, such as addresses or street segments, rather than larger geographical units (Brantingham et al., 2009; Weisburd et al., 2009). The works of Pierce et al. (1988) and Sherman et al. (1989) showed that crime events are concentrated in micro places (or hot spots of crime), and argued that place-based crime prevention strategies should be focused in those small areas where crime is more prevalent. The concentration of crime in micro places has been observed in different geographic contexts (Telep and Weisburd, 2018). Furthermore, policing strategies that target the hot spots of crime have shown to be successful in reducing crime rates (Braga et al., 2012, 2014; Weisburd, 2018). The study of small geographies in criminological research was named 'criminology of place' by Sherman et al. (1989), and Weisburd et al. (2012:5) state its five main arguments or evidences:

> "1) Crime is tightly concentrated at 'crime hot spots', suggesting that we can identify and deal with a large proportion of crime problems by focusing on a very small number of places.
> 2) These crime hot spots evidence very strong stability over time, and thus present a particularly promising focus for crime prevention efforts.
> 3) Crime at places evidences strong variability at micro levels of geography, suggesting that an exclusive focus on higher geographic units, like communities or neighbourhoods, will lead to a loss of important information about crime and the inefficient focus of crime prevention resources.
> 4) It is not only crime that varies across very small units of geography, but also the social and contextual characteristics of places. The criminology of place in this context identifies and emphasizes the importance of micro units of geography as social systems relevant to the crime problem.
> 5) Crime at place is very predictable, and therefore it is possible to not only understand why crime is concentrated at place, but also to develop effective crime prevention strategies to ameliorate crime problems at places."

The study of small geographical areas has become essential to understand crime and disorder events and to design evidence-based tools and strategies for crime prevention, but many researchers have also highlighted the need to analyse perceptions and emotions about crime in their immediate environment.

Some argue that the emotional responses of fear of crime are affected by the features of the immediate environment (Pain, 2000) and the conditions of each community (Brunton-Smith and Sturgis, 2011). Therefore, fear of crime events can be described as transitory, situational and context-dependent (Fattah and Sacco, 1989). Fisher and Nasar (1992, 1995) asked a group of participants about their perceptions of safety in different locations and observed their behaviour, and concluded that micro-places with refuge for potential offenders, low prospect (i.e. blocked view) and not many possible escape routes tend generate more fear of crime. Signal crimes and signal cues of social and physical disorder, which indicate that an area is not maintained properly, may also increase fear of crime reactions (Innes, 2004). Solymosi et al. (2019) conducted a systematic review of studies using crowdsourcing methods to examine the fear of crime and showed that 85% of studies identify that the fear of crime is spatially determined. Moreover, place-based methods can be used to capture the spatial-temporal specific nature of fear of crime events and to record data to analyse which architectural features are associated to the emotion of fear of crime (Solymosi et al., 2019).

The perceptions about crime and the criminal justice system are also affected by characteristics of the immediate environment and vary between small areas. This has been observed when analysing perceptions of disorder (Hipp, 2010a; Sampson and Raundenbush, 2004; Steenbeek and Hipp, 2011) and perceptions about police services (Jackson et al., 2013; Sampson and Bartusch, 1998). Crime reporting rates are dependent on each area’s conditions too (Baumer, 2002; Xie and Baumer, 2019). In summary, the study of small geographic areas is not only necessary for understanding and preventing crime events, but also for advancing criminological understanding about the citizens’ perceived safety, perceptions about police services and crime reporting rates, and for designing urban policies for improving public perceptions about crime and the police.

2.2.1 The issue of spatial scaling and the meaning of space

While the amount of research examining crime and crime-related issues at small spatial scales has increased during the last few years, some argue that criminological research has not sufficiently considered the effect of spatial scaling on research outputs and theoretical interpretations (Hipp, 2010a; Taylor, 2015; Wenger, 2019). Criminological research is moving towards the study of micro places, but further thinking may be needed about the meaning of spatial scales in criminology. The issue of spatial scaling considers that certain theoretical processes may depend on the spatial scales being investigated, and thus "there is ambiguity about the scale at which relationships occur because relationships between constructs at different levels of aggregation are distinct phenomena, resulting from potentially distinct mechanisms" (Wenger, 2019:2). For example, the ecological association between certain social conditions (e.g. social cohesion, residential stability) and crime may be used to explain differences between crime rates at a neighbourhood level but not at larger spatial scales (e.g. cross-national comparisons). This affects not only the decision about which level of spatial clustering should be chosen in each case, but also the theoretical interpretations that can be inferred from compiling and associating criminological data at the different spatial scales.

Taylor (2015) argues that the issue of spatial scaling is particularly concerning in geographic criminology and criminological studies conducted at small spatial scales because (a) many researchers generalise theories about social dynamics across different spatial scales and levels of analysis and assume that ecological connections found at a specific scale exist also at different scales; (b) these approaches may forget the effect of individual decisions on aggregate area conditions; and (c) some interpretations directly assume that relationships observed at the individual scale exist also for geographic areas. The author is particularly critical with certain theoretical interpretations drawn from studying crime at very detailed scales, such as micro places or hot spots of crime: "Places do not behave […] Micro-level places may be affected by crime or justice agency dynamics or may facilitate or impede dynamics that might lead to crime acts. But the etiology of crime acts is about individuals, perhaps in small groups, behaving in certain ways in certain places" (Taylor, 2015:122).

The study of micro places is becoming prominent in criminological research and evidence-based policing practise, but it is not free of risks. The selection of micro places as units of analysis without further ecological thinking may lead to erroneous theoretical interpretations of what certain social conditions mean at different scales and how they relate to crime rates and emotions and perceptions about crime (Wenger, 2019). While the issue of spatial scaling will not be directly examined in this thesis, the spatial scaling concern will be carefully considered in each of our case studies. Each study will consider the potential implications that chosen levels of geographic aggregation (e.g. individuals, households, neighbourhoods, cities, regions) may have for understanding the processes connecting social issues (i.e. covariates in SAE) and our outcome measures. This will be important to decide the target spatial scale at which we aim to produce small area estimates, but also to theoretically interpret the final estimates and model results.

2.3 Putting criminological phenomena on the map: Opportunities and limitations

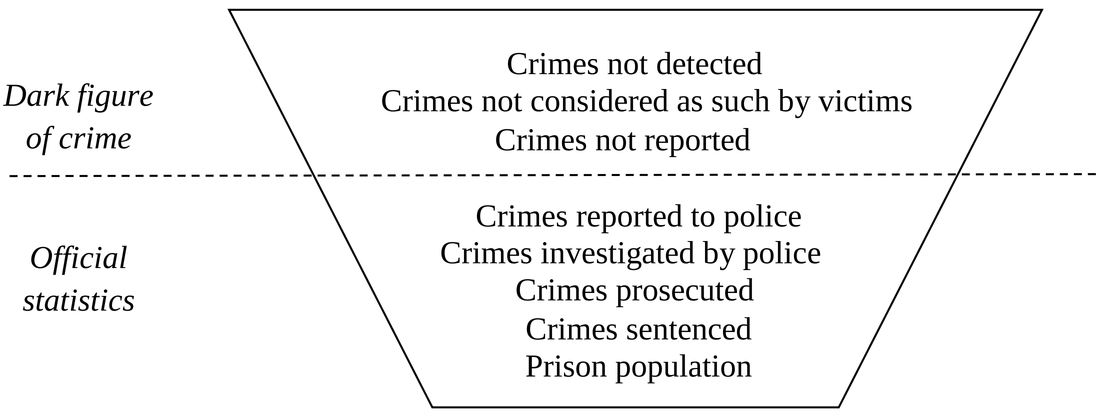
Although there is a need for producing maps of criminological phenomena at small geographical scales, there are today important methodological limitations that affect the precision and biases of maps produced from available sources of data.

The main aim for mapping criminological data at small geographical level is advancing understanding about the explanatory mechanisms that relate place and crime-related phenomena, and these maps are used to design evidence-informed policies and therefore are likely to have large effects on citizens' everyday lives. Thus, researchers are obliged to examine and account for potential sources of measurement error that may affect analytical results, evidence-based policies, crime prevention strategies and ultimately residents' lives. The following subsections detail potential opportunities and limitations for producing micro-level maps of crime and perceptions and emotions about crime and the criminal justice system.

2.3.1 Mapping crimes (known and unknown to police)

Among all official sources of crime data, police-recorded incidents are considered to be the closest to the total amount of crimes (O'Brien, 1985; Sellin, 1931). Not all crimes are recorded by police services, only a proportion of police-recorded incidents are prosecuted and even a smaller number of crimes are convicted and sentenced in court. Moreover, only a small proportion of convicted offenders are sentenced to prison. This has been named as the 'funnel' of crime data (see Figure 2.4). Therefore, police statistics are generally preferred over judicial or prison data to produce estimates of crime rates and map crimes.

Figure 2.4 'Funnel' of crime data.



Nevertheless, since the early 1830s there have been numerous researchers who have discussed the limitations of police statistics to analyse crime trends and crime differences across areas, for both large and small geographies (Biderman and Reiss, 1967; Kitsuse and Cicourel, 1963; Skogan, 1974, 1977). Candolle (1987a [1830], 1987b [1832]) argued that there are sources of measurement error in official statistics that affect crime statistics across time and space, and therefore geographical comparisons are likely to be affected by factors external to crime itself. Cross-national comparisons are affected by the legal, substantive and statistical rules used in each country to count crimes (Aebi, 2010). Comparisons across police jurisdictions within the same country may be affected by missing data, non-response from police forces and changes in recordkeeping (Maltz and Targonski, 2003; O'Brien, 1996).

At a lower spatial level, crime reporting rates are affected by neighbourhood conditions that affect some small areas more than others. For example, crime reporting rates and cooperation with police services are known to be lower in neighbourhoods characterised by a large economic disadvantage, crime rate and concentration of immigrants, and a low level of social cohesion (Baumer, 2002; Berg et al., 2013; Goudriaan et al., 2006; Jackson et al., 2013; Slocum et al., 2010; Xie, 2014; Xie and Baumer, 2019; Zhang et al., 2007). All these factors are likely to affect the 'dark figure of crime' in some areas more than others. The dark figure of crime is thus unequally distributed across small areas, and crime maps produced solely from police records are likely to be imprecise and biased by the effectiveness of police services in recording offences in each place.

Victimisation surveys may be used to record information about crimes unknown to police, but their sampling designs only allow for producing reliable direct estimates at large spatial scales (Groves and Cork, 2008). Skogan (1977) argued that victimisation surveys provide essential information to record information about the dark figure of crime. Nevertheless, sample surveys have their own methodological limitations, and sampling designs are usually planned to allow for reliable direct estimates only for large geographies, such as countries or regions, and small geographical areas tend to be unplanned domains for which direct estimates are unreliable. In other words, "victimisation surveys are undertaken to overcome problems of underreporting of crime. The results from them cannot be mapped at the very detailed micro-level because of confidentiality and the fact the number of responses are usually too small to support it" (Hirschfield, 2001:240).

2.3.2 Mapping perceptions and emotions about crime and the police

Crime-related perceptions and emotions are mainly recorded by social and victimisation surveys (Penick and Owens, 1976; UNODC, 2010). These sample surveys tend to be designed to allow for the production of reliable direct estimates only at large geographical levels, while small areas are usually unplanned domains with small sample sizes (Hirschfield, 2001). More advanced model-based techniques are thus needed to produce reliable small area estimates from available survey data (Rao and Molina, 2015). We note, however, that other sources of data are being explored to map certain perceptions and emotions about crime at detailed spatial scales.

The use of crowdsourcing techniques, defined here as methods for obtaining information by enlisting the services of large crowds of people into one collaborative project (Howe, 2008), are being used to obtain geo-located information about emotional reactions of fear of crime. For example, mobile apps may be a source of crowdsourced data to allow mapping time-specific emotions that arise due to immediate environmental cues (Solymosi et al., 2019). Although crowdsourced data offer many advantages over survey data (e.g. reduced cost of data collection and precise spatial information), their unique mode of production is affected by biases arising from participants' self-selection. Some have noted that educated and employed middle-age men are overrepresented in crowdsourced data (Haklay, 2010), and there are community conditions that explain why residents from certain neighbourhoods contribute to these platforms more than others (e.g. income deprivation, population density, dynamic population; Mashhadi et al., 2013; Solymosi et al., 2017). Moreover, a few users tend to be responsible for most contributions in crowdsourcing platforms (i.e. participation inequality) and certain neighbourhoods are under-represented due people's avoidance of stigmatised areas (Solymosi et al., 2017).

Systematic social observation (SSO) techniques have been used to obtain information and map the signs of social and physical disorder, but these methods may be limited by observer biases (Hoeben et al., 2016). Moreover, SSO shows little consistency with perceptual measures of disorder (Yang et al., 2018), and therefore it does not account for the neighbourhoods' stigmas and occasional signal events of social disorder, which are known to affect the residents' overall perceptions of disorder (Innes, 2004).

Survey data are usually preferred over other sources of data to examine and map the citizens' perceptions and emotions about crime and the police. This is because surveys tend to be designed to select random samples that are representative of the target population, and thus survey data do not suffer from many of the selection biases that are likely to characterise crowdsourced and SSO-recorded data. Nevertheless, victimisation surveys have their own methodological limitations, and small samples recorded at small area level do not allow producing direct estimates of adequate precision. This is the reason why using model-based SAE may be beneficial.

2.4 The use of social and victimisation surveys for crime mapping

For centuries, criminological research has used data provided by social and victimisation surveys. In 1730, the city of Aarhus, in Denmark, surveyed its residents to ask about instances in which they had been victims of burglary (Sparks, 1981). The Aarhus questionnaire is considered a predecessor of modern victimisation surveys. In 1945, Gallup Poll conducted a survey in Finland about public opinions that included a question about personal victimisation during the previous year. In case of positive answer, respondents were asked whether they had been victims of theft, burglary, robbery, assault, trespassing, fraud or another crime (Aebi and Linde, 2014). Twenty years later, in 1965, Gallup designed the first survey that included a question about fear of crime when walking alone.

However, the first survey specifically designed to measure crime and victimisation was sponsored by the US' President's Commission on Law Enforcement and Administration of Justice in 1965. It was called 'Attitudes and Experience Questionnaire. Victimization Study' and it asked a sample of US respondents about their experiences of victimisation related to burglary, car theft, robbery, larceny, malicious mischief or arson, counterfeiting, fraud, rape, other sex crimes, assault, threat, auto offenses, family-related crimes, consumer fraud, building violations, bribing, homicide and kidnapping. It also included questions about each crime, such as health and economic consequences, details of victim, details of offender, whether crime had been reported to police, and attitudes towards police services. It was probably the first victimisation survey as such. This survey was also the basis for the publication of the well-known report 'Criminal Victimization in the United States: A Report of a National Survey' (Ennis, 1967), which analysed the incidence and prevalence of crime victimisation and its distribution within American society. It also examined other variables such as victimisation loses, propensity to report crimes and attitudes towards the police.

After this report, the number of national victimisation surveys increased in Europe, North America and elsewhere (Aebi and Linde, 2014). The main objectives of victimisation surveys are detailed in Table 2.1. Victimization surveys have also been launched at a local and international level. Local surveys allow for crime to be analysed at lower geographical levels (Maguire, 1997), while international surveys are designed to allow cross-national comparisons (van Dijk et al., 2007).

Table 2.1 Objectives of victimisation surveys.

Objective	Description
(i) Measure the incidence of crime and changes over time	Measure incidence and prevalence of crime rates and perceived crime in particular areas and times, which allows studying the dark figure and crime trends.
(ii) Detailed information about crime	Obtain complementary information about circumstances surrounding crimes: victim-offender relationship, characteristics of offender, characteristics of victim, etc.
(iii) Identification of high-risk subgroups and victims	Analyse high-risk groups of victims and probability of re-victimisation.
(iv) Inter-area comparisons of victimisation rates	Geographic data collected to allow comparing crime rates and trends across areas.
(v) Calling police services	Examine patterns of crime reporting to police services.
(vi) Evaluation and strategy development	Evaluate criminal justice policies, crime-prevention campaigns and policing strategies.
(vii) Direct and indirect costs of crime	Evaluate economic, property, health, psychologic and social impacts of crime at individual and societal level.
(viii) Peripheral objectives	Concerns about crime, attitudes towards the police, fear of crime, feelings of safety, punitive attitudes, etc.

Source: Own elaboration based on Penick and Owens (1976) and UNODC (2010).

Nevertheless, victimisation surveys suffer from their own methodological limitations. In addition to traditional limitations of social surveys (e.g. memory problems, untruth), it has been noted that victimisation surveys suffer from particularly low response rates (van Dijk et al., 1990), not all offences can be included in questionnaires (e.g. victimless crimes, drug-related offences, homicides), some crime types are more easily recorded than others (Maguire, 1997) and the administration method used to survey households have large effects on response rates (Tourangeau and McNeeley, 2003). Some constructs, such as the fear of crime or the confidence in police work, have been measured using different questions, which makes comparative analyses complicated.

Moreover, sampling designs of most victimisation surveys are only planned to produce reliable direct estimates at large spatial scales, and small geographies suffer from small and zero sample sizes that do not allow producing direct estimates of adequate precision. The following subsections present the sampling designs of some important social and victimisation surveys measuring criminological variables.

Data recorded by those surveys will be used to produce small area estimates of criminological phenomena in Chapters 5, 6, 7 and 8. These are used to exemplify the limitations of sample surveys to produce reliable estimates at small spatial scales, and therefore similar limitations are expected to be found in other criminological surveys such as the NCVS or the International Crime Victims Survey (ICVS).

2.4.1 Crime Survey for England and Wales

The CSEW, previously named British Crime Survey (BCS), is one of the most powerful sources of information about crime and deviance in the UK. It allows for cross-sectional analyses and quantitative in-depth studies about victimisation, fear of crime (Brunton-Smith and Sturgis, 2011; Hale et al., 1994), perceptions of disorder (Brunton-Smith, 2011) and attitudes towards police services and the criminal justice system (Hough et al., 2013; Sindall et al., 2016), among others.

The BCS started in 1982 as a 10,000 sample survey. In 1996, the sample size was raised to 15,000 and in 2000 the sample size became 20,000. In 2001, the BCS became an annual survey and the sample was increased to 40,000 participants. The sample size has varied since then, and it was reduced from 46,000 to 35,000 in 2012/13. Nowadays, the CSEW sample consists of approximately 35,000 respondents, and it is representative of the population of England and Wales. It surveys a minimum of 650 households in each of the 42 Police Forces Areas (PFA)[1]. For this purpose, the City of London PFA and the Metropolitan PFA are merged. Therefore, all geographical scales below PFAs are unplanned and suffer from small sample sizes, and thus direct estimates tend to be unreliable.

The sampling design consists on a multi-stage stratified random sample by which a sole randomly selected adult (aged 16 or over) from a randomly selected household is asked about instances where he or she (household in some cases) had been victim of a crime in the last 12 months. The geographic units used for the

[1] The cluster design was revised and refined in 2012/13. Before 2012, the sample design used to discriminate between three types of areas regarding their density: high-density areas, which were unclustered; medium-density areas, where the sample was clustered with 32 addresses in each sampled MSOA; and low-density areas, where 16 addresses were samples per Lower Layer Super Output Area (LSOA), and two LSOAs were sampled per Middle Layer Super Output Area (MSOA). This design was modified in 2012, when the unclustered design was extended to all areas. After this transformation, every area has to be sampled and surveyed at least once every three-year period. This change is aimed to allow for an increasing precision of annual crime estimates (Office for National Statistics, 2015).

sampling frame are Postcode Address Files (PAF). Traditionally, the study only included citizens older than 16 years old, but from the 2009 edition onwards the CSEW also includes a sample of 10 to 15 years old residents (Office for National Statistics, 2015), which will not be used in this dissertation. The CSEW does not survey citizens living in care homes, halls of residence or other group residences. It does not cover commercial victimisation either.

The survey is conducted face-to-face with Computer Assisted Personal Interviewing (CAPI) techniques, and it uses Computer Assisted Self Interviewing (CASI) for sensitive variables, such as domestic violence and alcohol and drugs use (Office for National Statistics, 2015).

The CSEW does not include questions about 'victimless' crimes (e.g. drug possession, corporate and organised crime, white-collar crime), homicides and new crimes such as plastic card frauds. The questionnaire includes questions about perceptions of the evolution of crime rates, perception of national and local crime levels, perceived likelihood of being a victim of a crime, worry about crime, perceptions of antisocial behaviour, confidence and perceptions towards the police, and fairness and effectiveness of the criminal justice system, among others.

All questions in the CSEW are organised within modules and submodules: 85 submodules grouped in 19 modules. Not all questions are asked to every respondent, but a set of modules of the CSEW are asked to smaller sub-samples, and other questions are only asked to specific age ranges. In short, the whole sample is distributed in four groups of respondents (A, B, C and D), and each of them in two small sub-groups (e.g. A1 and A2). While some questions are asked to every respondent, others are only asked to specific groups.

2.4.2 Metropolitan Police Service Public Attitudes Survey

The MPSPAS is an annual survey conducted by the Greater London's Metropolitan Police Service since 1983, which records information about perceptions of policing needs, police legitimacy, worry about crime and perceived security and disorder. It consists of a face-to-face questionnaire conducted at the homes of respondents, and it obtains responses from a random probability sample of residents aged 16 or over in each of the 32 boroughs in Greater London (excluding the City of London).

The sampling design is a multi-stage stratified random sample. Around 12,800 interviews (400 per borough) are conducted annually. Household addresses are selected randomly in each borough, and then the person in each household whose next birthday is closest to the date of the interview is asked to answer the questionnaire. Whilst the sample is randomly selected within each borough, selected sample addresses are grouped spatially into work allocations assigned to quarters of the survey over the year (MOPAC, 2017). Before designating addresses to one of the four annual quarters, allocations are stratified to ensure that each quarter in each borough achieves broad spatial spread. This is done by using the coordinates for 'centroid' addresses in each work allocation. Work allocations are assigned to one of four quarters with equal probability. The sample is thus designed to be representative of the residents of Greater London aged 16 or over, and it should be large enough to allow for reliable direct estimates at a borough level but not at smaller spatial scales.

2.4.3 European Social Survey

The ESS is a biannual cross-national survey that has been conducted in 34 European countries since 2001. This survey measures attitudes, beliefs and behaviour patterns and allows for cross-national comparisons in Europe. The ESS questionnaire includes questions about victimisation, perceptions about police services, fear of crime and worry about crime, which may be of interest in criminological research.

ESS samples are designed to be representative of all individuals aged 15 and over living in private households in each participant country, regardless of their nationality, citizenship or language. ESS participant countries are responsible for producing their national sample designs within common sampling principles; this is the reason why countries with different population sizes have similar sample sizes (see European Social Survey, 2010). These common sampling principles state that respondents need to be selected by strict random probability methods at every stage, sampling frames may be individuals, households or addresses, every country must sample a minimum of 1,500 effective respondents (800 in countries with populations smaller than 2 million), quota sampling is not permitted, and substitution of non-responding units is not permitted. In most countries, all geographical levels below country level (e.g. regions, counties, cities) are unplanned domains and suffer from small sample sizes.

2.4.4 Manchester Residents Telephone Survey

The MRTS is a questionnaire designed for measuring general aspects of quality of life in the City of Manchester, England, and it includes questions about perceptions of neighbourhood disorder. It is carried out via telephone to a representative sample of Manchester households. The Manchester City Council published a series of reports describing the MRTS as a quota sample balanced survey based on age, gender, ethnicity, employment status and geographic location (see Manchester City Council, 2014).

It is undertaken on a quarterly basis, and a sample of 1,100 residents is surveyed in each quarter (i.e. 4,400 residents per year). According to survey administrators, the telephone survey is carried at convenient times for respondents and participants have the opportunity to reschedule the interviews to more convenient times. Moreover, although the main database used for sampling was of landline phone numbers, residents could also register their mobile numbers and some respondents were interviewed via mobile phone. The survey design does not allow producing reliable direct estimates at small geographical scales, such as wards, MSOAs (Middle Super Output Areas) or LSOAs (Lower Super Output Areas).

2.5 Summary: Motivating the use of small area estimation in criminological research

Although the primary focus of attention of criminological research has been the study of individuals to understand criminal behaviours, criminology has also been interested in researching the geographical inequalities of crime rates, and explaining why crimes concentrate in certain areas more than others (Bruinsma and Johnson, 2018). Since the mid-19th Century, when the first maps of crime were published, many authors have examined the distribution of crimes in space and associated the distribution of crimes to the areas' social and demographic conditions. This was essential to develop the social disorganisation theories that explained crime and delinquency in Chicago (Shaw and McKay, 1942), but also for the emergence of

CPTED and situational crime prevention approaches (Jeffery, 1971; Mayhew et al., 1976), and for the development of criminological theories such as routine activity model (Cohen and Felson, 1979) and crime pattern theory (Brantingham and Brantingham, 1984). The finding that crimes concentrate in micro places defined by small spatial units (e.g. addresses, street segments; Sherman et al., 1989; Telep and Weisburd, 2018; Weisburd et al., 2009) initiated a transition in geographic criminology from the study of large areas to the analysis of very small units of analysis. Moreover, research shows that focusing police actions and crime prevention measures on small areas with high crime rates tends to be beneficial to cut down crime rates (Braga et al., 2014).

In order to produce crime maps at detailed geographical scales, most researchers and police departments make use of police records (Chainey and Ratcliffe, 2005). However, police statistics are incomplete and are likely to be biased by unequal victims' reporting rates and an unequal police control on different areas (Berg et al., 2013; Goudriaan et al., 2006; Slocum et al., 2010; Xie and Baumer, 2019). The dark figure of crime is highly likely to be unequally distributed in space, and therefore crimes produced solely from police records can be biased and do not show a valid representation of crime rates. In order to account for the number of crimes unknown to police when producing crime maps, Skogan (1977) suggested the use of victimisation surveys. Surveys also provide essential information to produce maps of emotions about crime, perceptions about police services and other phenomena of interest for criminologists, and to understand the effect of environmental features and neighbourhood conditions on these perceptions and emotions.

While social and victimisation surveys offer many advantages over other sources of data to analyse crime and emotions and perceptions about crime, survey data are limited to analyse phenomena at a small area level. Samples recorded by surveys tend to be designed to allow for reliable direct estimates only for large geographies, while small areas tend to suffer from small and zero sample sizes (Hirschfield, 2001).

In order to allow for reliable small area estimates of crimes unknown to police, emotions and perceptions about crime and other social issues of criminological interest from victimization surveys' data, we suggest the use of model-based SAE. There is today a clear need for the incorporation of SAE in criminological research, which has already been highlighted by governmental reports (e.g. Groves and Cork, 2008; Tanton et al., 2001) and research papers. SAE techniques are designed to produce precise and unbiased estimates of parameters of interest for areas or domains for which direct estimates produced solely from survey data are not reliable enough (Rao and Molina, 2015). Chapter 3 presents the main SAE techniques used in this thesis and discusses previous SAE applications in criminological research.

CHAPTER 3 - Small area estimation in criminological research: Methods

3.1 Introduction

Victimisation and social surveys tend to be designed to allow for reliable direct estimates only for large geographies (e.g. countries, regions, counties), while small areas are usually unplanned domains and suffer from zero and small sample sizes. Small samples do not allow producing direct estimates of adequate precision at small area level (standards for what is deemed 'adequate' in SAE are presented in Subsection 3.2.7). Therefore, refined model-based techniques are needed to increase the reliability of small area estimates produced from small samples. Here we suggest the application of model-based SAE in criminological research. SAE is the term used to describe those techniques designed "to produce reliable estimates of characteristics of interest such as means, counts, quantiles, etcetera, for areas or domains for which only small samples or no samples are available" (Pfeffermann, 2013:40)[2].

Direct estimators use only area-specific samples and survey weights to obtain design-unbiased estimates, but these tend to produce unreliable estimates when sample sizes are small and do not allow producing estimates for areas with zero sample sizes. On the other hand, indirect model-based SAE techniques introduce explicit linking models to 'borrow strength' across related areas and improve the estimates' reliability. The availability of good auxiliary information (i.e. covariates) and the selection and validation of models are thus crucial for model-based SAE. Rao and Molina (2015:5) summarise the main four advantages of model-based SAE over direct estimators:

> "(i) 'Optimal' estimators can be derived under the assumed model.

[2] Rao and Molina (2015:xxiii) define SAE as the group of techniques that "deals with the problem of producing reliable estimates of parameters of interest and the associated measures of uncertainty for subpopulations (areas or domains) of a finite population for which samples of inadequate sizes or no samples are available".

(ii) Area-specific measures of variability can be associated with each estimator unlike global measures (averaged over small areas) often used with traditional indirect estimators.

(iii) Models can be validated from the sample data.

(iv) A variety of models can be entertained depending on the nature of the response variable and the complexity of data structures (such as spatial dependence and time series structures)."

SAE techniques have been widely used in economic, agricultural and sociological studies (e.g. Molina and Rao, 2010; Petrucci and Salvati, 2006; Pratesi, 2016), but these have been rarely applied to analyse and map criminological phenomena.

In SAE, an area is regarded as 'small' if the area sample size is "not large enough to support direct estimates of adequate precision" (Rao and Molina, 2015:2). Thus, small areas may also be large geographies where only small (or zero) sample sizes are available and where direct estimators produce unreliable estimates.

This chapter, in Section 3.2, presents the main SAE techniques that may be used to analyse criminological data. Then, Section 3.3 discusses previous applications using SAE to estimate crime or perceptions about crime. This chapter has two main aims:

1. Presenting the main SAE techniques that may be used in criminological research.
2. Discussing previous SAE applications to criminological data.

3.2 Small area estimation: Theory

Model-based SAE techniques are usually classified into two broad categories: unit-level SAE models and aggregate area-level SAE models. While the prior models relate the unit values of a survey to unit-specific auxiliary information (covariates), the latter relate the area means or totals recorded by the survey (i.e. direct estimates) to area-level covariates (Rao and Molina, 2015). The basic unit-level SAE model is as nested model developed by Battese et al. (1988) and the basic area-level SAE model was introduced by Fay and Herriot (1979).

Unit-level SAE models are known to perform better and produce more reliable small area estimates than area-level SAE models when the variable of interest is highly determined by unit-level conditions registered by the original survey (Hidiroglou and You, 2016). However, Namazi-Rad and Steel (2015) conducted a series of simulation experiments and showed that area-level SAE models should be prioritised when the outcome measure is particularly affected by contextual measures: “if important contextual variables are omitted, the parameter estimates obtained from an individual-level analysis will be biased, whereas an aggregated-level analysis can produce estimates with smaller bias” (Namazi-Rad and Steel, 2015:294). Many variables of interest in criminological research, such as crime rates and perceptions and emotions about crime, are known to be affected by contextual conditions that operate at the scales of small communities (see Section 2.2; Bruinsma and Johnson, 2018; Wortley and Townsley, 2017). Therefore, unit-level SAE models are likely to be misspecified by excluding important contextual covariates, and these could lead to biased small area estimates. On the contrary, all relevant contextual auxiliary information can be accounted for by using area-level SAE models. Moreover, while unit-level models assume that sampled units within each area obey the assumed model (i.e. these approaches assume the absence of selection bias), area-level models assume that area-level direct estimates obey the assumed population model, which is arguably more realistic and reduces the risk of model misspecification (Rao and Molina, 2015).

Existing area-level SAE models allow for the incorporation of temporally autocorrelated random effects (time series structures) and spatially autocorrelated random effects (proximity matrices). This may be of great value in criminological studies, which can benefit from accounting for the typically-high temporal stability of crime trends and typically-high spatial concentration of crime events (Elffers, 2003; Townsley, 2009; Weisburd et al., 2004) in order to improve the small area estimates’ reliability.

This doctoral dissertation will thus focus on the application of area-level model-based SAE techniques, while the use of unit-level SAE in topic of future research. Particular attention will be given to area-level spatial models for SAE, which have shown to improve the estimates’ reliability when the outcome measure is spatially concentrated (Pratesi and Salvati, 2008, Salvati, 2004).

The following subsections present some of the main area-level SAE techniques, which will be then applied to produce small area estimates of parameters of criminological interest in Chapters 5, 6, 7 and 8.

3.2.1 Horvitz-Thompson estimator

The Horvitz-Thompson estimator (Horvitz and Thompson, 1952) is one of the most common approaches to produce direct estimates. It makes use of original survey data and survey weights to obtain design-unbiased estimates in each small area, but direct estimates suffer from high variance and unreliability in areas with small sample sizes and estimates cannot be produced in areas with zero samples. Thus, model-based SAE approaches are needed for areas where direct estimates are not precise enough.

Let U be the target population, which is divided into D non-overlapping areas $U_1, \ldots, U_D$ of sizes $N_1, \ldots, N_D$. A sample s_d is drawn without replacement in area $U_d, d = 1, \ldots, D$. Population units are defined by i and areas by d, and π_{di} is the inclusion probability of unit i in area d. δ_d denotes the measure of interest in area d. The Horvitz-Thompson direct estimator for area d is given by:

$$\hat{\delta}_d^{DIR} = N_d^{-1} \sum_{i \in s_d} \frac{y_{di}}{\pi_{di}} = N_d^{-1} \sum_{i \in s_d} w_{di} y_{di}, \quad (3.1)$$

where w_{di} corresponds to the survey weight of unit i from area d (inverse of the probability of inclusion adjusted for non-response and calibration: $w_{di} = \pi_{di}^{-1}$) and y_{di} is the variable of interest of unit i from area d.

3.2.2 Synthetic estimator

Synthetic estimation is the umbrella term used to describe the group of SAE techniques that produce small area estimates by fitting a regression model with area-level direct estimates as the dependent variable and relevant area-level auxiliary information as covariates and then computing regression-based predictions (i.e. synthetic estimates). Synthetic estimators may be based, for example, on area-level linear models (e.g. Brugal et al., 1999), logistic models (e.g. Hser et al., 1998), multilevel models (e.g. Taylor, 2013; Whitworth, 2012) and spatial models (e.g. Wheeler et al., 2017).

Regression-based synthetic estimates can be produced for all areas regardless of their sample size (also areas with zero sample sizes). However, these are not based on a direct measurement of the variable in each area and suffer from a high risk of producing biased small area estimates (Levy, 1979; Rao and Molina, 2015).

In our research, due to their high risk of bias, synthetic estimates will only be used for areas with zero and one sample sizes, while optimal linear combinations between synthetic and direct estimates (i.e. the EBLUP and its extensions) will be used for areas with at least two respondents. Basic area-level linear models are used to produce regression-based synthetic estimates in this dissertation.

We assume area-level direct estimates $\hat{\delta}_d^{DIR}$ of parameter δ_d in area d to be related to a set of area-level covariates $x_{d1}, \dots, x_{dp}$. A linear regression is fitted by least squares to the data $(\hat{\delta}_d^{DIR}, x_{d1}, \dots, x_{dp})$ from sampled areas. Resulting estimators $\hat{\beta}_0, \hat{\beta}_1, \dots, \hat{\beta}_p$ of the regression coefficients are used to predict regression-based synthetic estimates for all sampled and non-sampled areas:

$$\tilde{\delta}_d^{SYNTH} = \hat{\beta}_0 + \hat{\beta}_1 x_{d1} + \dots + \hat{\beta}_p x_{dp}, \qquad d = 1, \dots, D. \tag{3.2}$$

3.2.3 EBLUP based on Fay-Herriot

The area-level EBLUP, which is based on the model developed by Fay and Herriot (1979), obtains an optimal combination of direct and regression-based synthetic estimates in each small area. The EBLUP combines both estimates in each area and gives more weight to the direct estimate when its sampling variance is small, while more weight is attached 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 the optimal combination of these in each area.

First, we use the direct estimates $\hat{\delta}_d^{DIR}$, together with their sampling errors e_d, and assume

$$\hat{\delta}_d^{DIR} = \delta_d + e_d, \qquad e_d \sim N(0, \psi_d), \qquad d = 1, \dots, D, \tag{3.3}$$

where ψ_d refers to the sampling variance of the direct estimates. Second, we assume δ_d to be linearly related to a set of covariates $\boldsymbol{x}_d'$ at area level,

$$\delta_d = \boldsymbol{x}'_d \boldsymbol{\beta} + v_d, \qquad v_d \sim N(0, A), \qquad d = 1, \dots, D, \tag{3.4}$$

where A denotes the variance of the area random effect v_d, and where v_d is independent of e_d. Then, we obtain

$$\hat{\delta}_d^{DIR} = \boldsymbol{x'}_d\boldsymbol{\beta} + v_d + e_d, v_d \sim N(0, A), e_d \sim N(0, \psi_d), d = 1, \dots, D. \quad (3.5)$$

The Best Linear Unbiased Predictor (BLUP) of δ_d is given by

$$\tilde{\delta}_d = \hat{\delta}_d^{DIR} - \frac{\psi_d}{A + \psi_d}\{\hat{\delta}_d^{DIR} - \boldsymbol{x'}_d\tilde{\boldsymbol{\beta}}(A)\} = \{1 - \gamma_d(A)\}\hat{\delta}_d^{DIR} + \gamma_d(A)\boldsymbol{x'}_d\tilde{\boldsymbol{\beta}}(A), \quad (3.6)$$

where $\gamma_d(A) = \psi_d/(A + \psi_d)$ and $\tilde{\beta}(A)$ is the maximum likelihood estimator of β. Since we do not know A, we replace it by an estimator $\hat{A}$ obtained from restricted maximum likelihood (REML). Then, we modify $\hat{A}$ by A and we obtain the EBLUP (Fay and Herriot, 1979; Rao and Molina, 2015):

$$\hat{\delta}_d^{EBLUP} = \{1 - \gamma_d(\hat{A})\}\hat{\delta}_d^{DIR} + \gamma_d(\hat{A})\boldsymbol{x'}_d\tilde{\boldsymbol{\beta}}(\hat{A}). \quad (3.7)$$

3.2.4 Spatial EBLUP (SEBLUP)

The SEBLUP adds spatially autocorrelated random effects to the area-level EBLUP and borrows strength from neighbouring areas (Petrucci and Salvati, 2006; Salvati, 2004). It has shown to improve small area estimates when the variable of interest has medium or high levels of spatial autocorrelation (i.e. when values cluster together in a map), as is typical in criminological studies (Anselin et al., 2000; Baller et al., 2001; Mooney et al., 2018; Townsley, 2009).

We first consider the area level model

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{v} + \boldsymbol{e}, \quad (3.8)$$

where $\boldsymbol{y}$ is the vector of direct estimates $(\hat{\delta}_1^{DIR}, \dots, \hat{\delta}_D^{DIR})'$ for D areas, $\boldsymbol{X}$ is a matrix $(x_1, \dots, x_D)'$ of area-level explanatory variables for D areas, $\boldsymbol{v}$ is a vector $(v_1, \dots, v_D)'$ of area effects and $\boldsymbol{e}$ is a vector $(e_1, \dots, e_D)'$ of sampling errors independent of $\boldsymbol{v}$, with $\boldsymbol{e} \sim N(\boldsymbol{0}_D, \boldsymbol{\Psi})$, where $\boldsymbol{\Psi} = diag(\psi_1, \dots \psi_D)$. Then, $\boldsymbol{v}$ is assumed to follow a spatial autoregressive (SAR) process (Cressie, 1993) with unknown autoregression parameter $\rho \epsilon (-1,1)$ and a contiguity matrix $\boldsymbol{W}$:

$$\boldsymbol{v} = \rho\boldsymbol{Wv} + \boldsymbol{u}. \quad (3.9)$$

We assume $(\boldsymbol{I}_D - \rho\boldsymbol{W})$ to be non-singular, where $\boldsymbol{I}_D$ is referred to the $D \times D$ identity matrix, so we can express

$$\boldsymbol{v} = (\boldsymbol{I}_D - \rho\boldsymbol{W})^{-1}\boldsymbol{u}, \tag{3.10}$$

where $\boldsymbol{u} = (u_1, \dots, u_D)'$ satisfies $\boldsymbol{u} \sim N(\boldsymbol{0}_D, A\boldsymbol{I}_D)$ for an unknown A. Then, we obtain

$$\boldsymbol{y} = \boldsymbol{X\beta} + (\boldsymbol{I_D} - \boldsymbol{\rho W})^{-\boldsymbol{1}}\boldsymbol{u} + \boldsymbol{e}. \tag{3.11}$$

The vector of variance components is now denoted as $\boldsymbol{\theta} = (\theta_1, \theta_2)' = (A, \rho)'$. The Spatial BLUP of $\delta_d = \boldsymbol{x'_d\beta} + v_d$ is given by

$$\tilde{\delta}_d^{SBLUP}(\boldsymbol{\theta}) = \boldsymbol{x'_d}\widetilde{\boldsymbol{\beta}}(\boldsymbol{\theta}) + \boldsymbol{b'_d G}(\boldsymbol{\theta})\boldsymbol{\Sigma}^{-\boldsymbol{1}}(\boldsymbol{\theta})\{\boldsymbol{y} - \boldsymbol{X}\widetilde{\boldsymbol{\beta}}(\boldsymbol{\theta})\}, \tag{3.12}$$

where $\boldsymbol{b'_d}$ is a $1 \times d$ vector (0,…,1,0,…,0) with 1 in position d, $\boldsymbol{G}(\boldsymbol{\theta})$ is the covariance matrix of $\boldsymbol{v}$ defined as $\boldsymbol{G}(\boldsymbol{\theta}) = A\{(\boldsymbol{I_D} - \boldsymbol{\rho W})'(\boldsymbol{I_D} - \boldsymbol{\rho W})\}^{-\boldsymbol{1}}$, $\boldsymbol{\Sigma}(\boldsymbol{\theta})$ is the covariance matrix of $\boldsymbol{y}$ obtained as $\boldsymbol{\Sigma}(\boldsymbol{\theta}) = \boldsymbol{G}(\boldsymbol{\theta}) + \boldsymbol{\Psi}$, and $\widetilde{\boldsymbol{\beta}}(\boldsymbol{\theta})$ is the weighted least squares estimator of $\boldsymbol{\beta}$ defined as $\widetilde{\boldsymbol{\beta}}(\boldsymbol{\theta}) = \{\boldsymbol{X'\Sigma^{-1}}(\boldsymbol{\theta})\boldsymbol{X}\}^{-\boldsymbol{1}}\boldsymbol{X'\Sigma^{-1}}(\boldsymbol{\theta})\boldsymbol{y}$ (Petrucci and Salvati, 2006; Salvati, 2004). If we replace a consistent estimator of $\widehat{\boldsymbol{\theta}} = (\hat{A}, \hat{\rho})'$, which is obtained from REML, by $\boldsymbol{\theta}$**,** we obtain the SEBLUP:

$$\hat{\delta}_d^{SEBLUP} = \hat{\delta}_d^{SEBLUP}(\widehat{\boldsymbol{\theta}}) = \boldsymbol{x'_d}\widetilde{\boldsymbol{\beta}}(\widehat{\boldsymbol{\theta}}) + \boldsymbol{b'_d G}(\widehat{\boldsymbol{\theta}})\boldsymbol{\Sigma}^{-\boldsymbol{1}}(\widehat{\boldsymbol{\theta}})\{\boldsymbol{y} - \boldsymbol{X}\widetilde{\boldsymbol{\beta}}(\widehat{\boldsymbol{\theta}})\}. \tag{3.13}$$

3.2.5 Rao-Yu model

The Rao-Yu model (Rao and Yu, 1994) is an extension of the area-level EBLUP for time series or cross-sectional data. It adds temporally autocorrelated random effects to the EBLUP estimator and the estimates borrow strength over time. The Rao-Yu model has shown to provide better estimates than the area-level EBLUP when the between-time variation relative to sampling variation is small (Rao and Molina, 2015; Rao and Yu, 1994).

Let δ_{dt} be the target measure for area d in time t, for $d = 1, \dots, D$ and $t = 1, \dots, T$. The temporal Rao-Yu model is given by

$$\hat{\delta}_{dt}^{DIR} = \boldsymbol{x'}_{dt}\boldsymbol{\beta} + u_d + v_{dt} + e_{dt},\ d = 1, \dots, D,\ t = 1, \dots, T, \tag{3.14}$$

with linear linking model

$$\delta_{dt} = \boldsymbol{x}'_{dt}\boldsymbol{\beta} + u_d + v_{dt},\ d = 1, \dots, D,\ t = 1, \dots, T. \tag{3.15}$$

where $\hat{\delta}_{dt}$ is the direct estimate of the measure of interest in area *d* and time instant *t*, $\boldsymbol{x}'_{dt}$ is the vector of known population values of *p* covariates for small area *d* at time *t*, $\boldsymbol{\beta}$ is the vector of regression coefficients, e_{dt} are sampling errors related to direct estimates $\hat{\delta}_{dt}$, which are uncorrelated over area and time and the variances ψ_{dt} are known. u_d are time-independent domain effects, which are assumed $u_d \sim N(0, \sigma_u^2)$, and v_{dt} are time random effects nested in area effects u_d.

Rao and Yu (1994) proposed a first order autoregressive AR(1) specification to account for the time random effects v_{dt}. Therefore, this model depends on both area-specific effects and area-by-time specific effects correlated across time. v_{dt} is given by

$$v_{dt} = \rho v_{d,t-1} + \varepsilon_{dt},\ |\rho| < 1, \tag{3.16}$$

where $\varepsilon_{dt} \sim iid\ N(0, \sigma^2)$ and ρ is the temporal autocorrelation parameter. We assume that u_d, ε_{dt} and e_{dt} are independent of each other. The authors considered the case of $|\rho| < 1$ and assumed stationary for the series. The stationarity assumption implies minimum change of the mean, variance and autocorrelation structure over time. This assumption implies

$$Var(v_{dt}) = \sigma^2/(1 - \rho^2) \tag{3.17}$$

when $\rho = 1$. Assuming that σ^2, σ_u^2 and ρ are known, the BLUP for area *d* at time instant *t* is given by

$$\tilde{\delta}_{dt}^{RYBLUP} = \boldsymbol{x}'_{\boldsymbol{dt}}\widetilde{\boldsymbol{\beta}} + (\sigma_u^2\mathbf{1}_t + \sigma^2\boldsymbol{\gamma}_t)'(\boldsymbol{\Psi}_d + \sigma^2\boldsymbol{\Gamma} + \sigma_u^2\boldsymbol{J}_t)^{-1}(\delta_d - \boldsymbol{X}_d\widetilde{\boldsymbol{\beta}}), \tag{3.18}$$

where $\boldsymbol{\Gamma}$ is a $T \times T$ matrix with elements $\rho^{|i-j|}/(1 - \rho^2)$, $\boldsymbol{J}_t$ is a $T \times T$ matrix with elements = 1, $\widetilde{\boldsymbol{\beta}}$ is the generalised least squares estimator of $\boldsymbol{\beta}$ defined by $\widetilde{\boldsymbol{\beta}} = (\boldsymbol{X}'\boldsymbol{V}^{-1}\boldsymbol{X})^{-1}\boldsymbol{X}'\boldsymbol{V}^{-1}\boldsymbol{y}$, where $\boldsymbol{V} = diag_d(\boldsymbol{V}_d) = Cov(\boldsymbol{y})$ and $\boldsymbol{V}_d = \boldsymbol{\Psi}_d + \sigma^2\boldsymbol{\Gamma} + \sigma_u^2\boldsymbol{J}_t = Cov(\boldsymbol{y}_d)$, and $\boldsymbol{\gamma}_t$ is the *t*th column of $\boldsymbol{\Gamma}$. Then, small area estimates are given by the EBLUP based on a estimation of σ^2, σ_u^2 and ρ, which we obtain using a REML model fitting procedure (Rao and Molina, 2015).

3.2.6 Spatial-temporal EBLUP (STEBLUP)

The STEBLUP is an extension of the EBLUP, but this time it accounts for both temporally and spatially autocorrelated random effects (Marhuenda et al., 2013). It is expected to improve the small area estimates' reliability when the variable of interest is stable across time (i.e. medium or high levels of temporal autocorrelation) and shows medium or high levels of spatial autocorrelation.

Let δ_{dt} be the target measure for area d in time t, for $d = 1, \dots, D$ and $t = 1, \dots, T$, and let $\hat{\delta}_{dt}^{DIR}$ be the direct estimate of δ_{dt}. $\boldsymbol{x}'_{dt}$ is the vector of population values for p covariates linearly related to δ_{dt}. First, we assume

$$\hat{\delta}_{dt}^{DIR} = \delta_{dt} + e_{dt},\ d = 1, \dots, D,\ t = 1, \dots, T, \qquad (3.19)$$

where sampling errors e_{dt} are assumed to be independent and normally distributed, and their variances ψ_{dt} are known. Then, the target outcomes for all areas and times are connected through the model

$$\delta_{dt} = \boldsymbol{x}'_{dt}\beta + u_{1d} + u_{2dt},\ d = 1, \dots, D,\ t = 1, \dots, T. \qquad (3.20)$$

Area-time random effects $(u_{2d1}, \dots, u_{2dT})'$ are independent and identically distributed for all areas following an AR(1) process with ρ_2 (i.e. temporal autocorrelation parameter). Hence,

$$u_{2dt} = \rho_2 u_{2d,t-1} + \epsilon_{2dt},\ |\rho_2| < 1,\ \epsilon_{2dt} \overset{iid}{\sim} N(0, \sigma_2^2). \qquad (3.21)$$

Area effects $(u_{11}, \dots, u_{1D})'$ follow a SAR(1) process with variance σ_1^2, spatial autocorrelation parameter ρ_1 and a proximity matrix $\boldsymbol{W} = (w_{d,l})$. Therefore,

$$u_{1dt} = \sum_{l \neq d} w_{d,l} u_{1l} + \epsilon_{1d},\ |\rho_1| < 1,\ \epsilon_{1d} \overset{iid}{\sim} N(0, \sigma_1^2,\ d = 1, \dots D). \qquad (3.22)$$

The definitions of the following vectors and matrices are obtained by stacking the model element into columns:

$$\boldsymbol{y} = \underset{1 \le d \le D}{col} \left(\underset{1 \le t \le T}{col} (\hat{\delta}_{dt}^{DIR}) \right),$$
$$\boldsymbol{X} = \underset{1 \le d \le D}{col} \left(\underset{1 \le t \le T}{col} (\boldsymbol{x}'_{dt}) \right),$$
$$\boldsymbol{e} = \underset{1 \le d \le D}{col} \left(\underset{1 \le t \le T}{col} (e_{dt}) \right),$$
$$\boldsymbol{u}_1 = \underset{1 \le d \le D}{col} (u_{1d}),$$
$$\boldsymbol{u}_2 = \underset{1 \le d \le D}{col} \left(\underset{1 \le t \le T}{col} (u_{2dt}) \right).$$

In addition, we define $\boldsymbol{Z}_1 = \boldsymbol{I}_D \otimes \mathbf{1}_T$, where $\boldsymbol{I}_D$ is a $D \times D$ identity matrix, $\otimes$ is the Kronecker product, and $\mathbf{1}_T$ is a vector of ones; $\boldsymbol{Z}_2 = \boldsymbol{I}_n$, where $n = DT$ is the number of observations; $\boldsymbol{u} = (\boldsymbol{u}_1', \boldsymbol{u}_2')$; and $\boldsymbol{Z} = (\boldsymbol{Z}_1, \boldsymbol{Z}_2)$. The model can be expressed as

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{Zu} + \boldsymbol{e}. \tag{3.23}$$

The vector of unknown parameters associated with covariance matrix $\boldsymbol{y}$ is $\boldsymbol{\theta} = (\sigma_1^2, \rho_1, \sigma_2^2, \rho_2)'$. $\boldsymbol{e} \sim N(\mathbf{0}_n, \boldsymbol{\Psi})$, where $\mathbf{0}_n$ is a vector or 0s of size n and $\boldsymbol{\Psi}$ is a diagonal matrix $\boldsymbol{\Psi} = diag_{1\le d\le D}\big(diag_{1\le t\le T}(\psi_{dt})\big)$. $\boldsymbol{u} \sim N(\mathbf{0}_n, \boldsymbol{G}(\boldsymbol{\theta}))$, where the covariance matrix is $\boldsymbol{G}(\boldsymbol{\theta}) = diag\{\sigma_1^2 \Omega_1(\rho_1), \sigma_2^2 \Omega_2(\rho_2)\}$, where

$$\Omega_1(\rho_1) = \{(\boldsymbol{I}_D - \rho_1 \boldsymbol{W})'(\boldsymbol{I}_D - \rho_1 \boldsymbol{W})\}', \tag{3.24}$$

$$\Omega_2(\rho_2) = diag_{1\le d\le D}\{\Omega_{2d}(\rho_2)\}, \tag{3.25}$$

$$\Omega_{2d} = \frac{1}{1-\rho_2^2}\begin{pmatrix} 1 & \rho_2 & \dots & \rho_2^{T-2} & \rho_2^{T-1} \\ \rho_2 & 1 & \ddots & . & \rho_2^{T-2} \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \rho_2^{T-2} & . & \ddots & 1 & \rho_2 \\ \rho_2^{T-1} & \rho_2^{T-2} & \dots & \rho_2 & 1 \end{pmatrix}_{T\times T}, d = 1, \dots D. \tag{3.26}$$

Therefore, the covariance matrix of $\boldsymbol{y}$ is defined by

$$\boldsymbol{\Sigma}(\boldsymbol{\theta}) = \boldsymbol{ZG}(\boldsymbol{\theta})\boldsymbol{Z}' + \boldsymbol{\Psi}. \tag{3.27}$$

The weighted least squares estimate of $\boldsymbol{\beta}$ and $\boldsymbol{u}$ are given by

$$\widetilde{\boldsymbol{\beta}}(\boldsymbol{\theta}) = \{\boldsymbol{X}'\boldsymbol{\Sigma}^{-1}(\boldsymbol{\theta})\boldsymbol{X}\}^{-1}\boldsymbol{X}'\boldsymbol{\Sigma}^{-1}(\boldsymbol{\theta})\boldsymbol{y}, \tag{3.28}$$

$$\widetilde{\boldsymbol{u}}(\boldsymbol{\theta}) = \boldsymbol{G}(\boldsymbol{\theta})\boldsymbol{Z}'\boldsymbol{\Sigma}^{-1}(\boldsymbol{\theta})\big\{\boldsymbol{y} - \boldsymbol{X}\widetilde{\boldsymbol{\beta}}(\boldsymbol{\theta})\big\}. \tag{3.29}$$

Regarding that $\boldsymbol{u} = (\boldsymbol{u}_1', \boldsymbol{u}_2')$, the second identity leads to the BLUP estimator of $\boldsymbol{u}_1$ and $\boldsymbol{u}_2$:

$$\widetilde{\boldsymbol{u}}_{\boldsymbol{1}}(\boldsymbol{\theta}) = \sigma_1^2 \Omega_1(\rho_1)\boldsymbol{Z}_1'\boldsymbol{\Sigma}^{-1}(\boldsymbol{\theta})\big\{\boldsymbol{y} - \boldsymbol{X}\widetilde{\boldsymbol{\beta}}(\boldsymbol{\theta})\big\}, \tag{3.30}$$

$$\widetilde{\boldsymbol{u}}_{\boldsymbol{2}}(\boldsymbol{\theta}) = \sigma_2^2 \Omega_2(\rho_2)\boldsymbol{\Sigma}^{-1}(\boldsymbol{\theta})\big\{\boldsymbol{y} - \boldsymbol{X}\widetilde{\boldsymbol{\beta}}(\boldsymbol{\theta})\big\}. \tag{3.31}$$

If we replace an estimator of $\widehat{\boldsymbol{\theta}}$ for $\boldsymbol{\theta}$, we obtain the EBLUP estimator of $\boldsymbol{u}_1$ and $\boldsymbol{u}_2$:

$$\widehat{\boldsymbol{u}}_{\boldsymbol{1}} = \widetilde{\boldsymbol{u}}_{\boldsymbol{1}}(\widehat{\boldsymbol{\theta}}) = (\hat{u}_{11}, \dots, \hat{u}_{1D})', \tag{3.32}$$

$$\widehat{\boldsymbol{u}}_{\boldsymbol{2}} = \widetilde{\boldsymbol{u}}_{\boldsymbol{2}}(\widehat{\boldsymbol{\theta}}) = (\hat{u}_{211}, \dots, \hat{u}_{2DT})'. \tag{3.33}$$

The STEBLUP of δ_{dt} is thus given by

$$\hat{\delta}_{dt}^{STEBLUP} = \boldsymbol{x}'_{dt}\widehat{\boldsymbol{\beta}} + \hat{u}_{1d} + \hat{u}_{2dt},\ d = 1, \dots, D,\ t = 1, \dots, T. \tag{3.34}$$

We estimate $\boldsymbol{\theta}$ and $\boldsymbol{\beta}$ following a REML model fitting procedure (see Marhuenda et al., 2013).

3.2.7 The estimates' Relative Root Mean Squared Error (RRMSE)

In SAE, each small area estimate needs to be accompanied by its estimated measure of uncertainty, which is frequently defined by the MSE or the RRMSE. The MSE is a measure of the estimate's reliability and refers to the averaged squared error of the estimate. Hence, it represents the squared difference between the estimated value and what is measured. The MSE is always non-negative, and values closer to zero indicate a higher reliability of the small area estimate. The MSE accounts for both the variance of the estimates (i.e. spread of estimates from one sample to another) and their bias (i.e. distance between the averaged estimated value and the true value). The RRMSE is obtained by taking the square root of the MSE (i.e. the Root Mean Squared Error, RMSE) and dividing it by the corresponding small area estimate. The RRMSE is usually presented as a percentage. This allows for direct comparisons between the measures of reliability of estimates obtained from direct and indirect model-based SAE techniques.

The RRMSE can be used to examine which SAE method produces the most reliable estimates and which estimates suffer from inadequate reliability. SAE methods may produce reliable estimates in some areas and unreliable estimates in others. SAE standards tend to establish that "estimates with RRMSEs greater than 25% should be used with caution and estimates with RRMSEs greater than 50% are considered too unreliable for general use" (Commonwealth Department of Social Services, 2015:13).

The measure of uncertainty of direct estimates is defined by their Coefficient of Variation (CV), which is the corresponding measure to the RRMSE for unbiased estimators (Rao and Molina, 2015). RRMSEs of model-based estimates can be estimated following analytical and bootstrap procedures. The exact measures of uncertainty of EBLUP estimators cannot be analytically derived, and therefore these must be estimated (see González-Manteiga et al., 2008; Rao and Molina, 2015). The MSE of the area-level EBLUP may be estimated analytically by using the large sample approximation first described by Prasad and Rao (1990) and then adjusted by Datta and Lahiri (2000) for the REML fitting procedure. Singh et al. (2005) and Molina et al. (2009) proposed the analytical approximations to estimate the MSE of SEBLUP estimates. Analytical approximations to the MSE tend to show adequate levels of accuracy under assumptions of regularity, non-complex model parameters and a large number of areas (González-Manteiga et al., 2008; Molina et al., 2009), but resampling techniques (e.g. bootstrapping, jackknife) are today accepted as good alternatives to asymptotic analytical approximations under non-normality of errors and complex model parameters.

Molina et al. (2009) argue that bootstrapping is conceptually simpler than analytical approximations and requires fewer assumptions, and therefore it is easier to apply to complex statistical models. Moreover, bootstrapping is less reliant on the number of areas under study. González-Manteiga et al. (2008) developed a parametric bootstrap approximation to estimate the reliability of EBLUP estimates, which is more robust than analytical approximations under non-normality of errors and when true distributions are logistic or Gumbel. It tends to perform better and produce less biased MSE estimates than analytical approximations. Molina et al. (2009) adjusted the parametric bootstrap developed by González-Manteiga et al. (2008) to estimate the MSE of the SEBLUP estimates, and Marhuenda et al. (2013) adjusted it to the STEBLUP estimator. Moretti et al. (2019) further developed the parametric bootstrap to account for errors arising from the use of latent scores in SAE. We refer to the original articles to obtain further information about the parametric bootstrap to compute the MSE of EBLUP estimates (see González-Manteiga et al., 2008) and about the extensions of the parametric bootstrap to calculate the MSE of spatial, temporal and spatial-temporal extensions of the EBLUP (see Marhuenda et al., 2013; Molina et al., 2009; Pereira and Coelho, 2012).

3.2.8 Software

In this dissertation, small area estimates and the estimates' MSE are computed in `R` software (R Core Team, 2019) with the assistance of two packages for SAE: `'sae'` (Molina and Marhuenda, 2015) and `'sae2'` (Fay and Diallo, 2015b). Other `R` packages used in this research are `'maptools'` (Bivand and Lewin-Koh, 2019) and `'spdep'` (Bivand, 2019), which are used to compute the proximity matrices needed to fit spatial and spatial-temporal SAE models. The main functions used to produce small area estimates and estimates' MSE are detailed in Table 3.1.

Table 3.1 Main `R` functions used to compute small area estimates and estimates' MSE.

Function	**Package**	**Description**
`'direct'`	`'sae'`	Calculates direct estimates of domain means, as well as their standard deviation and CV.
`'eblupFH'`	`'sae'`	Produces EBLUP estimates based on the area-level FH model.
`'mseFH'`	`'sae'`	Calculates the analytical expression of the MSE of EBLUP estimates.
`'eblupSFH'`	`'sae'`	Produces SEBLUP estimates.
`'mseSFH'`	`'sae'`	Calculates the analytical expression of the MSE of SEBLUP estimates.
`'pbmseSFH'`	`'sae'`	Calculates the parametric bootstrap MSE of SEBLUP estimates.
`'eblupSTFH'`	`'sae'`	Produces STEBLUP estimates.
`'pbmseSTFH'`	`'sae'`	Calculates the parametric bootstrap MSE of STEBLUP estimates.
`'eblupRY'`	`'sae2'`	Calculates Rao-Yu estimates and their MSE.
`'readShapeSpatial'`	`'maptools'`	Reads data from a shapefile into a spatial object.
`'poly2nb'`	`'spdep'`	Builds a list of neighbouring areas based on contiguous boundaries (i.e. sharing one or more boundary points).
`'nb2mat'`	`'spdep'`	Generates a weights matrix for a list of neighbours with spatial weights for a chosen coding scheme.

3.2.9 Other approximations for small area estimation

Besides the SAE techniques described above, there are many other SAE approaches, some based on unit-level models and others in area-level models. Most of existing

SAE approaches are described by Pfeffermann (2002, 2013) and Rao and Molina (2015). There are several SAE techniques that could be used in criminological research, and this is the reason why some of these are briefly introduced below. However, the examination and application of these techniques in criminological research is topic of future research and these are not covered in this thesis. For example, unit-level SAE approaches (e.g. Battese et al., 1988) may be used to estimate variables highly determined by individual characteristics, multivariate SAE approaches can be used to estimate multiple area characteristics correlated between them (Datta et al., 1991; Moretti, 2018), and Empirical Bayes (EB) and Hierarchical Bayes (HB) approaches may be applied to handle models for binary and count data and deal with normal linear mixed models and non-normality of random effects (Rao and Molina, 2015).

Secondly, spatial microsimulation is the umbrella term used to refer to the group of geographical SAE approaches that do not follow the statistical notions of prediction and imputation. Three main methodologies have been classified within the family of spatial microsimulation techniques: iterative proportional fitting (IPF), combinational optimisation (CO) and generalised regression reweighting (GREGWT). These three approaches follow different methods to 'fit' the available survey units to the multi-dimensional characteristics of every area for a set of explanatory variables (defined as 'area constraints') in order to generate synthetic micro-populations for each small area, and in turn produce small area estimates (Rahman and Harding, 2016; Whitworth et al., 2017). IPF and GREGWT consist of reweighting all sample units to the area constraints in every small area so that area-level samples match the area's profile for selected constraints. In IPF approaches, the reweighting process is conducted sequentially across the area constraints. CO selects the required number of respondents per area from the original sample, and survey units are swapped with unselected units in order to optimise the fit between selected units and area constraints.

Although spatial microsimulation and statistical SAE approaches have the same objective, SAE methodologists have made great efforts to develop techniques to estimate the unreliability measure of each estimate (i.e. estimates' MSE). This has not been the case in spatial microsimulation techniques, whose small area estimates tend not to be accompanied by their measures of reliability. As argued by Whitworth et al. (2017), reliability measures in SAE are needed by users to understand the precision of estimates, but especially by policy makers who need to allocate resources and underpin decision-making for small areas. Although novel approaches are being developed to estimate the measure of uncertainty in spatial microsimulation approaches (see Lovelace et al., 2015; Moretti and Whitworth, 2019; Whitworth et al., 2017), the amount of research devoted to assessing the reliability of small area estimated produced from statistical SAE approaches is extensive and therefore available methods are highly reliable. Hence, only statistical SAE approaches will be used in this thesis, while the use of spatial microsimulation in criminological research is topic of future research.

3.3 Small area estimation applications to criminological data

Prior to this doctoral thesis there have been several applications of different SAE techniques to produce small area estimates of criminological data. This subsection will briefly present the first SAE applications to analyse criminological variables.

A large group of researchers have used different regression-based synthetic estimators to produce small area estimates in criminology. Although regression-based synthetic estimates can be produced for all areas (also for domains with zero and one sample sizes), these are known to suffer from a high risk of producing biased estimates due to model misspecification (Levy, 1979; Rao and Molina, 2015). Hser et al. (1998) fitted an area-level logistic regression to predict synthetic estimates of drug use among arrestees in 185 American cities. Brugal et al. (1999) used an area-level log-linear model with interactions and produced regression-based synthetic estimates of the prevalence of addiction to opioids in the neighbourhoods of Barcelona. Tanton et al. (2001) used different area-level linear regression modelling approaches to produce synthetic estimates of victimisation rates at a local and regional level in Australia. Magnusson (2001) made use of linear and logistic generalised regression models to estimate crime rates at a municipality and county level in Sweden. Whitworth (2012) used multilevel modelling to produce synthetic estimates of fear of crime at neighbourhood level in England and Wales, and Taylor (2013) used a similar approach to estimate perceived antisocial behaviour at the local and neighbourhood level in England and Wales. Wheeler et al. (2017) used multilevel and spatial models to predict synthetic estimates of attitudes towards police services at the neighbourhood level in an American city.

Others have used the basic unit-level or area-level SAE models, or the temporal extensions of the area-level EBLUP, to produce estimates of crime rates. Buelens and Benschop (2009) used the area-level EBLUP based on FH model (Fay and Herriot, 1979) to produce estimates of victimisation rates in police zones in the Netherlands. Fay and colleagues developed the area-level dynamic SAE model, which is an extension of the temporal model developed by Rao and Yu (1994), and produced estimates of crime rates in states and large counties in the US (Fay and Diallo, 2012, 2015a; Fay and Li, 2011; Fay et al., 2013). D'Alò et al. (2012) made use of the basic unit-level and area-level EBLUP models to produce estimates of rates of violence against women at a regional level in Italy.

A third group of researchers make use of different Bayesian approaches to produce small area estimates of criminological data. van den Brakel and Buelens (2014) used a HB approach to estimate victimisation, perceived neighbourhood degeneration and contact with police at local level in Netherlands. Law et al. (2014) and Williams et al. (2019) made use of Bayesian spatiotemporal modelling to estimate crime rates at a neighbourhood level in the municipality of York (Canada) and confidence in police work in London, respectively.

Finally, other methodological approaches have also been used to produce small area estimates of crime and associated constructs. For example, Kongmuang (2006) used spatial microsimulation to estimate crime at a ward level in Leeds, England. Mooney et al. (2018) examined the use of universal kriging to produce small area estimates of physical disorder for 1,826 block faces in four American cities (Detroit, New York, Philadelphia and San Jose).

3.4 Summary

Model-based SAE is the term used to describe the group of methods designed to produce reliable model-based estimates of parameters of interest (and associated measures of reliability) for areas or domains for which only small or zero sample sizes are available (Rao and Molina, 2015). Two main categories are used to classify model-based SAE approaches: unit-level models and area-level models. It is widely accepted that unit-level SAE models are preferred when the outcome measure is mainly explained by individual variables, while area-level SAE approaches should be used when the variable of interest is determined by the areas' conditions (Hidiroglou and You, 2016). Moreover, unit-level SAE approaches suffer from a higher risk of model misspecification due to their implicit assumptions that (i) sampled units within small areas obey the assumed unit-level model, and (ii) sampled units within small areas are not affected by selection biases (Namazi-Rad and Steel, 2015; Rao and Molina, 2015). Many variables of interest in criminological research are known to be context-dependent and influenced by environmental conditions (see Section 2.2; Bruinsma and Johnson, 2018) and therefore this doctoral dissertation will focus on the use of area-level model-based approaches for SAE.

More specifically, the following chapters will use the area-level EBLUP and the extensions of the EBLUP that include spatially autocorrelated random area effects (i.e. SEBLUP and STEBLUP) to produce small area estimates of different criminological phenomena. Crime rates, but also emotions about crime and perceptions of neighbourhood disorder, tend to be spatially aggregated and show medium or high levels of spatial autocorrelation (see Anselin et al., 2000; Baller et al., 2001; Brunton-Smith and Jackson, 2012; Mooney et al., 2018; Townsley, 2009), and thus the use of spatial SAE models may improve the small area estimates' reliability. To the extent of my knowledge there has been no previous application of the SEBLUP or the STEBLUP in criminological research. Spatial area-level SAE models will be used in this dissertation to produce small area estimates of confidence in police work in London from METPAS data (Chapter 5), worry about burglary at home and violent crimes in European regions from ESS data (Chapter 6), perceived neighbourhood disorder in Manchester from MRTS data (Chapter 7) and crimes unknown to police at the local and neighbourhood level in England and Wales from CSEW data (Chapter 8).

CHAPTER 4 - Outline of papers

Article 1 - Applying the Spatial EBLUP to place-based policing. Simulation study and application to confidence in police work

Accepted (pending minor corrections) in *Applied Spatial Analysis and Policy*.

Authors: David Buil-Gil, Angelo Moretti, Natalie Shlomo and Juanjo Medina.

Abstract: There is growing need for reliable survey-based small area estimates of crime and confidence in police work to design and evaluate place-based policing strategies. Crime and confidence in policing are geographically aggregated and police resources can be targeted to areas with the most problems. High levels of spatial autocorrelation in these variables allow for using spatial random effects to improve small area estimation models and estimates' reliability. This article introduces the Spatial Empirical Best Linear Unbiased Predictor (SEBLUP), which borrows strength from neighbouring areas, to place-based policing. It assesses the SEBLUP under different scenarios of number of areas and levels of spatial autocorrelation and provides an application to confidence in policing in London. SEBLUP should be applied for place-based policing strategies when the variable's spatial autocorrelation is medium/high, and the number of areas is large. Confidence in policing is higher in Central and West London and lower in East London.

Keywords: Spatial correlation, contiguity matrix, spatial model, police legitimacy.

Original contribution of the PhD candidate to this article: David Buil-Gil had the original idea of this study, undertook and wrote the literature review, coded the simulation study in R software, and analysed and discussed the results of the simulation study. He also contacted the Mayor's Office for Policing and Crime to apply for access to survey data and conducted the analyses of the application study to produce small area estimates of confidence in policing in Greater London. Angelo Moretti offered technical advice for coding the simulation study in R and inspected the final R codes. Natalie Shlomo and Juanjo Medina supervised the work from the original idea to the final manuscript, inspected the equations of the small area estimators and suggested changes to the final manuscript.

Article 2 - Worry about crime in Europe: A model-based small area estimation from the European Social Survey

Published in *European Journal of Criminology*. https://doi.org/10.1177/1477370819845752.

Authors: David Buil-Gil, Angelo Moretti, Natalie Shlomo and Juanjo Medina.

Abstract: Worry about crime is known to be higher in some European regions than others. However, cross-national surveys, which are the main source of information to map worry about crime across Europe, are designed to be representative of large areas (countries), and regions often suffer from small and unrepresentative sample sizes. This research produces reliable model-based small area estimates of worry about crime at regional level from European Social Survey data, in order to map the phenomenon and examine its macro-level predictors. Model-based small area estimation techniques borrow strength across areas to produce reliable estimates of parameters of interest. Estimates of worry about crime are higher in most Southern and Eastern European regions, in contrast to Northern and Central Europe.

Keywords: Fear of crime, model-based estimation, spatial distribution, Fay-Herriot, EBLUP.

Original contribution of the PhD candidate to this article: David Buil-Gil had the original idea of this study, undertook and wrote the literature review, accessed and downloaded ESS data, conducted the analyses, produced the small area estimates of worry about crime at a regional level in Europe, and wrote the paper. Angelo Moretti inspected the equations of the small area estimators and inspected the final R codes before running the analyses. Natalie Shlomo and Juanjo Medina supervised the work from the original idea to the final manuscript and suggested changes to the final manuscript.

Article 3 - The geographies of perceived neighbourhood disorder. A small area estimation approach

Published in *Applied Geography*. https://doi.org/10.1016/j.apgeog.2019.102037.

Authors: David Buil-Gil, Juanjo Medina and Natalie Shlomo.

Abstract: This research examines the geographical distribution of perceived neighbourhood disorder in Manchester, England, by using small area estimates. Sample surveys are the main source of information to analyse perceived disorder. However, most surveys are only representative of large areas, and direct estimates may be unreliable at small area level. Small area estimation techniques borrow strength from related areas to produce reliable small area estimates. This research produces Spatial Empirical Best Linear Unbiased Predictor (SEBLUP) estimates, which account for spatially correlated random area effects, of perceived neighbourhood disorder from the Manchester Resident Telephone Survey. The highest levels of perceived disorder are found in the city centre and some Northern and Central-Eastern areas. Perceived disorder is higher in areas with higher population churn, income deprivation and crime. Small area estimation techniques are a potential tool to map perceived disorder.

Keywords: Antisocial behaviour, model-based estimation, subjective security, mapping, environmental criminology, EBLUP.

Original contribution of the PhD candidate to this article: David Buil-Gil undertook and wrote the literature review, conducted the analyses and produced the small area estimates, and wrote the paper. Juanjo Medina had the original idea of this study and contacted the Manchester City Council to apply for access to survey data, and he also suggested final changes to the final manuscript version. He had previously produced a report for Greater Manchester Police (GMP) approaching this problem from the perspective of spatial interpolation. Natalie Shlomo supervised the work from the original idea to the final manuscript and suggested changes to the final manuscript.

Article 4 - The measurement of the dark figure of crime in geographic areas. Small area estimation based on the Crime Survey for England and Wales

Under review in *Criminology*.

Authors: David Buil-Gil, Juanjo Medina and Natalie Shlomo.

Abstract: The drive towards policing place and predictive policing has been predicated in an understanding of the geography of crime anchored on police statistics. However, these statistics may offer a distorted picture of the geography of crime. The dark figure of crime is not randomly distributed and is driven by factors that affect some areas more than others. This paper uses small area estimation to explore the geographical inequality of the dark figure of crime. We produce estimates of crimes unknown to police at local and neighbourhood level from the Crime Survey for England and Wales, to establish a basis for future research aiming to produce crime maps accounting for the dark figure. At a local level, spatial-temporal small area estimation techniques produce the most reliable estimates. The dark figure of crime is larger in small cities with low incomes and low house prices, but also in wealthy municipalities. At a neighbourhood level, all survey editions were merged to meet model assumptions and temporal models were not used. Spatial small area estimation models produce the most reliable estimates. The dark figure is larger in suburban and low-housing neighbourhoods with large concentrations of unqualified citizens with low-level occupations, immigrants and non-Asian minorities.

Keywords: Model-based, crime mapping, GIS, neighbourhood, divergence, environmental criminology.

Original contribution of the PhD candidate to this article: David Buil-Gil had the original idea of this study, undertook and wrote the literature review, applied for Secure Access to the CSEW via UK Data Service Safe Lab, accessed the survey data, conducted the analyses, produced the small area estimates, requested the outputs to the survey administrators and wrote the paper. Juanjo Medina and Natalie Shlomo supervised the work from the original idea to the final manuscript and suggested changes to the final manuscript.

CHAPTER 5: Article 1 - Applying the Spatial EBLUP to place-based policing. Simulation study and application to confidence in police work

5.1 Introduction

Policing analyses and intelligence-led policing are moving towards the study of small geographic areas, or micro places, to develop place-based policing strategies to reduce crime and disorder (Hutt et al., 2018; Weisburd, 2018; Weisburd et al., 2012). Place-based policing draws from the empirical observation that crime is concentrated at micro geographical units, which are sometimes referred to as 'hot spots of crime' (Weisburd et al., 2012; Weisburd, 2015, 2018). Sherman et al. (1989) found that only 3.5% of addresses in the city of Minneapolis produce 50% of all the annual crime calls to the police. Pierce et al. (1988) found similar results in Boston: 2.6% of addresses produce the 50% of police calls. Weisburd et al. (2004) examined the distribution of crime in Seattle from 1989 to 2002, and found that 50% of crimes were located at 4.5% of street segments, which showed that the concentration of crimes in small areas is stable across time. Therefore, Weisburd (2015) argues that there is a law of crime concentration, which states that "for a defined measure of crime at a specific microgeographic unit, the concentration of crime will fall within a narrow bandwidth of percentages for a defined cumulative proportion of crime" (Weisburd, 2015:138). Place-based policing interventions target those areas with high levels of crime and are successful in reducing crime and disorder, as shown by Braga et al. (2014) in their meta-analysis of quasi-experimental evaluations of hot spots policing. Braga et al. (2014) also found that the crime control benefits of such strategies diffuse into areas surrounding targeted places. This shows the need for the study of small areas in policing research and practice. However, the police effectiveness in reducing crime in places highly depends on its relationship with the public (Bennett et al., 2014; Jackson et al., 2013; Tyler and Bies, 1990; Weisburd, 2018). Areas with higher confidence in police work tend to have larger citizens' cooperation with the police, thus enhancing the police capacity to prevent crime and deviance. Moreover, government inspections into police forces assess not only their effectiveness in reducing crime, but also they expect the police to develop programs to enhance its legitimacy and public confidence in those geographical areas where public cooperation with police services is lower (HMICFRS, 2017). The confidence in police work is also distributed at micro places (Williams et al., 2019), and thus should be taken into account to design place-based policing strategies.

Police-recorded offences and crime calls are relatively easy to geocode and map, and advanced geographical analyses can be drawn from crime maps with a high level of spatial accuracy (Hutt et al., 2018). However, the confidence in policing cannot be directly observed and is mainly recorded by crime surveys, such as the CSEW and the NCVS in the US. Crime surveys are usually designed to record large samples and provide reliable direct estimates only for large geographies, such as regions or cities, and small areas within these are usually unplanned domains and have small or even zero sample sizes. This is the reason why more advanced statistical methods are needed to map the confidence in police work. Groves and Cork (2008) argue that model-based SAE techniques are a potential tool to overcome such limitations and produce reliable small area estimates from crime surveys. SAE seeks to produce reliable estimates for unplanned areas or domains where direct estimates are not precise enough (Rao and Molina, 2015). Those estimates allow for advanced geographical analyses and precise maps of the confidence in policing and associated constructs.

In this paper we provide background information, a simulation study and an application to introduce area-level model-based SAE techniques that account for spatially correlated random area effects to place-based policing. This is one of the first papers that evaluates and applies these methods in policing research and practice. Confidence in police work tends to show high levels of spatial clustering (Jackson et al., 2013; Williams et al., 2019), which can be taken into account in SAE models to increase the estimates' precision (Elffers, 2003; Townsley, 2009). In SAE, the use of spatially correlated random area effects is increasingly in use (Chandra et al., 2007; Marhuenda et al., 2013; Petrucci et al., 2005; Petrucci and Salvati, 2006; Pratesi and Salvati, 2009; Salvati et al., 2014). Small area estimators that incorporate the spatial autocorrelation parameter have been shown to reduce the estimates' MSE when the level of spatial autocorrelation (henceforth ρ) is large. ρ measures the correlation of a variable with itself across neighbouring areas. Thus, a large ρ means that geographically nearby areas tend to have similar values (i.e. high values of a variable in one area are surrounded by high values in neighbouring areas and low values of a variable in one area are surrounded by low values in neighbouring areas), while a ρ close to zero represents a geographically random phenomenon. Specifically, this paper introduces the SEBLUP to place-based policing. The SEBLUP is an extension of the EBLUP, which is based on the FH model (Fay and Herriot, 1979), considering correlated random area effects between neighbouring areas through the simultaneous autoregressive (SAR) process (Cressie, 1993; Salvati, 2004).

The level of ρ of the variable of interest has shown to be relevant to improve SEBLUP estimates. Less attention has been paid to the effect of the number of areas under study, D, on SEBLUP's performance, and particularly how D interacts with ρ to explain the SEBLUP's increased precision. D measures the number of geographical areas for which we aim to produce estimates. For example, confidence in police work can be estimated in London at a metropolitan (D = 1), borough (D = 32) or ward level (D = 610), or even at lower geographical scales with larger number of areas. This is especially relevant for crime analysts and police departments aiming to select appropriate methods to estimate confidence in police work at different geographical scales with dissimilar number of areas. There are few studies examining the efficiency of the SEBLUP under different geographical conditions and these show contradicting results (Asfar and Sadik, 2016; Petrucci and Salvati, 2006; Pratesi and Salvati, 2008, 2009; Salvati, 2004). Thus, further examinations and applications of the method are needed.

This paper assesses the SEBLUP performance, in terms of bias and MSE, under different scenarios with unequal D and ρ, and provides an empirical evaluation and application to confidence in police work in London. The confidence in policing is measured here by the proportion of people who think that the police do a good job (Stanko and Bradford, 2009). Thus, we gain evidence about the SEBLUP estimates' reliability under different conditions, to examine the cases in which this estimator provides better estimates than basic model-based estimators when applied to policing data. In the simulation study, quality measures for the SEBLUP estimates are compared to post-stratified and EBLUP estimates controlling for D and ρ. In the empirical evaluation, estimates of confidence in police work are produced at ward level in five London sub-regions with different number of wards. Furthermore, the application contributes to the increasing criminological research on understanding the geographical distribution of citizens' confidence in the police (Jackson and Bradford, 2010; Jackson et al., 2013; Jang et al., 2010; Tankebe, 2012).

Section 5.2 provides background information on the need for accounting for the confidence in police work in policing strategies, and Section 5.3 bridges the gap between SAE techniques and place-based policing. Section 5.4 describes the SEBLUP and results of previous studies. Section 5.5 presents the simulation study and its results. Section 5.6 applies SEBLUP to produce estimates of confidence in police work in London. Finally, Section 5.7 draws final conclusions.

5.2 Confidence in the police and policing strategies

The police effectiveness in maintaining order and preventing crime depends on its relationship with the public (Jackson and Bradford, 2010; Jackson et al., 2013). Citizens' willingness to cooperate and support police officers is essential for an effective policing service, and public cooperation with the police is shaped by the citizens' trust and confidence in police work (Bennett et al., 2014; Tyler, 2004). The residents' confidence in police services, which shows heterogeneity between neighbourhoods, affects the unequal police capacity to prevent crime in different areas. Thus, effective policing strategies need to develop measures to enhance the public confidence in police work, and inspections into police forces assess the efforts made by the police to increase their public confidence at different geographical areas (HMICFRS, 2017). This is especially important in the case of place-based policing strategies, which have been criticised for having negative impacts on the perceptions about the police of targeted communities (Rosenbaum, 2006).

Confidence in policing and police legitimacy are known to be driven by a series of demographic and social variables that operate at individual, micro and meso levels, and increasing research focuses on understanding their predictors at different scales. Several individual characteristics have been related with decreased confidence in police work and less willingness to cooperate with the police, such as being male and young, belonging to an ethnic minority, low education, poverty, negative perceptions of procedural justice and negative experiences with the police (Jackson et al., 2013; Jang et al., 2010; Sampson and Bartusch, 1998; Staubli, 2017;

Tankebe, 2012; Tyler, 2004). Particular attention has been given to the study of the relationship between procedural justice and public confidence in police: citizens tend to be more confident in police services and legitimize police activities when police officers are perceived to treat people with respect and dignity (Tyler, 2004; Tyler and Bies, 1990).

Research has also found that confidence in policing is higher in certain neighbourhoods than others, and the confidence and trust in the police are known to be influenced by neighbourhood-level variables that operate at the scales of small communities (Jackson et al., 2013; Sampson and Bartusch, 1998). Some of the variables used to explain the unequal distribution of the neighbours' confidence in police work and associated constructs are the average income, unemployment rates, social cohesion, residential mobility, concentration of minorities and immigrants, and crime rates (Bradford et al., 2017; Dai and Johnson, 2009; Jackson et al., 2013; Kwak and McNeeley, 2017; Sampson and Bartusch, 1998; Wu et al., 2009). Wu et al. (2009:150) argue that "racial composition, concentrated disadvantage, residential mobility, and violence crime rate are all good neighbourhood-level predictors in determining public perception of police". Sampson and Bartusch (1998) found that the combined effect of concentrated disadvantage, crime and ethnic concentration explains 82% of the variation between small areas in levels of satisfaction with police. Neighbourhood poverty and unemployment, as forms of concentrated disadvantage, are known to shape neighbours' social identities and decrease citizens' attitudes and perceptions of policing services (Wu et al., 2009). Confidence in police work tends to be lower in deprived areas, while wealthy neighbourhoods have more confidence in the police. While some argue that this is due to the larger police control and the more violent techniques used by the police in deprived areas (Dai and Johnson, 2009), others argue that it is explained by differential social identities within cities: "residents of more socially integrated neighbourhoods may feel they are connected to larger formal institutions such as the police" (Kwak and McNeeley, 2017:10). People living in poor socioeconomic conditions are not only likely to be dissatisfied with the police, but with all government services (Dai and Johnson, 2009).

The concentration of minorities and immigrants has also been used to explain neighbourhood-level confidence in policing. Areas with larger concentrations of minorities and immigrants are likely to have lesser confidence in police work (Sampson and Bartusch, 1998; Wu et al., 2009), although research conducted in the United Kingdom has found the opposite: “trust in the police was on average higher among immigrants to the United Kingdom than among the UK-born population” (Bradford et al., 2017:381). Dai and Johnson (2009) argue that the relationship between concentration of minorities and dissatisfaction with the police in the US is likely to be explained by the neighbourhood concentrated disadvantage, as citizens from minority groups are disproportionately represented in deprived areas. In relation to the crime rates, Kwak and McNeeley (2017) and Wu et al. (2009) found that, contrarily to what one might expect, these are not significant in predicting confidence in policing and dissatisfaction with the police. We will use this information to select covariates to fit our SAE models of confidence in policing.

5.3 Small area estimation in place-based policing

Since 2008, when the US Panel to Review the Programs of the Bureau of Justice Statistics suggested the use of model-based small area estimators to produce estimates from the NCVS (Groves and Cork, 2008), there have been several applications of SAE methods to policing data. Buelens and Benschop (2009) used the EBLUP based on the FH model to produce estimates of victimization rate per police zone in Netherlands. Fay and Diallo (2012) presented an extension of the temporal model developed by Rao and Yu (1994) and applied it to estimate crime by states in the US. Whitworth (2012) produced regression-based synthetic estimates of fear of crime in England and Wales. Taylor (2013) made use of multilevel models to produce synthetic estimates of perceived antisocial behaviour in England and Wales. Williams et al. (2019) introduced the spatially correlated random area effects and produced neighbourhood estimates of public confidence in policing from a spatiotemporal Bayesian approach. Wheeler et al. (2017) made use of multilevel and spatial models to produce synthetic estimates of attitudes towards the police. Regression-based synthetic estimates, however, are known to suffer from a high risk of bias arising from possible misspecification of models (Rao and Molina, 2015). Other approaches, such as spatial microsimulation (Kongmuang, 2006) and universal kriging (Mooney et al., 2018), have also been used to produce small area estimates of crime and physical disorder, respectively.

Several of these studies have shown the need for incorporating the spatial autocorrelation parameter to SAE when producing estimates for designing place-based policing strategies. The spatial autocorrelation accounts for the geographical concentration of attitudes towards policing and estimators that incorporate it tend to provide more precise estimates than basic model-based estimators. The SEBLUP has shown promising results not only in simulation studies (Asfar and Sadik, 2016; Chandra et al., 2007; Pratesi and Salvati, 2009; Salvati, 2004), but also when it has been applied to social science research, such as the estimation of poverty (Salvati et al., 2014). Thus, the SEBLUP is expected to produce promising results in the field of place-based policing. Hence, we aim to bridge this gap by demonstrating its use for estimating confidence in police work at small area level. In order to gain evidence about the cases in which the SEBLUP provides better estimates than basic model-based estimators when applied to policing data, we provide a simulation study and an application.

5.4 Model description: SEBLUP

Let us consider a target population partitioned into D small areas. In our application, estimates of confidence in policing will be produced for London wards, thus, D equals 610. In the traditional EBLUP derived from the FH model (Fay and Herriot, 1979), we assume that a linking model linearly relates the quantity of inferential interest (i.e. proportion of citizens who think that police do a good job), which is usually an area mean or total δ_d, to p area level auxiliary variables $\boldsymbol{x}_d = (x_{d1}, \dots, x_{dp})'$ with a random effect v_d:

$$\delta_d = \boldsymbol{x}'_d\boldsymbol{\beta} + v_d, \qquad d = 1, \dots, D, \tag{5.1}$$

where $\boldsymbol{\beta}$ is the $p \times 1$ vector of regression parameters and $v_d \sim N(0, \sigma_u^2)$. In our case, δ_d represents the confidence in police work in area d and $\boldsymbol{x}_d$ denotes the covariates known to be associated to confidence in policing (e.g. unemployment, concentration of minorities, poverty). The model assumes that a design-unbiased direct estimate denoted y_d for δ_d, which is obtained from the observed sample, is available for each area $d = 1, \dots, D$:

$$y_d = \delta_d + e_d, \qquad d = 1, \dots, D, \tag{5.2}$$

where $e_d \sim N(0, \psi_d)$ denotes the sampling errors, independent of v_d, and ψ_d refers to the sampling variance of the direct estimates (Fay and Herriot, 1979; Rao and Molina, 2015).

The SEBLUP borrows strength from neighbouring areas by adding spatially correlated random area effects (Petrucci and Salvati, 2006; Salvati, 2004). If we combine (5.1) with (5.2) we can write the following model:

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{v} + \boldsymbol{e}, \tag{5.3}$$

where $\boldsymbol{y} = (y_1, \dots, y_D)'$ is the vector of direct estimates of confidence in policing for D areas, $\boldsymbol{X} = (\boldsymbol{x}_1, \dots, \boldsymbol{x}_D)'$ denotes the covariates associated to the outcome measure for D areas, $\boldsymbol{v} = (v_1, \dots, v_D)'$ is a vector of area effects and $\boldsymbol{e} = (e_1, \dots, e_D)'$ is a vector of sampling errors independent of $\boldsymbol{v}$. We assume $\boldsymbol{v}$ to follow a SAR process with unknown autoregression parameter $\rho \epsilon (-1, 1)$ and a contiguity matrix $\boldsymbol{W}$ (Cressie, 1993):

$$\boldsymbol{v} = \rho \boldsymbol{W} \boldsymbol{v} + \boldsymbol{u}, \tag{5.4}$$

where ρ represents the spatial autocorrelation coefficient of our outcome measure (i.e. confidence in policing) and $\boldsymbol{W}$ is a standardised matrix that relates each area with all neighbouring areas.

We also assume $(\boldsymbol{I}_D - \rho \boldsymbol{W})$ to be non-singular, where $\boldsymbol{I}_D$ is a the $D \times D$ identity matrix, so we can express (5.4) as follows:

$$\boldsymbol{v} = (\boldsymbol{I}_D - \rho \boldsymbol{W})^{-1} \boldsymbol{u}, \tag{5.5}$$

where $\boldsymbol{u} = (u_1, \dots, u_D)'$ satisfies $\boldsymbol{u} \sim N(\boldsymbol{0}_D, \sigma_u^2 \boldsymbol{I}_D)$. Thus,

$$\boldsymbol{y} = \boldsymbol{X\beta} + (\boldsymbol{I}_D - \boldsymbol{\rho W})^{-\boldsymbol{1}} \boldsymbol{u} + \boldsymbol{e}. \tag{5.6}$$

The vector of variance components are denoted as $\boldsymbol{\theta} = (\theta_1, \theta_2)' = (\sigma_u^2, \rho)'$. Then, the Spatial Best Linear Unbiased Predictor (SBLUP) of $\delta_d = \boldsymbol{x}'_d \boldsymbol{\beta} + v_d$ is given by

$$\tilde{\delta}_d^{SBLUP}(\boldsymbol{\theta}) = \boldsymbol{x}'_d \widetilde{\boldsymbol{\beta}}(\boldsymbol{\theta}) + \boldsymbol{b}'_d \boldsymbol{G}(\boldsymbol{\theta}) \boldsymbol{\Sigma}^{-\boldsymbol{1}}(\boldsymbol{\theta}) \{\boldsymbol{y} - \boldsymbol{X} \widetilde{\boldsymbol{\beta}}(\boldsymbol{\theta})\}, \tag{5.7}$$

where $\boldsymbol{b}'_d$ is a $1 \times D$ vector (0,…,1,0,…,0) with 1 in position d. $\boldsymbol{G}(\boldsymbol{\theta})$, the covariance matrix of $\boldsymbol{v}$, is given by $\boldsymbol{G}(\boldsymbol{\theta}) = \sigma_u^2 \{(\boldsymbol{I}_D - \boldsymbol{\rho W})'(\boldsymbol{I}_D - \boldsymbol{\rho W})\}^{-\boldsymbol{1}}$. $\boldsymbol{\Sigma}(\boldsymbol{\theta})$, which is the covariance matrix of $\boldsymbol{y}$, is defined as $\boldsymbol{\Sigma}(\boldsymbol{\theta}) = \boldsymbol{G}(\boldsymbol{\theta}) + \boldsymbol{\Psi}$, where $\boldsymbol{\Psi} =$

$diag(\psi_1, \ldots, \psi_D)$. And $\widetilde{\boldsymbol{\beta}}(\boldsymbol{\theta})$, the weighted least squares estimator of $\boldsymbol{\beta}$, is obtained as $\widetilde{\boldsymbol{\beta}}(\boldsymbol{\theta}) = \{\boldsymbol{X}'\boldsymbol{\Sigma}^{-1}(\boldsymbol{\theta})\boldsymbol{X}\}^{-1}\boldsymbol{X}'\boldsymbol{\Sigma}^{-1}(\boldsymbol{\theta})\boldsymbol{y}$.

The SEBLUP is obtained by replacing a consistent estimator of $\boldsymbol{\theta}$ by $\widehat{\boldsymbol{\theta}} = (\hat{\sigma}_u^2, \hat{\rho})'$:

$$\hat{\delta}_d^{SEBLUP} = \tilde{\delta}_d^{SEBLUP}(\widehat{\boldsymbol{\theta}}) = \boldsymbol{x}'_d\widetilde{\boldsymbol{\beta}}(\widehat{\boldsymbol{\theta}}) + \boldsymbol{b}'_d\boldsymbol{G}(\widehat{\boldsymbol{\theta}})\boldsymbol{\Sigma}^{-1}(\widehat{\boldsymbol{\theta}})\{\boldsymbol{y} - \boldsymbol{X}\widetilde{\boldsymbol{\beta}}(\widehat{\boldsymbol{\theta}})\}. \tag{5.8}$$

If we assume the normality of the random effects, we can estimate σ_u^2 and ρ based on different procedures. In this research, we consider the Restricted Maximum Likelihood (REML) estimator, which takes into account for the loss in degrees of freedom derived from estimating $\boldsymbol{\beta}$, while other estimators, such as the Maximum Likelihood (ML) estimator, do not (Rao and Molina, 2015). The assumption of normality of the random effects is reasonable in those cases in which area-level direct estimates are normally distributed, as tends to be the case in criminological studies looking into the confidence in police work (Williams et al., 2019), emotions about crime (Whitworth, 2012) and rates of some crime types at large spatial scales (Fay and Diallo, 2012). However, such assumption may be considered invalid in those cases in which the normality of direct estimates is not met. This may be the case of studies analysing specific crime types at detailed spatial scales, as these may show zero-inflated skewed distributions and thus robust SAE techniques adjusted to non-normal distributions are needed (Dreassi et al., 2014).

5.4.1 Previous studies using the SEBLUP

The SEBLUP has not yet been used to estimate crime rates or confidence in the police. However, a series of simulation studies and applications analysing economic and agricultural outcomes have shown that the SEBLUP tends to outperform EBLUP estimators when ρ moves away from zero, especially when it is close to -1 or 1 (Chandra et al., 2007; Petrucci and Salvati, 2006; Pratesi and Salvati, 2008, 2009). There are very few simulation studies that investigate the impact of D, and the interaction between D and ρ, on the SEBLUP's performance, and these show contradicting results. Salvati (2004) examined the precision of SEBLUP estimates for D equal to 25 and 50, and ρ={±0.25,±0.5,±0.75}, and concluded that the improvement in the estimates' accuracy is higher when the spatial autoregressive coefficient increases, but also that "benefit is bigger as the number of small areas increase" (Salvati, 2004:11). In policing research, the SEBLUP is thus expected to produce more reliable estimates than the EBLUP when the values of the variable of interest geographically cluster together, as observed in many studies on crime and crime perceptions (Baller et al., 2001; Williams et al., 2019), and when the number of areas for which we aim to produce estimates is large. Therefore, in cases like the one encountered by Gemmell et al. (2004), who produced estimates of drug use for ten local authorities in Greater Manchester, the EBLUP is expected to produce better estimates than the SEBLUP due to the small number of areas under study.

Asfar and Sadik (2016) analyzed the SEBLUP's relative MSEs under D equal to 16, 64 and 144, and they found large relative improvement of SEBLUP estimates even when ρ is very small ($\rho = 0.05$) and small ($\rho = 0.25$), also in cases of very few areas under study ($D = 16$). In addition, such improvement was sometimes larger when D was equal to 16 than in cases of D equal to 64 and 144. These results are not consistent with other simulation studies, which show that SEBLUP's relative performance improves as the number of areas increases (Salvati, 2004), and the SEBLUP's precision is not improved if $\rho \cong 0$ in cases of D equal to 25 and 50 (Salvati, 2004), 61 (Petrucci and Salvati, 2006), 23 (Chandra et al., 2007) and 42 (Pratesi and Salvati, 2008, 2009). Therefore, further research is needed to understand how both ρ and D affect the SEBLUP's relative precision, and we assess the performance of the SEBLUP in subsection 5.5.

5.5 Simulation study

In this section we describe the simulation study designed to assess the effect of D and ρ on the SEBLUP's performance in comparison to EBLUP and post-stratified estimators.

5.5.1 Generating the population and simulation steps

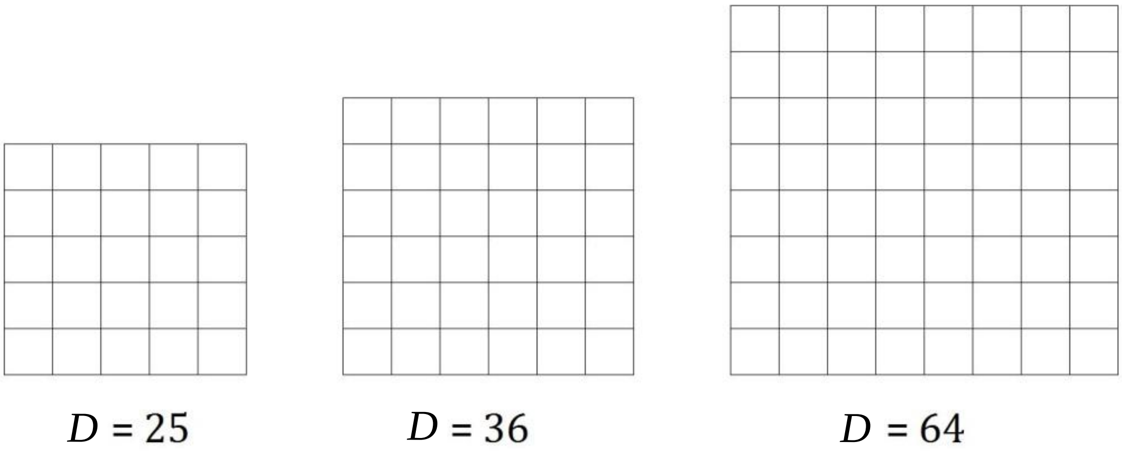
The population is generated based on previous simulation studies such as Petrucci and Salvati (2006) and Pratesi and Salvati (2008). Similar approaches have also been used in Asfar and Sadik (2016), Molina et al. (2009) and Salvati (2004). Simulation parameters are based on previous simulation experiments to allow comparisons and reproducibility. The population is generated following a linear mixed-effect model with random area effects of neighbouring areas correlated to the SAR dispersion matrix with fixed autoregressive coefficient:

$$y_{di} = x_{di}\beta + v_d + e_{di}, \qquad d = 1, \dots, D, \qquad i = 1, \dots, N_d, \tag{5.9}$$

where x_{di} is the value of the covariate x for unit i in area d, v_d denotes the area effect and e_{di} is the individual error. The simulation parameters are given as follows: $\beta = 0.74$, $\sigma_u^2 = 90$, $\sigma^2 = 1.5$ (Petrucci and Salvati, 2006). $\mathbf{v} = [v_1, \dots, v_D]'$ is generated from a $\text{MVN}(0, \sigma_u^2[(\mathbf{I} - \rho\mathbf{W})(\mathbf{I} - \rho\mathbf{W}')]^{-1})$, and $\mathbf{e} = [e_{11}, e_{12}, \dots, e_{di}, \dots, e_{DN_D}]'$ from a $N(0, \sigma^2)$. x_{di} values are generated from a uniform distribution between 0 and 1000 and $N_d = [N_1, \dots, N_D]$ is generated from uniform distribution between 100 and 300. The population size is $N = \sum_{d=1}^{D} N_d$. Thus, we simulate 42 different populations based on different values of spatial autoregressive coefficient, $\rho = \{0, \pm 0.25, \pm 0.5, \pm 0.75\}$, and number of areas, $D = \{16, 25, 36, 64, 144, 225\}$. y_{di} is then produced as a continuous and normally-distributed variable with random area effects of contiguous areas. As a result, area-level aggregates and estimates are continuous, normally distributed and geographically aggregated, as is usually the case of many criminological variables such as confidence in police services, fear of crime or general crime rates at large scales (Fay and Diallo, 2012; Williams et al., 2019; Whitworth, 2012). Future research should also examine different simulation parameters with smaller intra-class correlations.

All maps used are hypothetical maps based on perfect squares divided into D number of areas, where the maximum number of neighbors is 8 and the minimum is 3 at the corners (see Figure 5.1). Future research should conduct similar studies using more realistic maps. Neighbouring areas are defined based on a 'Queen Contiguity' matrix, typically the most common structure used in simulation studies, which defines as neighbours all areas that share borders or at least one vertex. The $\boldsymbol{W}$ matrix is standardised by rows, so that every row adds up to 1.

Figure 5.1 Three examples of hypothetical maps used in simulation study.



The simulation consists in the following steps for each simulated population:

1. Selection of $t = 1, \dots, T$ $(T = 1000)$ simple random samples without replacement. Sample sizes are drawn with the only constraint of a minimum of two units selected in each area (Salvati, 2004). The average sample size per area is $\bar{n}_d = 48.8$.

2. In each sample, post-stratified, EBLUP and SEBLUP estimates are computed and compared based on Pratesi and Salvati (2008). The post-stratified estimator is given by the following:

$$\hat{Y}_d(pst) = \sum_{i \in s_d} \frac{y_{di}}{n_d}, \tag{5.10}$$

   where s_d is the set of n_d sample units falling in area d.

3. The results are evaluated by the absolute relative bias, absolute relative error, relative root mean squared error, and mean squared error averaged through the samples and small areas (Petucci and Salvati, 2006). These are denoted by $\overline{ARB}$, $\overline{ARE}$, $\overline{RRMSE}$, and $\overline{MSE}$, and given by the following formulas, respectively:

$$\overline{ARB} = \frac{1}{D} \sum_{d}^{D} \left| \frac{1}{T} \sum_{t=1}^{T} \left(\frac{\hat{Y}_{dt}}{Y_d} - 1\right) \right| \tag{5.11}$$

$$\overline{ARE} = \frac{1}{D}\sum_{d}^{D}\frac{1}{T}\sum_{t=1}^{T}\left(\left|\frac{Y_{dt}}{Y_d} - 1\right|\right) \tag{5.12}$$

$$\overline{RRMSE} = \frac{1}{D}\sum_{d}^{D}\frac{\left[\overline{MSE}(\hat{Y}_d)^{1/2}\right]}{Y_d} \tag{5.13}$$

with

$$\overline{MSE} = \frac{1}{D}\sum_{d}^{D}\frac{1}{T}\sum_{t=1}^{T}(\hat{Y}_{dt} - Y_d)^2, \tag{5.14}$$

where $\hat{Y}_{dt}$ denotes the estimate (post-stratified, EBLUP or SEBLUP) for small area *d* in sample *t* and Y_d the true value observed in the population for area *d*.

The simulation study has been coded and conducted in R software (Molina and Marhuenda, 2015) and results are detailed in Table 5.1, Table 5.2, Table 5.3 and Table 5.4.

Table 5.1 Estimates' Relative Root Mean Squared Error, Absolute Relative Bias and Absolute Relative Error ($\times$ 100).

			D = 16	D = 25	D = 36	D = 64	D = 144	D = 225
ρ = -0.75	$\hat{Y}(pst)$	$\overline{RRMSE}\%$	12.91	12.50	14.54	12.61	13.08	13.18
		$\overline{ARB}\%$	0.38	0.32	0.42	0.36	0.33	0.31
		$\overline{ARE}\%$	8.95	8.55	10.09	8.78	9.07	9.15
	$\hat{\delta}^{EBLUP}$	$\overline{RRMSE}\%$	11.99	11.53	14.29	11.30	11.80	11.89
		$\overline{ARB}\%$	2.95	2.50	3.85	2.58	2.80	2.57
		$\overline{ARE}\%$	8.56	8.16	10.08	8.13	8.46	8.51
	$\hat{\delta}^{SEBLUP}$	$\overline{RRMSE}\%$	12.23	11.57	14.25	11.21	11.42	11.51
		$\overline{ARB}\%$	2.99	2.53	3.87	2.57	2.78	2.55
		$\overline{ARE}\%$	8.69	8.19	10.05	8.09	8.25	8.34
ρ = -0. 5	$\hat{Y}(pst)$	$\overline{RRMSE}\%$	12.32	13.09	12.40	12.99	12.92	13.15
		$\overline{ARB}\%$	0.29	0.31	0.33	0.33	0.36	0.31
		$\overline{ARE}\%$	8.57	9.07	8.57	9.04	8.94	9.12
	$\hat{\delta}^{EBLUP}$	$\overline{RRMSE}\%$	11.31	12.21	11.21	11.72	11.24	11.86
		$\overline{ARB}\%$	2.59	2.40	2.31	2.66	2.65	2.90
		$\overline{ARE}\%$	8.11	8.65	7.99	8.42	8.10	8.51
	$\hat{\delta}^{SEBLUP}$	$\overline{RRMSE}\%$	11.60	12.36	11.25	11.59	11.23	11.71
		$\overline{ARB}\%$	2.66	2.46	2.36	2.65	2.63	2.87
		$\overline{ARE}\%$	8.27	8.74	8.02	8.37	8.07	8.43
ρ = -0.25	$\hat{Y}(pst)$	$\overline{RRMSE}\%$	13.11	12.62	12.93	12.61	12.68	13.06
		$\overline{ARB}\%$	0.35	0.31	0.24	0.29	0.29	0.31
		$\overline{ARE}\%$	9.14	8.77	8.92	8.76	8.78	9.03
	$\hat{\delta}^{EBLUP}$	$\overline{RRMSE}\%$	12.35	11.40	11.71	11.49	11.18	11.34
		$\overline{ARB}\%$	2.80	2.35	2.57	2.51	2.56	2.79
		$\overline{ARE}\%$	8.79	8.16	8.35	8.23	8.04	8.18
	$\hat{\delta}^{SEBLUP}$	$\overline{RRMSE}\%$	12.50	11.52	11.71	11.41	11.09	11.25
		$\overline{ARB}\%$	2.86	2.39	2.58	2.51	2.54	2.77
		$\overline{ARE}\%$	8.88	8.22	8.34	8.20	8.02	8.15
ρ = 0	$\hat{Y}(pst)$	$\overline{RRMSE}\%$	11.97	12.47	12.77	12.65	12.69	12.99
		$\overline{ARB}\%$	0.36	0.28	0.33	0.36	0.33	0.35
		$\overline{ARE}\%$	8.34	8.65	8.86	8.75	8.79	8.97
	$\hat{\delta}^{EBLUP}$	$\overline{RRMSE}\%$	10.26	10.96	11.52	11.19	10.99	11.47
		$\overline{ARB}\%$	2.38	2.60	2.95	2.61	2.76	2.63
		$\overline{ARE}\%$	7.46	7.93	8.29	8.03	7.95	8.23
	$\hat{\delta}^{SEBLUP}$	$\overline{RRMSE}\%$	10.62	11.08	11.60	11.23	11.03	11.46
		$\overline{ARB}\%$	2.59	2.67	3.00	2.63	2.77	2.62
		$\overline{ARE}\%$	7.70	7.98	8.35	8.06	7.97	8.22
ρ = 0.25	$\hat{Y}(pst)$	$\overline{RRMSE}\%$	11.18	11.58	13.84	11.78	12.77	12.92
		$\overline{ARB}\%$	0.27	0.31	0.44	0.25	0.31	0.33
		$\overline{ARE}\%$	7.77	8.04	9.60	8.16	8.84	8.95
	$\hat{\delta}^{EBLUP}$	$\overline{RRMSE}\%$	9.99	9.96	12.39	10.29	11.48	11.32
		$\overline{ARB}\%$	2.26	2.04	3.29	2.44	2.68	2.67
		$\overline{ARE}\%$	7.20	7.20	8.91	7.41	8.22	8.16
	$\hat{\delta}^{SEBLUP}$	$\overline{RRMSE}\%$	10.15	10.12	12.59	10.30	11.45	11.29
		$\overline{ARB}\%$	2.29	2.12	3.35	2.45	2.68	2.66
		$\overline{ARE}\%$	7.29	7.30	9.01	7.41	8.21	8.15
ρ = 0.5	$\hat{Y}(pst)$	$\overline{RRMSE}\%$	11.25	15.13	12.92	15.23	12.26	12.97
		$\overline{ARB}\%$	0.23	0.39	0.29	0.37	0.31	0.32
		$\overline{ARE}\%$	7.76	10.54	8.99	10.53	8.48	8.98
	$\hat{\delta}^{EBLUP}$	$\overline{RRMSE}\%$	9.85	13.24	11.81	14.12	10.73	11.50
		$\overline{ARB}\%$	2.23	2.97	2.64	3.03	2.45	2.66
		$\overline{ARE}\%$	7.04	9.58	8.48	9.99	7.72	8.27
	$\hat{\delta}^{SEBLUP}$	$\overline{RRMSE}\%$	10.01	13.36	11.66	13.99	10.63	11.26
		$\overline{ARB}\%$	2.28	3.02	2.68	3.04	2.44	2.65
		$\overline{ARE}\%$	7.13	9.65	8.41	9.95	7.67	8.13
ρ = 0.75	$\hat{Y}(pst)$	$\overline{RRMSE}\%$	12.81	11.02	13.06	11.15	15.71	15.06
		$\overline{ARB}\%$	0.21	0.27	0.29	0.29	0.34	0.39
		$\overline{ARE}\%$	8.88	7.65	9.08	7.69	10.88	10.42
	$\hat{\delta}^{EBLUP}$	$\overline{RRMSE}\%$	11.81	10.36	11.62	10.50	14.61	13.94
		$\overline{ARB}\%$	2.64	2.11	2.84	1.97	2.95	2.84
		$\overline{ARE}\%$	8.41	7.33	8.37	7.39	10.35	9.90
	$\hat{\delta}^{SEBLUP}$	$\overline{RRMSE}\%$	11.96	10.07	11.33	9.98	13.69	13.02
		$\overline{ARB}\%$	2.66	2.13	2.86	1.98	2.95	2.82
		$\overline{ARE}\%$	8.51	7.19	8.22	7.04	9.86	9.41

5.5.2 Results: Comparison of EBLUP and SEBLUP estimates

Table 5.1 shows the $\overline{RRMSE}$, $\overline{ARB}$ and $\overline{ARE}$ of post-stratified, EBLUP and SEBLUP estimates from each simulated population. Both EBLUP and SEBLUP estimators outperform post-stratified estimators in all cases, in terms of $\overline{RRMSE}$ and $\overline{ARE}$, regardless of the spatial correlation parameter and the number of areas under study. The post-stratified estimator performs better in terms of $\overline{ARB}$, as expected. ρ and D do not affect the EBLUP or SEBLUP's relative difference towards post-stratified estimates regardless of the quality measure selected. The relative difference between post-stratified and SEBLUP estimates' $\overline{RRMSE}$, which expresses the absolute percentage change of the estimate quality measure, has been calculated as follows:

$$RD\% = \frac{\overline{RRMSE}\left[\hat{\delta}^{SEBLUP}\right] - \overline{RRMSE}\left[\hat{Y}(pst)\right]}{\overline{RRMSE}\left[\hat{Y}(pst)\right]} \times 100 \qquad (5.15)$$

Equation (5.15) gives the measure of efficiency of $\hat{\delta}^{SEBLUP}$ over $\hat{Y}(pst)$ estimates.

The relative difference between post-stratified and SEBLUP estimates' $\overline{RRMSE}$ varies between a maximum of -5.83% in the case of $D = 64$ and $\rho = 0.75$ and a minimum of -14.29% in the case of $D = 16$ and $\rho = 0$, having also small values such as -13.99% in the case of $D = 25$ and $\rho = 0.25$, -13.40% in the case of $D = 144$ and $\rho = 0$, and -13.00% in the case of $D = 144$ and $\rho = -0.5$. In other words, neither ρ nor D can be used to interpret the increased precision, in terms of $\overline{RRMSE}$ and $\overline{ARE}$, of EBLUP and SEBLUP estimates when compared to post-stratified estimates. However, both ρ and D have a large impact in the improvement of the SEBLUP estimates, which perform substantially better than EBLUP estimates for those cases with a medium and large spatial correlation parameter (especially $\rho = \{\pm 0.50, \pm 0.75\}$) and a large number of areas (notably $D = \{144, 255\}$) (see Table 5.2, Table 5.3 and Table 5.4).

Table 5.2 Relative difference between EBLUP and SEBLUP's RRMSE (× 100).

	D = 16	D = 25	D = 36	D = 64	D = 144	D = 255
ρ = -0.75	2.00	0.35	-0.28	-0.80	-3.22	-3.20
ρ = -0.5	2.56	1.23	0.36	-1.11	-0.09	-1.26
ρ = -0.25	1.21	1.05	0.00	-0.70	-0.81	-0.79
ρ = 0	3.51	1.09	0.69	0.36	0.36	-0.09
ρ = 0.25	1.60	1.61	1.61	0.10	-0.26	-0.27
ρ = 0.5	1.62	0.91	-1.27	-0.92	-0.93	-2.09
ρ = 0.75	1.27	-2.80	-2.50	-4.95	-6.30	-6.60

Table 5.3 Relative difference between EBLUP and SEBLUP's ARB (× 100).

	D = 16	D = 25	D = 36	D = 64	D = 144	D = 255
ρ = -0.75	1.36	1.20	0.52	-0.39	-0.71	-0.78
ρ = -0.5	2.70	2.50	2.16	-0.38	-0.75	-1.03
ρ = -0.25	2.14	1.70	0.39	0.00	-0.78	-0.72
ρ = 0	8.82	2.69	1.69	0.77	0.36	-0.38
ρ = 0.25	1.33	3.92	1.82	0.41	0.00	-0.37
ρ = 0.5	2.24	1.68	1.52	0.33	-0.41	-0.38
ρ = 0.75	0.76	0.95	0.70	0.51	0.00	-0.70

Table 5.4 Relative difference between EBLUP and SEBLUP's ARE (× 100).

	D = 16	D = 25	D = 36	D = 64	D = 144	D = 255
ρ = -0.75	1.52	0.37	-0.30	-0.49	-2.48	-2.00
ρ = -0.5	1.97	1.04	0.38	-0.59	-0.37	-0.94
ρ = -0.25	1.02	0.74	-0.12	-0.36	-0.25	-0.37
ρ = 0	3.22	0.63	0.72	0.37	0.25	-0.12
ρ = 0.25	1.25	1.39	1.12	0.00	-0.12	-0.12
ρ = 0.5	1.28	0.73	-0.83	-0.40	-0.65	-1.69
ρ = 0.75	1.19	-1.91	-1.79	-4.74	-4.73	-4.95

Table 5.2 shows the relative difference between EBLUP and SEBLUP estimates' $\overline{RRMSE}$, as shown in Eq. (5.15), formatting the cells based on a black-to-white colour scale. Darker scales represent positive values, meaning a better performance of EBLUP estimates with respect to their quality measure, and white scales refer to negative values, which show that SEBLUP estimates improve their quality measure when compared to EBLUP estimates. First, it is clear from Table 5.2 that SEBLUP estimates outperform EBLUP estimates, in terms of $\overline{RRMSE}$, when the spatial correlation parameter is large, while EBLUP estimates tend to be more precise than the SEBLUP when ρ is close to 0. The SEBLUP is thus preferred over the EBLUP to examine social issues that spatially cluster together, as is the case of crime rates (Baller et al., 2001) and perceptions about crime and the police (Jackson et al., 2013; Williams et al., 2019). Second, the relative difference between EBLUP and SEBLUP estimates' $\overline{RRMSE}$ shows that the benefit obtained by borrowing strength from neighboring areas is larger as the number of areas increases. For example, for $D = 25$ the relative difference of $\overline{RRMSE}$ shows that SEBLUP estimates are more precise than the EBLUPs only when the spatial correlation parameter is very large ($\rho = 0.75$), while the SEBLUP outperforms the EBLUP in all cases for $D = 255$, even when $\rho = 0$. In other words, the EBLUP is expected to outperform the SEBLUP in studies producing estimates for a small number of areas (e.g. estimates of drug use for ten local authorities; Gemmell et al., 2004); while the SEBLUP produces more reliable estimates when the number of areas under study is large. Therefore, both ρ and D need to be taken into account to explain SEBLUP estimates increased precision in terms of $\overline{RRMSEs}$, and SEBLUP estimates perform better as the number of areas under study increases.

Table 5.3 shows the relative difference between EBLUP and SEBLUP estimates' $\overline{ARB}$ and Table 4 shows the relative difference between their $\overline{ARE}$. Looking at Table 3, it is clear that SEBLUP estimates perform better than the EBLUPs, in terms of $\overline{ARB}$, when the number of areas is large (especially $D = \{144, 255\}$), but not in cases of $D = \{16, 25, 36\}$. For $D = 64$, SEBLUP estimates' $\overline{ARB}$ is only improved when $\rho = -0.5$ and $\rho = -0.75$. Again, while the $\overline{ARB}$ of SEBLUP estimates were not improved in any case for $D = \{16, 25, 36\}$, such quality measure shows that SEBLUP estimates outperform EBLUPs, in terms of $\overline{ARB}$, in all simulations performed for $D = 255$.

Table 5.4 also shows that both ρ and D have a large impact to improve SEBLUP estimates' precision, now in terms of $\overline{ARE}$. For example, for $D = 25$ the relative difference between EBLUP and SEBLUP's $\overline{ARE}$ shows that EBLUP estimates outperform SEBLUPs in all cases except for $\rho = 0.75$; while for $D = 144$ such value shows a better precision of SEBLUP estimates except when $\rho = 0$, and for $D = 255$ the SEBLUP produces better estimates than the EBLUP in every single case.

5.6 Empirical evaluation and application: Confidence in police work in London

In this section we assess and apply the SEBLUP in a real case scenario. We produce direct, EBLUP and SEBLUP estimates of confidence in police work at ward level in Greater London from MPSPAS 2012 data. Such an application provides further evidence about the SEBLUP performance when applied to policing data. Moreover, this application produces a reliable map of the confidence in police work in London and deepens the meso-level explanatory mechanisms of confidence in policing, by which we mean the proportion of citizens who think the police do a good job (Jackson and Bradford, 2010; Stanko and Bradford, 2009; Staubli, 2017). We then draw the map of the distribution of confidence in policing in London.

There are various reasons why this research has been conducted using London survey data instead of any other city. First, London is one of the few cities with an available local survey designed to measure the confidence in police work. Second, the Greater London Authority website provides information about many auxiliary variables that are relevant for this research and may be used as covariates. Third, London is a well-researched city (Hutt et al., 2018; Jackson et al., 2013; Stanko and Bradford, 2009) and thus it is easier to exclude the possibility of drawing spurious associations due to uncontrolled variables. Fourth, during preliminary conversation with Greater London Authority's officers it was acknowledged that this research's potential insights may be of great value for decision-making purposes.

5.6.1 Data and methods

Data from the MPSPAS 2012 have been used to produce estimates of confidence in police work. MPSPAS is an annual survey conducted by the Metropolitan Police

Service since 1983, which records information about perceptions of policing needs, worry about victimization and perceived security and disorder. It consists on a face-to-face questionnaire conducted at the homes of respondents, and it obtains responses from a random probability sample of residents in each of the 32 boroughs in Greater London. Household addresses are selected randomly in each borough, and then the person in each household whose next birthday is closest to the date of the interview is asked to answer the questionnaire. The sample is representative of residents aged 16 or over and it should be large enough to allow analyses at borough level but not at smaller scales. Access to the low level geographies of the MPSPAS was only granted for the 2012 edition, and thus small area estimates of confidence in policing are only produced for this year.

Small area estimates will be produced at the ward level for the five London sub-regions. Each sub-region contains a different number of wards: Central ($D = 114$), North ($D = 61$), South ($D = 120$), East ($D = 192$) and West ($D = 140$). Central London is composed of 114 wards in six boroughs: Camden (*n*=399), Kensington and Chelsea (*n*=400), Islington (*n*=399), Lambeth (*n*=387), Southwark (*n*=401) and Westminster (*n*=400). North London is composed of 61 wards in three boroughs: Barnet (*n*=400), Enfield (*n*=400) and Haringey (*n*=401). South London is composed of 120 wards in six boroughs: Bromley (*n*=402), Croydon (*n*=414), Kingston upon Thames (*n*=402), Merton (*n*=401), Sutton (*n*=402) and Wandsworth (*n*=400). East London is composed of 192 wards in ten boroughs: Barking and Dagenham (*n*=404), Bexley (*n*=399), Greenwich (*n*=400), Hackney (*n*=400), Havering (*n*=402), Lewisham (*n*=399), Newham (*n*=407), Redbridge (*n*=401), Tower Hamlets (*n*=401) and Waltham Forest (*n*=401). Finally, West London is composed of 140 wards within seven boroughs: Brent (*n*=403), Ealing (*n*=401), Hammersmith and Fulham (*n*=399), Harrow (*n*=401), Richmond upon Thames (*n*=401), Hillingdon (*n*=403) and Hounslow (*n*=403). The average sample size per ward is similar in all sub-regions: in Central London $\bar{n} = 20.23$, in the North $\bar{n} = 19.02$, in the South $\bar{n} = 19.37$, in the East $\bar{n} = 20.6$, and in West London $\bar{n} = 19.44$. On average, there are 19.85 citizens sampled per ward. Note that three wards in Central London, and fourteen in East London, suffered from zero sample sizes, and thus were not included in our analyses. Regression-based synthetic estimates are used in these seventeen areas.

The variable used to measure confidence in police work has been obtained from the question “Taking everything into account, how good a job do you think the police in this area are doing?”, as suggested by Stanko and Bradford (2009). In order to produce more easily interpretable results, responses were dichotomised to a 0-1 measure, where 1 refers to “Excellent” or “Good”, while “Very poor”, “Poor” and “Fair” responses were recoded as 0. “Don’t know” answers were coded as missing data. We then produce estimates of the proportion of people who think the police are doing a good or excellent job in local area (defined in the survey as the area within about 15 minutes’ walk from home). Based on the literature review, we fitted EBLUP and SEBLUP models using the following area-level covariates: proportion of black and minority ethnic groups 2011, mean household income 2011-12, crime rate 2011-12, proportion of residents born outside the UK 2011, and proportion of citizens unemployed 2011. All covariates are recorded by the Greater London Authority’s Ward Profiles and Atlas (https://data.london.gov.uk/dataset/ward-profiles-and-atlas). We found no available or reliable estimates at the ward level of other covariates explored by previous literature, such as residential instability, perceived disorder and collective efficacy, and thus these are subject of future research.

Direct estimates of the proportion of residents who think that police services do a good job are produced from the following estimator (Horvitz and Thompson, 1952):

$$\hat{Y}_d(dir) = N_d^{-1} \sum_{i \in s_d} w_{di} y_{di}, \tag{5.16}$$

where w_{di} corresponds to the survey weight of unit i from area d (provided by the original survey), and y_{di} is the score of unit i from area d. Original survey weights are computed as the proportional distribution by borough of all citizens aged 15 or more across London (derived from Census data) divided by the proportional distribution of the unweighted sample by borough. In order to produce the SEBLUP estimates, a first-order ‘Queen Contiguity’ structure is used to define neighbouring areas.

5.6.2 Estimates reliability measures

In order to assess the estimates produced in each sub-region, Table 5 shows direct, EBLUP and SEBLUP estimates' average $RRMSE$, as well as the average Relative Difference ($\overline{RD}\%$) between EBLUP and SEBLUP's estimates $\overline{RRMSE}$. The direct estimates' $RRMSE$ is the Coefficient of Variation (Rao and Molina, 2015), while the EBLUP estimates' $RRMSE$ is obtained from Prasad-Rao analytical approximation (Prasad and Rao, 1990) and SEBLUPs' $RRMSEs$ have been produced using an analytical approximation as in Molina et al. (2009).

Table 5.5 Estimates' quality measures.

	Central	*North*	*South*	*East*	*West*	*All areas*
$\bar{\rho}$	0.74	0.03	0.38	0.06	0.60	0.46
D	111	61	120	178	140	610
$\overline{RRMSE}\%\left[\hat{Y}(dir)\right]$	18.31	20.30	17.93	20.64	19.55	19.40
$\overline{RRMSE}\%\left[\hat{\delta}^{EBLUP}\right]$	11.05	14.38	11.24	13.44	14.04	12.21
$\overline{RRMSE}\%\left[\hat{\delta}^{SEBLUP}\right]$	10.31	14.45	11.18	13.69	13.97	11.91
$\overline{RD}\%\left[\hat{\delta}^{EBLUP}, \hat{\delta}^{SEBLUP}\right]$	-7.25	-0.28	-2.05	-1.89	-5.27	-4.76

Table 5.5 shows that direct estimates are the least precise (larger $\overline{RRMSE}$) in all cases, as expected. SEBLUP estimates are more reliable than EBLUPs, in terms of $\overline{RRMSE}$, in all six scenarios. The $\overline{RD}\%$ shows that the averaged increased precision of SEBLUP estimates compared to EBLUPs is larger as both the ρ and D increase. First, although ρ is similar in North ($\rho = 0.03$) and East London (ρ =0.06), the $\overline{RD}\%$ shows better results in the East ($\overline{RD}\% = -1.89$) compared to the North ($\overline{RD}\% = -0.28$) partly due to the larger D in East London (D =178). Then, even though the low ρ partly explains the small increased precision of SEBLUP estimates when compared to EBLUPs, the spatial autocorrelation parameter cannot be used on its own to explain why such increased precision is higher in the case of $D = 178$ than $D = 61$. Second, although D is slightly larger in South London (D =120) compared to Central London (D =111), $\overline{RD}\%$ is higher in Central London ($\overline{RD}\% = -7.25$) due to the high spatial autocorrelation parameter ($\rho = 0.74$). Finally, the best relative results of the SEBLUP estimator have been obtained in Central London, where both D (111) and ρ (0.74) are large, and West London, for the same reason (D =140 and ρ =0.60). In the case of all areas, D is large (610) and ρ is equal to 0.46, and thus the

Relative Difference between EBLUP and SEBLUP's estimates $\overline{RRMSE}$ is quite high ($\overline{RD}\% = -4.76$). These results provide empirical evidence to support the simulation study results: the SEBLUP should be used in those studies producing estimates of geographically concentrated phenomena (Baller et al., 2001) for a large number of areas; while the EBLUP is preferred when producing estimates of non-geographically concentrated phenomena with a small spatial autocorrelation coefficient for a small number of domains.

Table 5 also shows that the level of spatial clustering of the public confidence in police work is much larger in Central and Western London than in the North and East, and there is a medium level of spatial concentration in the South. In other words, while neighbouring areas tend to show similar values of confidence in the police in Central and Western London, and thus policing interventions may be planned for groups of areas, in the North and East place-based policing strategies should be adjusted to the characteristics and needs of each small area.

5.6.3 Mapping the confidence in police work

Goodness-of-fit indices are analysed to assess the models used in this application. Log-likelihood, AIC and BIC measures show that the SEBLUP has a better goodness of fit than the EBLUP model, and thus we focus on its results (see Table 5.6).

Table 5.6 Goodness-of-fit indices of EBLUP and SEBLUP models of confidence in policing.

		Central	*North*	*South*	*East*	*West*	*All areas*
EBLUP	*Log-likelihood*	60.54	23.34	58.23	77.46	52.63	266.55
	AIC	-121.43	-35.12	-107.78	-140.79	-98.56	-519.11
	BIC	-98.23	-25.99	-90.32	-117.34	-80.02	-488.22
SEBLUP	*Log-likelihood*	69.06	27.40	60.56	80.28	56.80	275.58
	AIC	-126.12	-40.81	-109.12	-148.56	-101.61	-535.58
	BIC	-109.86	-30.14	-92.39	-129.47	-83.96	-499.86

Table 5.7 shows the results of the EBLUP and SEBLUP models fitted to produce estimates of confidence in police work for all London wards. All covariates but the

crime rate show significant relations with the confidence in police work (Kwak and McNeeley, 2017; Wu et al., 2009). The proportion of citizens unemployed is the most important covariate introduced in our area-level SEBLUP model, followed by the concentration of ethnic minorities and the proportion of immigrants (Dai and Johnson, 2009; Kwak and McNeeley, 2017; Sampson and Bartusch, 1998; Wu et al., 2009). The mean income also shows a significant but smaller positive relation with the confidence in the police.

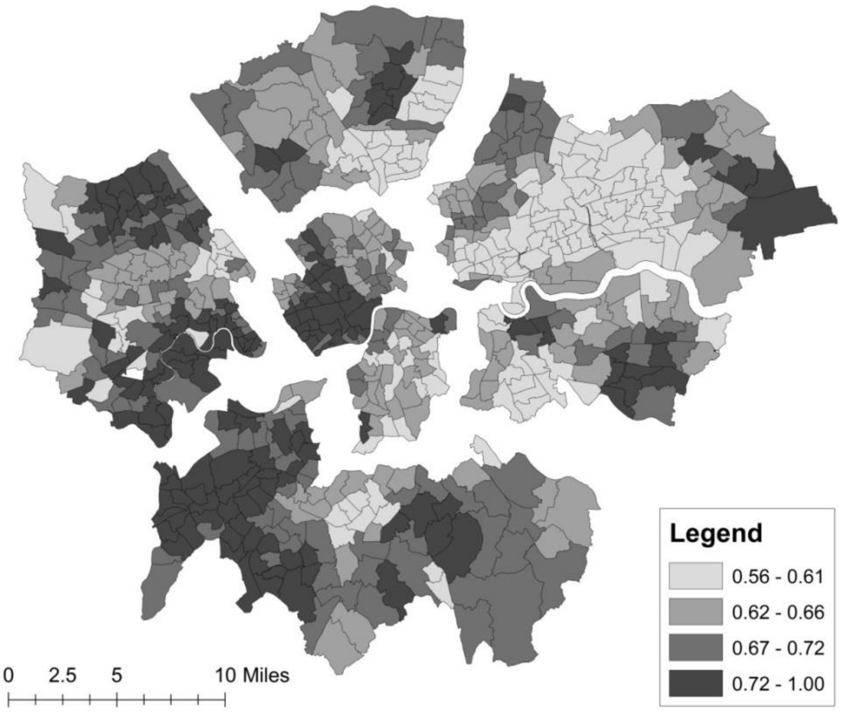
Table 5.7 EBLUP and SEBLUP models of confidence in police work (all areas).

	EBLUP				SEBLUP			
	Coeff.	SE	t-value	p-value	Coeff.	SE	t-value	p-value
(Intercept)	0.615	0.05	10.24	0.000	0.588	0.06	9.32	0.000
Proportion minorities	-0.114	0.08	-1.37	0.049	-0.112	0.09	-1.17	0.048
Mean income	0.001	0.00	3.20	0.001	0.001	0.00	3.09	0.002
Crime rate	-0.001	0.00	-0.69	0.132	-0.001	0.00	-0.99	0.123
Proportion immigrants	-0.027	0.09	-1.13	0.037	-0.031	0.09	-1.12	0.036
Proportion unemployed	-0.317	0.15	-1.90	0.004	-0.293	0.17	-1.70	0.009
AIC	-519.11				-535.17			
BIC	-488.22				-499.86			
Spatial correlation					0.46			

Figure 5.2 shows the geographical distribution of SEBLUP estimates of confidence in police work at ward level in Greater London, where lighter scales of grey indicate a lower proportion of citizens who think that police do a good or excellent job, and darker scales of grey shows higher confidence in police work. The highest estimates of confidence in police work have been found in eight wards located in Central London, six of which are in Kensington and Chelsea (Chelsea Riverside (97.3%), Campden (89.99%), Earl's Court (86.66%), Courtfield (86.28%), Queen's Gate (85.47%) and Brompton and Hans Town (84.62%)) and two in Westminster (Lancaster Gate (88.46%) and Marylebone High Street (88.38%)). There are also high proportions of citizens who think that police do a good in some western areas of Harrow, Richmond upon Thames and Hammersmith and Fulham. The lowest proportions have been estimated in Alexandra, located in Haringey (43.79%), followed by 27 eastern wards distributed among Lewisham, Newham, Barking and Dagenham, Redbridge, Tower Hamlets, Barking and Dagenham and Greenwich. From a broader perspective, these results add evidence to the estimates produced by

the London Mayor’s Office for Policing and Crime (https://maps.london.gov.uk/NCC/) at a larger geographical scale, which show the highest levels of trust in policing in Central and Southwest London and lower trust in the police in East and North London.

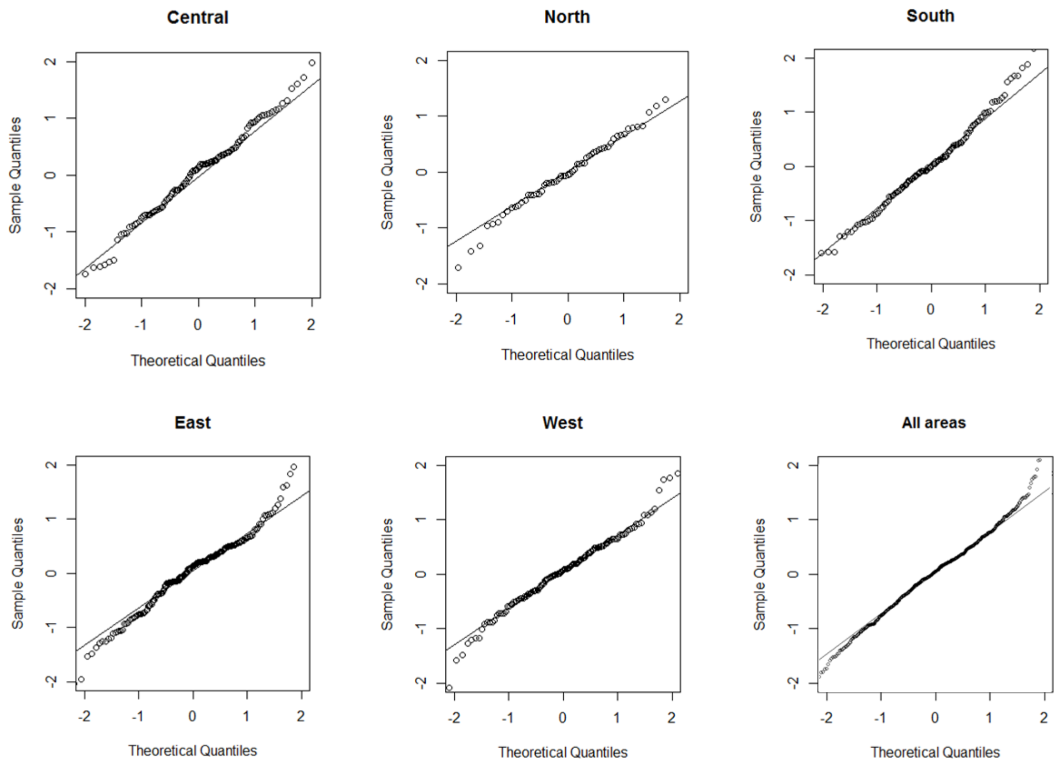
Figure 5.2 Proportion of citizens who think the police do a good or an excellent job (SEBLUP estimates). Division based on quartiles.



5.6.4 Model diagnostics

We provide diagnostics of our spatial models by analysing the normality of SEBLUP standard residuals. Residuals are produced as suggested by Petrucci and Salvati (2006:178) and normal *q*-*q* plots are shown in Figure 5.3. Most residuals show no important deviations. The Shapiro-Wilk test for normality fails to reject the null hypothesis of normal distribution in all five cases: $W = 0.984$ and $p - value = 0.204$ in the case of Central London, $W = 0.969$ and $p - value = 0.128$ in the model fitted for North London, $W = 0.967$ and $p - value = 0.089$ for South, $W = 0.939$ and $p - value = 0.079$ in the case of East London, and $W = 0.975$ and $p - value = 0.098$ for West London. We also fail to reject the null hypothesis of normal distribution for the model fitted with all areas: $W = 0.964$ and $p - value = 0.121$.

Figure 5.3 Normal q-q plots of standardised residuals of SEBLUP estimates.



5.7 Conclusions

Place-based policing requires the incorporation of SAE techniques when producing maps of confidence in police work at small geographical levels. By producing reliable small area estimates of confidence in policing, we allow for advanced spatial analyses to explain its distribution and provide precise maps to develop place-based interventions to enhance confidence in police work and reduce crime and disorder. While police records are easily geocoded and mapped, advanced statistical analyses are required to produce reliable estimates of survey-recorded confidence in the police (Groves and Cork, 2008). Small geographical areas are unplanned domains in most crime surveys, and thus model-based SAE techniques are needed to produce estimates of adequate precision (Rao and Molina, 2015). Due to the typically high levels of spatial autocorrelation of confidence in policing, we propose making use of the SEBLUP to increase the reliability of estimates produced from crime surveys. The simulation study and application results allow examining the cases in which the SEBLUP produces better estimates than traditional model-based estimators when applied to policing data. Our estimates of confidence in police work not only have tactical and strategical value to design place-based policing interventions, but they also are important from an accountability point of view: government and auditors' inspections into the police expect that police forces enhance their public confidence and legitimacy (HMICFRS, 2017).

We have assessed the SEBLUP performance under different scenarios with unequal number of areas and spatial correlation parameters. Our results show that the SEBLUP tends to outperform the EBLUP not only when ρ moves away from zero and is close to 1 and -1, but also when D is large. The SEBLUP performs better as the number of areas under study increases, while EBLUP estimator outperforms the SEBLUP both when $\rho \cong 0$ and D is small. Future work will investigate the SEBLUP using different simulation parameters with smaller intra-class correlations and more complex contiguity matrices, such as second-order 'Queen Contiguity' and distance weighted matrices. Furthermore, future research will examine whether small area estimators that borrow strength from temporal series, such as the Rao and Yu (1994) model and the STEBLUP (Marhuenda et al., 2013), provide more reliable estimates in policing research, as confidence in policing is known to be quite stable over time and thus temporally correlated random effect can be used in this field.

From a substantive perspective, our estimates show that citizens are more confident in policing in most Central and South-western London neighbourhoods, while estimates show a lower confidence in the police in East and North London. Unlike previous research, our estimates are produced at a ward level and thus allow not only for mapping the distribution of confidence in police work at a large scale, but these also bring to light internal heterogeneity in the levels of confidence at a neighbourhood level. In Central London, for example, estimates are significantly higher in the northern part of the River Thames, where Westminster and Kensington and Chelsea are located, than in the Southern part of the river. Although crime rates are higher in the northern part of the river, these do not appear to be as significant as the unemployment rate and concentration of minorities, which are more prominent in the southern part of Central London, to explain the distribution of confidence in policing. Our estimates also allow distinguishing clear differences within West London, where confidence in police is clearly higher in most Hounslow wards than in the majority of Ealing neighbourhoods, where unemployment and deprivation is more common. These estimates are useful to develop more accurate explanations of the distribution of confidence in police work and to design place-based policing strategies to increase the public confidence in policing and their cooperation with police services.

The unemployment rates, concentration of minorities and immigrants and average income have shown to be good area-level predictors of the confidence in police work (Bradford et al., 2017; Dai and Johnson, 2009; Jackson et al., 2013; Kwak and McNeeley, 2017; Sampson and Bartusch, 1998; Wu et al., 2009). The two most important covariates (among those included in our models) to explain the geographies of confidence in police work in London are the unemployment rates and concentration of ethnic minorities. As argued by Sampson and Bartusch (1998:801): "perhaps we should not be surprised that those most exposed to the numbing reality of pervasive segregation and economic subjugation become cynical about human nature and legal systems of justice". High levels of unemployment and ethnic segregation, as forms of deprivation, might explain that neighbours' local identities shaped by deprivation are less willing to trust and cooperate with police services (Kwak and McNeeley, 2017), but also with other government services (Dai and Johnson, 2009). Other researchers argue that this might also be due to an excessive police control and use of force on certain communities with larger concentration of minorities (Dai and Johnson, 2009). Open access to Metropolitan Police stop and search data was available only after 2015 and the spatial information about police use of stop and search was available only since mid-2016, and thus we could not include this covariate in our analyses (based on survey data from 2012). However, our area-level estimates of confidence in police work from 2012 show a significant negative Spearman correlation with the proxy measure of stop and search in 2017 (stop and search count: $\rho=-0.22$, *p-value*<0.01; stop and search per resident: $\rho=-0.16$, *p-value*<0.01). Thus, future research with newer survey data should incorporate this covariate to explore the effect of stop and search on the confidence in police work. Similar mechanisms are used to explain the effect of the concentration of immigrants and average income in the confidence in police work, although these show smaller coefficients in our study. Immigrants and citizens with low income tend to cluster in areas large levels of concentrated disadvantage -and possibly higher police control and use of force- where social attitudes of distrust towards the police are likely to emerge.

Future research with newer survey data will focus on scoping for other available covariates (e.g. residential instability, collective efficacy, stop and search) to estimate confidence in the police at a ward or smaller spatial levels; and to examine causal mechanisms between economic deprivation, ethnic segregation and confidence in police work (Dai and Johnson, 2009). Further research will also replicate similar analyses in other cities and countries with different social and demographic characteristics (and available survey data) to assess generalisability of the current study's findings. In addition, new SAE methods are needed that deal with semicontinuous zero-inflated skewed data in policing data (see Dreassi et al., 2014). By expanding the body of research that makes use of SAE techniques in policing research and practice, these methods may become a core tool in survey-based crime analysis and place-based policing.

Acknowledgments

The authors thank the Metropolitan Police Service and the Mayor's Office for Policing and Crime for providing the data used in this research.

CHAPTER 6: Article 2 - Worry about crime in Europe. A model-based small area estimation from the European Social Survey[3]

6.1 Introduction

Worry about crime is not homogeneously distributed across space. There are countries where people are more worried about crime and more likely to feel unsafe than others (Hummelsheim et al., 2011; Vauclair and Bratanova, 2017; Visser et al., 2013). In Europe, cross-national surveys show that Southern and Eastern-European countries have the highest levels of worry about crime, while worry is lower in Scandinavia and Central Europe (Jackson and Kuha, 2014). Worry about crime is also known to be unequally distributed across the regions in each country (Fitzgerald et al., 2012; Rueda and Stegmueller, 2015), and it is higher in certain neighbourhoods than others (Brunton-Smith and Sturgis, 2011).

Different and heterogeneous measures have been used to capture the citizens' emotions about the threat of becoming victims of crime (Gabriel and Greve, 2003; Rader, 2004). Questions about perceived risk, feelings of unsafety, fear, concern and worry about crime have been equally used to theorise an ambiguous construct of 'fear of crime' (DuBow et al., 1979), and hence there is a need to provide conceptual clarity and precision in the field. Jackson and Gouseti (2014) argue that the concept of 'worry about crime' captures most people's anxiety-producing concerns about crime, and it draws links between perceived threats and emotions, thus being preferred to examine the citizens' emotions about crime (Williams et al., 2000). Conversely, the fear of crime is an emotional response that humans have in very specific threatening situations, and it is difficult to operationalise and measure (Castro-Toledo et al., 2017; Solymosi et al., 2015). According to Hough (2004), fear of crime can be referred to as a 'mental event' taking place at a specific time and place, while worry is a 'mental state' reflecting concerns about crime and insecurities. Some authors also distinguish between 'functional' and 'dysfunctional' worry, where the prior refers to the type of worry that improves well-being by

[3] *Full reference:* Buil-Gil, D., Moretti, A., Shlomo, N., & Medina, J. (2019). Worry about crime in Europe. A model-based small area estimation from the European Social Survey. *European Journal of Criminology*. https://doi.org/10.1177/1477370819845752.

making citizens take precautions and the latter refers to the type of worry that damages citizens' quality of life (Gray et al., 2011).

Research has tended to agree that emotions about the threat of victimisation have different meanings and explanatory processes at different geographic scales. At the individual level, these emotions tend to be explained as the result of the citizens' experience with crime; at a neighbourhood level, these are understood as a function of people's understanding of their local areas; and at a macro level, it can be interpreted as "a social phenomenon shaped by media and as part of a generalised and diffused anxiety generated by current global and social changes" (Ceccato, 2012:10).

Cross-national differences in levels of worry about crime and feelings of unsafety are partly explained by countries' levels of social and economic insecurity (Vauclair and Bratanova, 2017; Vieno et al., 2013). These processes are also reflected in an unequal regional distribution of worry about crime within countries (Fitzgerald et al., 2012; Rueda and Stegmueller, 2015), and thus the regions' characteristics are also likely to affect the citizens' emotions about crime. This is why some argue that, at a macro level, emotions about crime shall be interpreted as 'umbrella sentiments' that hide not only crime-related concerns but also social and economic anxieties (Vieno et al., 2013).

The conceptual framework of 'worry about crime' is thus preferred to examine emotions about the threat of victimisation at a macro-geographic level. The interpretation of such emotions and their macro-level distribution resemble 'mental states' of general concerns and anxieties affected by macro-level socio-economic insecurity, rather than 'mental events' driven by immediate threatening situations. Others prefer the use of measures of feelings of unsafety to conduct macro-level comparisons between countries (e.g. Hummelsheim et al., 2011), but these measures have been highly criticised for struggling to capture the emotional component –either physical responses (fear) or softer ruminations or anxieties (worry)– rather than only perceived risks.

Cross-national analyses of worry about crime are needed to facilitate understanding of its macro-level predictors. And the development of maps of its distribution at regional level are of great value for regional, national and supranational administrators to design and implement targeted policies to reduce concerns and anxieties about the threat of crime. In order to map the worry about crime across countries, cross-national surveys are the most important source of information. These are often designed to record representative samples at a state level, and smaller geographical units (e.g. regions) are unplanned areas and suffer from small and unrepresentative samples. Thus, direct estimates, which use only area-specific sample data, may suffer from low precision. Instead, model-based SAE techniques make use of auxiliary data to 'borrow strength' across related areas and produce precise estimates in unplanned areas (Rao and Molina, 2015), yet they are underutilised in criminology[4]. This research aims to produce reliable small area estimates of dysfunctional worry about crime at a regional level in Europe based on ESS data. By providing these estimates, this article presents the first map of the regional distribution of dysfunctional worry about crime in Europe, identifying subnational internal heterogeneity in levels of worry and providing precise information about its macro-level predictors.

We make use of the SEBLUP under the FH model (Fay and Herriot, 1979), which borrows strength both from related and neighbouring areas (Petrucci and Salvati, 2006). Much like the geographical distribution of crime, emotions about crime are known to be spatially aggregated (Vauclair and Bratanova, 2017; Vieno et al., 2013) and show high levels of spatial autocorrelation (Wyant, 2008). We thus expect to improve the precision of our estimates by borrowing strength from neighbouring areas.

Section 6.2 discusses the nature, measurement and prediction of worry about crime. Section 6.3 describes data and methods. Section 6.4 presents model results, estimates, estimates' reliability checks, and model diagnostics. Finally, Section 6.5 discusses findings and conclusions.

[4] In 2008, the US Panel to Review the Programs of the Bureau of Justice Statistics suggested the use of model-based small area estimation to produce estimates of crime rates (Groves and Cork, 2008). Despite their potential, small area estimation techniques have rarely been applied in criminological research. Some examples are: Whitworth (2012) used a multilevel logistic regression approach to produce synthetic estimates of fear of crime at neighbourhood level in England; Taylor (2013) produced synthetic multilevel regression estimates of perceptions of antisocial behaviour at local authority level in England; and van den Brakel and Buelens (2014) used a HB approach to estimate victimisation, perceived neighbourhood degeneration and contact with police at local level in Netherlands.

6.2 Background

6.2.1 Concept and measurement of worry about crime

Criminological research about the emotions about crime cannot be understood without a brief reference to the theoretical quagmire built around the construct of 'fear of crime'. Questions involving potential danger/risk to self or others, fear, concern, worry and anxiety have been equally considered to be about 'fear'. Even when the majority of the community accepts now the definition of 'fear of crime' as an emotional response of dread or anxiety to crime (Ferraro, 1995:4); numerous questions have been used for its measurement, and most have been criticised for failing to record its multiple dimensions.

Fear of crime have been conceptualised as a multidimensional phenomenon composed of: (a) cognitive perception of being threatened, (b) feeling or emotion of fear, and (c) action tendency or behavioural response (Caro Cabrera and Navarro Ardoy, 2017; Gabriel and Greve, 2003). Gabriel and Greve (2003) argue that a paradigmatic example of the so-called 'fear of crime' should encompass these three dimensions. Thus, questions about feelings of unsafety have been criticised as measures of fear of crime, as they capture perceived risks but not the emotion of threat: respondents might answer 'very unsafe' when they do not experience an emotional response. Conversely, Rader (2004) argues that 'fear of crime' should only refer to the emotional component, while the cognitive perception should be referred to as 'perceived risk' and the behavioural response as 'constrained behaviours', and all three would be dimensions of a larger construct named 'threat of victimisation'. There is also a conceptual distinction between dispositional (personal tendency to react fearfully) and situational fear (each episode/event of fear), between concrete and abstract fear, and between its locus of projection (internal or external) (see Caro Cabrera and Navarro Ardoy, 2017; Gabriel and Greve, 2003).

The debate about the concept and measure of fear of crime is still open nowadays. Some argue that even the best measures suffer from lack of precision and suggest a move towards the study of worry about crime (Jackson and Gouseti, 2014; Jackson and Kuha, 2014; Williams et al., 2000). Hough (2004) argues that research on fear of crime should not be equally preoccupied about anxieties, concerns, worries and perceived risks, and concludes that fearfulness if qualitatively different from anxiety and worry: while fear is a ‘mental event’, worry is a ‘mental state’. Fear is an emotional and physiological response that humans have in time- and context-dependent threatening situations (Castro-Toledo et al., 2017; Solymosi et al., 2015), and thus it is difficult to operationalise and measure. Conversely, worry captures both evaluations of immediate situations and anxiety-producing thoughts about future events (Jackson and Gouseti, 2014).

Jackson and Gouseti (2014) argue two main reasons for focusing on the worry about crime. First, while fear arises only in the presence of immediate dangers, citizens’ emotions about crime are usually closer to general concerns and anxieties about the risk of victimisation (worry about crime). Second, the psychological literature about the phases of worrying (see Berenbaum’s (2010) *initiation-termination two phase model*) can be used to explain the citizens’ most common emotions towards crime. Worry starts after one episode of perceived risk of victimisation, but repetitive thought continues until the individual accepts the prospect of an uncertain future threat: “people continue to worry unless they can accept the uncertain future possibility of a threat, and have taken whatever efforts they can to prevent or cope with it” (Jackson and Gouseti, 2014:1594). Berenbaum (2010:963) defines worry as (1) repetitive thoughts concerning an uncertain future outcome; (2) the uncertain outcome about which the person is thinking is undesirable; and (3) the experience of having such thoughts is unpleasant. In the case of worry about crime, such thoughts are related to the threat of victimisation. Moreover, citizens’ emotions about crime are known to be highly connected to macro-level social and economic insecurities, which can be conceptualised as general concerns or anxieties (worry about crime) but not situational responses of fear (Ceccato, 2012).

In relation to the measurement of worry about crime, the ESS included, in its editions 3, 4 and 5, two questions designed to measure worry about burglary at home and worry about violent crime:

- How often, if at all, do you worry about your home being burgled?
- How often, if at all, do you worry about becoming a victim of violent crime?

Response options are ‘All or most of the time’, ‘Some of the time’, ‘Just occasionally’ and ‘Never’. When the response is other than ‘Never’, respondents are asked whether this worry has '... serious effects on the quality of life', '... some effect' or '... no real effect on the quality of life'. Jackson and Kuha (2014) argue that prior questions were designed, in part, to allow examining cases in which worry damages (or not) respondents' well-being. These questions allow distinguishing between 'functional' and 'dysfunctional' worry. 'Functional' worry can improve well-being by stimulating constructive precautions to make citizens feel safer, in contrast to 'dysfunctional' worry that reduces quality of life (Jackson and Gray, 2010). One could also argue that the combination of these questions might result in a measure that captures the three dimensions that make up the emotions about crime (perceived risk, emotion, and behavioural response).

6.2.2 Mapping worry about crime: theory

The criminological and interdisciplinary studies looking at the geographical distribution of emotions about crimes have grown during the past two decades. On the one hand, environmental micro-level approaches argue that fear of crime episodes are more frequent under certain situational and social organisation circumstances (Castro-Toledo et al., 2017; Solymosi et al., 2015), thus pointing out the need to "consider fear of crime events at the smallest possible scale to be able to un-erroneously associate them spatially with elements of the environment" (Solymosi et al., 2015:198). Certain community characteristics and neighbourhood-level social processes, such as the neighbourhood disorder, residential instability and racial composition are used to explain the worry about crime (Brunton-Smith and Jackson, 2012; Brunton-Smith and Sturgis, 2011).

On the other hand, the macro-level geographical distribution of the emotions about crime has been interpreted more as the distribution of general concerns and anxieties (or 'mental states' of worry) than as actual emotional responses towards crime (or 'mental events' of fear) (Hummelsheim et al., 2011; Vieno et al., 2013). Researchers analyse the international and regional distribution of worry about crime and feelings of unsafety and explain their geographical differences by making use of variables such as unemployment, crime rates, income inequality, rates of higher education and welfare state measures (Hummelsheim et al., 2011; Vauclair and Bratanova, 2017; Vieno et al., 2013; Visser et al., 2013). Note that the studies described below make use of different operational definitions of worry about crime and perceived unsafety. This literature review will serve as a basis to select potential area-level predictors (i.e. covariates in SAE) of worry about crime and produce reliable regional estimates.

Unemployment and income inequality are known to be two predictors of the macro-level geographical distribution of worry about crime and feelings of unsafety (Fitzgerald et al., 2012; Rueda and Stegmueller, 2015; Vauclair and Bratanova, 2017; Vieno et al., 2013). High unemployment and income inequality have been pointed out as macro-level signals for low social protection that increase concerns about economic and social insecurity, resulting into more feeling of unsafety and worry (Hummelsheim et al., 2011; Vieno et al., 2013; Visser et al., 2013). This is the reason why some argue that, when analysing the distribution of the emotions about crime at large geographical levels, these emotions might be interpreted as 'umbrella sentiments' people develop to disguise the high levels of social and economic insecurity in their societies (Vieno et al., 2013). Hummelsheim et al. (2011) measure the impact of country-level social protection on feelings of unsafety, concluding that political welfare measures, such as benefits in kind for families and expenditure on education, might reduce people's feelings of lack of protection and perceived unsafety.

Some researchers have shown that the actual crime rates are positively correlated to worry about crime (Fitzgerald et al., 2012; Krahn and Kennedy, 1985): "crime occurring in the broader region of the individual's immediate neighbourhood had a significantly negative relationship with fear" (Breetzke and Pearson, 2014:51). However, other studies show that crime rates affect only certain groups (e.g. white citizens; Liska et al., 1982) or have no effect on feelings of unsafety (Hummelsheim et al., 2011; Vieno et al., 2013). The level of urbanisation and the population density are also related to worry about crime (Brunton-Smith and Sturgis, 2011).

Finally, certain individual factors such as age, gender, income or level of education have been well explored in academic research about emotions about crime (Gray et al., 2018; Hale, 1996; Killias, 1990; Pantazis, 2000). We expect ageing and less educated regions to have a higher proportion of citizens worried about crime.

6.2.3 Mapping worry about crime: methodological limitations

It has been shown that cross-national surveys, such as the ESS or the International Crime Victims Survey, are required to examine the macro-level explanations of worry about crime. However, survey data are limited for mapping phenomena at lower levels than the spatial scale designed by the original survey. ESS data, for example, are representative at a country level, but sample sizes are not representative for many spatial units within countries (e.g. Nomenclature of Territorial Units for Statistics 2 (NUTS-2) areas). Regions are, in most cases, unplanned domains.

To allow comparisons at smaller geographical levels than the scales planned by the survey, model-based SAE techniques introduce models to 'borrow strength' from related areas and produce reliable estimates of target parameters at small area level (Rao and Molina, 2015). In SAE, small areas are defined as areas/domains for which direct estimates of adequate precision cannot be produced (Rao and Molina, 2015:2). Thus, methodologically, small areas are also large geographical units for which direct estimation techniques produce unreliable estimates. Available area-level auxiliary data from the census and administrative data sources are required as covariates in area-level model-based estimation.

The RRMSE is the measure of reliability (accounting for precision and accuracy) used in SAE. We expect a reduction in the RRMSE when using model-based estimators compared to direct estimators. Moreover, model-based estimators that borrow correlated random area effects from neighbouring areas are expected to show smaller RRMSEs than traditional model-based estimators, especially when the spatial autocorrelation of the variable of interest is high (Pratesi and Salvati, 2008), as is the case of our outcome measure (Wyant, 2008).

6.2.4 Hypotheses

Based on previous research, we expect to find higher dysfunctional worry about crime in Southern and Eastern-European regions than in Scandinavia and Central Europe:

> *H6.1* The proportion of citizens dysfunctionally worried about crime is higher in Southern and Eastern-European regions and lower in Scandinavian and Central-European regions.

In relation to the predictors (i.e. covariates in SAE) of the distribution of worry about crime, we expect the proportion of citizens worried about crime to be higher in:

H6.2 regions with higher unemployment rates,

H6.3 ageing regions,

H6.4 regions with lower education levels,

H6.5 regions with higher crime rates, and

H6.6 regions with higher population density

Note that only covariates with available data for all regions have been included as hypotheses. Other possible covariates (e.g. inequality, deprivation, public investment on education/health) suffered from missing data in at least one region or were not available at the target geographical level. Thus, these could not be analysed.

From a methodological perspective, we expect that model-based small area estimators produce more reliable estimates than direct estimators. We also expect to find more precise estimates when producing model-based estimates with spatially correlated random area effects than traditional model-based approaches (i.e. the EBLUP):

H6.7 Model-based small area estimation produces more reliable estimates than direct estimators.

H6.8 SEBLUP produces more reliable estimates than traditional EBLUP.

6.3 Methodology

6.3.1 Data: European Social Survey

Estimates will be produced from ESS 5 data (2010/11). The ESS is a biannual cross-national survey that has been conducted in 34 countries since 2001. We use the 2010/11 edition instead of a more current one due to the absence of newer data available: measures on worry about crime were not included in ESS questionnaires from the 6th edition onwards. ESS samples are designed to be representative of all population aged 15 and over in each participant country. In most countries, all geographical levels below country level are unplanned domains.

After deleting the samples from Israel, Russia, Switzerland and Ukraine, whose regions are not included in most comparative datasets at a European level, the ESS has a sample size of 46,391 citizens covering 24 countries: Austria (n=2259), Belgium (n=1704), Bulgaria (n=2434), Croatia (n=1649), Cyprus (n=1083), Czech Republic (n=2386), Denmark (n=1576), Estonia (n=1793), Finland (n=1878), France (n=1728), Germany (n=3031), Greece (n=2715), Hungary (n=1561), Ireland (n=2576), Lithuania (n=1677), Netherlands (n=1829), Norway (n=1548), Poland (n=1751), Portugal (n=2150), Slovakia (n= 1856), Slovenia (n=1403), Spain (n=1885), Sweden (n=1497) and United Kingdom (n=2422). Other European countries, such as Italy or Romania, were not included in ESS 5. ESS participant countries are responsible for producing their national sample designs (within common sampling principles); this is the reason why countries with different population sizes have similar sample sizes (see European Social Survey, 2010).

Geographical information at NUTS-2 level is available for all countries except United Kingdom and Germany, for which estimates will be produced at NUTS-1 level. In total, we will produce small area estimates for 192 regions across 24 countries. The average of citizens sampled per region is $\bar{n}$ =239.8. Since most areas are large regions, the average sampling fraction is very low ($\bar{f}$ =0.0002). The areas with the smallest samples are the Spanish regions of Melilla (n=5) and La Rioja (n=9) and the German state of Saarland (n=20). The areas with the highest samples are Estonia (n=1793), Southern and Eastern Ireland (n=1717) and Lithuania (n=1677). Note that Estonia, Lithuania and Cyprus are countries with one single NUTS-2 region.

In order to allow international comparisons from ESS data, we have combined design and population weights to compute new weights (European Social Survey, 2014).

6.3.2 Data: Outcome measure

The ESS included (in its 3rd, 4th and 5th editions) four questions to measure the worry about crime. Based on previous research, we combine these questions to analyse dysfunctional worry about crime: "if individuals who say they are fairly or very worried also report that their quality of life is reduced by either their worries or their precautions against crime, then assign these individuals to the dysfunctionally worried group" (Jackson and Gray, 2010:5). Moreover, Jackson and Kuha (2014) computed the probabilities of ESS respondents to fall within six latent classes, in part, to distinguish between respondents functionally and dysfunctionally worried: those who reported no effect of worry on their quality of life had a higher probability to fall within the class of citizens unworried or functionally worried; while those who reported some effect had a higher probability to be within the class 'frequently worried' (and zero probability of falling within 'functionally worried'), and respondents whose worry had a serious effect on their quality of life tended to fall within the group of citizens 'persistently worried'. Both the classes 'frequent worry' and 'persistent worry' can be grouped within 'dysfunctional worry'.

We combine both questions to create simple categorical dichotomous measures of dysfunctional worry about burglary at home and dysfunctional worry about violent crime derived from the questionnaire (see Table 6.1). For each variable, individuals responding some worry ('All or most of the time', 'Some of the time' or 'Just occasionally') and some effect of worry on quality of life ('serious effects on the quality of life' or 'some effect') are coded as 1, while respondents with no worry or no effect of worry on quality of life are coded as 0. 'Don't know', 'No answer' and 'Refusal' are coded as missing data. Note that this is also the operationalisation used by the ESS (European Social Survey, 2013).

Table 6.1 Classification of responses of worry about crime into two classes.

		Worry about crime			
		Never	Just occasionally	Some of the time	All or most of the time
Effect on quality of life	No effect	0	0	0	0
	Some effect		1	1	1
	Serious effects		1	1	1

In the case of worry about burglary at home, 26% of valid responses across all countries reported some worry ('just occasionally', 'some of the time' and 'all or most of the time') and some or serious effect of worry on quality of life; while the 25.5% reported some worry about violent crime and this worry affected their quality of life (see Table 6.2).

Table 6.2 Frequencies of worry about burglary/violent crime and effect of worry on quality of life.

	Never	Just occasionally	Some of the time	All or most of the time
Worry about burglary at home				
No effect		12774 (24.0%)	4765 (9.0%)	557 (1.0%)
Some effect	21198 (39.8%)	5726 (10.7%)	4799 (9.0%)	1226 (2.3%)
Serious effects		434 (0.8%)	757 (1.4%)	975 (1.8%)
Worry about violent crime				
No effect		12550 (23.7%)	2425 (4.6%)	153 (0.3%)
Some effect	24333 (46.0%)	6337 (12.0%)	4523 (8.5%)	592 (1.1%)
Serious effects		475 (0.9%)	775 (1.5%)	777 (1.5%)

Source: Own elaboration. Data from the ESS 5.

6.3.3 Data: Covariates

Area-level covariates are required in area-level model-based SAE. Considering the substantive literature review, but also having in mind that covariates cannot have missing data for any area, we explored the correlation of different variables with our response variables to decide which covariates should be included in our models. Six covariates were finally included: (i) proportion of citizens unemployed aged 15 or more 2011, (ii) proportion of population aged 65 or more 2011, (iii) population density 2011, (iv) proportion of population aged 25-65 with tertiary education 2011, (v) intentional homicides per 100.000 inhabitants 2010, and (vi) burglaries of private residential premises per 1000 inhabitants 2010. All these measures are provided by EUROSTAT (http://ec.europa.eu/eurostat/data/database). Note that EUROSTAT does not publish regional crime statistics since 2010; this is the reason why two of our covariates refer to 2010. Model results are provided in Section 6.4.1.

Other covariates were also explored, but their bivariate Spearman correlations (denoted as ρ) with area-level dysfunctional worry about crime (measured here by direct estimates) were very small or not significant. Some examples are: Gross Domestic Product per capita (worry about burglary: ρ=-0.28, p-value>0.05 / worry about violent crime: ρ=-0.37, p-value>0.05), infant mortality (worry about burglary: ρ=0.03, p-value>0.1 / worry about violent crime: ρ=0.04, p-value>0.1) and migration rate (worry about burglary: ρ=-0.24, p-value>0.05 / worry about violent crime: ρ=-0.24, p-value>0.05).

6.3.4 Method: SEBLUP based on Fay-Herriot model

Small area estimates will be produced using three approaches: Horvitz-Thompson (HT) direct estimator, EBLUP under FH model, and SEBLUP with spatially correlated random area effects.

First, the HT direct estimator uses only area-specific sample data and survey weights to produce design-unbiased estimates (Horvitz and Thompson, 1952). Direct estimates can suffer from a high variance and unreliability in areas with small sample sizes.

Second, the EBLUP, which is based on FH model (Fay and Herriot, 1979), combines direct estimates with synthetic estimates in each area, with more weight attached to the direct estimate when the direct estimate's error is small, and more weight given to the synthetic estimate when the error of the direct estimate is large (Rao and Molina, 2015). Synthetic estimates are produced from fitting a model with a set of area-level covariates. Thus, the EBLUP is preferred over regression-based synthetic estimates because it obtains an optimal combination between direct and synthetic estimates in each area; while regression-based estimates "are likely to be biased since they are not based on direct measurement of the variable of interest in the small area of interest" (Levy, 1979:9).

Third, the SEBLUP adds spatially correlated random area effects to the EBLUP in order to borrow strength from neighbouring areas (Petrucci and Salvati, 2006; Pratesi and Salvati, 2008). It allows for more reliable estimates when the target variable shows medium/high levels of spatial autocorrelation, as is the case of our variable of interest (Wyant, 2008). A proximity matrix is needed to bring in spatially correlated random area effects. The proximity matrix used here follows a 'Queen contiguity' approach, which defines as neighbouring areas not only polygons that share borders, but also polygons that share vertices.

EBLUP and SEBLUP estimates' RRMSE are expected to be smaller than direct estimates' RRMSE (Pratesi and Salvati, 2008; Rao and Molina, 2015). RRMSEs of direct estimates are obtained from the Coefficient of Variation. EBLUP and SEBLUP's RRMSEs are computed from a parametric bootstrap ($B=500$ replications) (Molina et al., 2009; Rao and Molina, 2015). Small area estimates and

RRMSEs are produced using the `‘sae’` package for `R` software (Molina and Marhuenda, 2015).

6.4 Findings

Findings are organised as follows. First, model results are presented. Second, SEBLUP estimates are mapped. Third, RRMSEs of all estimates are examined to check their reliability. Finally, model diagnostics of SEBLUP models are presented.

6.4.1 Fitting a model of worry about crime for small area estimation

In order to produce reliable EBLUP and SEBLUP estimates, area-level models need to be fitted. Although the main objective of SAE models is to improve the estimates' reliability, model results provide a consistent set of information about the macro-level explanation of worry about crime, and hence we discuss these results below.

Table 6.3 shows the results of the EBLUP and SEBLUP models fitted to estimate dysfunctional worry about burglary at home, and Table 6.4 shows the results of the models fitted to estimate dysfunctional worry about violent crime. AIC and BIC measures are lower in the SEBLUP models than in the linear and EBLUP models, showing that model-based SAE methods not only improve the estimates' reliability but also the models show a better goodness of fit. In the case of worry about burglary, the AIC measure is reduced from -242.3 of the linear regression to -329.1 of the SEBLUP; and, in the case of worry about violence, from -304.7 of the linear model to -347.6 of the SEBLUP. The BIC is reduced from -226.5 of the linear regression to -299.7 of the SEBLUP for worry about burglary; and from -250.6 of the linear model to -318.3 of the SEBLUP in the case of worry about violent crime.

Table 6.3 EBLUP and SEBLUP models of dysfunctional worry about burglary.

	EBLUP				SEBLUP			
	Coeff.	SE	t-value	p-value	Coeff.	SE	t-value	p-value
(Intercept)	0.102	0.07	1.9	0.073	0.172	0.07	2.6	0.010
Proportion unemployed	0.910	0.17	5.4	0.000	0.624	0.19	3.1	0.001
Proportion aged +65	0.539	0.25	2.2	0.034	0.299	0.25	1.1	0.041
Population density	0.002	0.00	1.6	0.044	0.001	0.00	1.4	0.032
Proportion tertiary education	-0.426	0.11	-3.8	0.001	-0.389	0.17	-3.4	0.001
Homicide rate	0.028	0.01	2.6	0.010	0.023	0.01	2.3	0.015
Burglary rate	0.009	0.00	2.1	0.037	0.007	0.00	1.5	0.021
AIC	-278.86				-329.05			
BIC	-252.80				-299.73			
Spatial correlation					0.70			

Table 6.4 EBLUP and SEBLUP models of dysfunctional worry about violent crime.

	EBLUP				SEBLUP			
	Coeff.	SE	t-value	p-value	Coeff.	SE	t-value	p-value
(Intercept)	0.111	0.05	2.0	0.031	0.147	0.07	2.4	0.010
Proportion unemployed	0.811	0.15	5.3	0.000	0.676	0.17	3.7	0.000
Proportion aged +65	0.321	0.23	1.3	0.043	0.159	0.24	0.8	0.040
Population density	0.002	0.00	1.5	0.037	0.001	0.00	1.3	0.044
Proportion tertiary education	-0.299	0.10	-3.0	0.002	-0.275	0.12	-2.6	0.007
Homicide rate	0.030	0.01	2.9	0.004	0.029	0.01	2.9	0.006
Burglary rate	0.002	0.00	0.3	0.040	0.001	0.00	0.3	0.034
AIC	-314.45				-347.59			
BIC	-288.39				-318.27			
Spatial correlation					0.61			

Both Table 6.3 and Table 6.4 show that, among all variables, the most explanatory covariate is the proportion of citizens unemployed: higher unemployment explains higher worry about burglary and violence (worry about burglary: β^{EBLUP}=0.91, β^{SEBLUP}=0.62, *p-value*<0.001 / worry about violent crime: β^{EBLUP}=0.81, β^{SEBLUP}=0.68, *p-value*<0.001) (H6.2). High unemployment is known to be a macro-level signal for low social protection that increase not only concerns and insecurities about the socio-economic problems of the region/country, but also specific worries towards crime and victimisation (Hummelsheim et al., 2011; Visser et al., 2013).

Again, the macro-level worry about crime shows to be an ‘umbrella sentiment’, and it arises in regions where social and economic insecurity is high (Vieno et al., 2013).

The second strongest significant relation in both EBLUP models is shown between dysfunctional worry about crime and the proportion of citizens aged 65 or more (worry about burglary: β^{EBLUP}=0.54, *p-value*<0.05 / worry about violent crime: β^{EBLUP}=0.32, *p-value*<0.05) (H6.3). However, the coefficients of the SEBLUP models show that the second strongest covariate is the proportion of citizens with higher education, which have negative model coefficients (H6.4) (worry about burglary: β^{SEBLUP}=-0.39, *p-value*<0.01 / worry about violent crime: β^{SEBLUP}=-0.28, *p-value*<0.01). Regarding the proportion of citizens with higher education, the difference between the EBLUP and SEBLUP model coefficients is small, while the coefficients referred to the proportion of citizens aged +65 are greatly reduced from EBLUP to SEBLUP models. Area-level models that do not account for spatially correlated random area effects might be overestimating the effect of the latter on the worry about crime. Thus, ignoring the spatial autocorrelation parameter when we aim to predict outcome measures with an implicit spatial dimension (Wyant, 2008) might lead to misleading results. Both variables (age and education level) are well-explored predictors in the study of fear of crime at individual and aggregated levels. These increase and reduce, respectively, the citizens’ perceived vulnerability and, in turn, the worry about victimisation (Hale, 1996; Killias, 1990).

Police-detected rates of homicides and burglaries are also relevant to explain the regional distribution of worry about crime (H6.5) (Breetzke and Pearson, 2014; Krahn and Kennedy, 1985; Liska et al., 1982), though their effect sizes show smaller relations than the three prior covariates. The rates of both types of crimes correlate with the proportion of citizens worried about crime, but the homicide rate shows to be slightly more relevant that the rate of burglaries in both cases (worry about burglary: β^{EBLUP}=0.03, β^{SEBLUP}=0.02, *p-value*<0.05 / worry about violent crime: β^{EBLUP}=0.03, β^{SEBLUP}=0.03, *p-value*<0.01). Finally, the population density shows a significant but small relation with worry about crime. The estimated spatial correlation coefficient is $\hat{\rho}$=0.70 for worry about burglary and $\hat{\rho}$=0.61 for worry about violence.

6.4.2 Small area estimates of worry about crime at regional level in Europe

Results from our model-based estimates reveal important differences in the worry about crime at a regional level in Europe. As will be shown in Section 6.4.3, SEBLUP estimates have the lowest RRMSEs (i.e. are the most reliable estimates), and hence we focus on these.

In relation to the proportion of citizens dysfunctionally worried about burglary, SEBLUP estimates show a variation between the minimum of $\hat{\delta}^{SEBLUP}$=2.1% in the Dutch province of Flevoland and the maximum of $\hat{\delta}^{SEBLUP}$=62.6% in the Greek county of Atikki (where Athens is located). Particularly low dysfunctional worry about burglary at home is also estimated in the Spanish region of Extremadura ($\hat{\delta}^{SEBLUP}$=2.7%) and the Norwegian regions of Vestlandet ($\hat{\delta}^{SEBLUP}$=4.4%) and Trøndelag ($\hat{\delta}^{SEBLUP}$=4.6%). At the other end, high dysfunctional worry about violent crime has been estimated in the Greek regions of Sterea Ellada ($\hat{\delta}^{SEBLUP}$=62.5%), Ionia Nisia ($\hat{\delta}^{SEBLUP}$=60.5%) and Peloponnisos ($\hat{\delta}^{SEBLUP}$=52.8%). Nine of the ten most worried regions about burglary at home are from Greece.

Table 6.5 Summary of small area estimates of dysfunctional worry about crime and average RRMSE.

	Minimum	Lower quartile	Mean	Median	Upper quartile	Maximum	Average RRMSE
Worry about burglary at home							
Direct	1.6%	13.4%	23.3%	19.5%	31.1%	72.0%	22.5%
EBLUP	2.0%	14.3%	22.6%	19.7%	28.9%	59.4%	18.2%
SEBLUP	2.4%	14.4%	22.5%	19.8%	28.9%	63.0%	17.2%
Worry about violent crime							
Direct	1.6%	13.6%	21.8%	19.9%	28.4%	65.5%	22.6%
EBLUP	2.0%	13.8%	21.1%	19.9%	26.4%	49.6%	18.6%
SEBLUP	2.3%	13.9%	20.9%	19.8%	26.8%	50.2%	16.9%

With respect to the SEBLUP estimates of dysfunctional worry about violent crime, the least worried European regions are Flevoland (Netherlands) ($\hat{\delta}^{SEBLUP}$=2.0%), Extremadura (Spain) ($\hat{\delta}^{SEBLUP}$=2.9%), Jadranska Hrvatska (Croatia) ($\hat{\delta}^{SEBLUP}$=3.3%) and Vestlandet (Norway) ($\hat{\delta}^{SEBLUP}$=5.5%). The regions most worried about violent crime are the Greek regions of Ionia Nisia ($\hat{\delta}^{SEBLUP}$=51.1%), Attiki ($\hat{\delta}^{SEBLUP}$=49.5%), Sterea Ellada ($\hat{\delta}^{SEBLUP}$=46.4%) and Peloponnisos

($\hat{\delta}^{SEBLUP}$=45.2%). Again, eight of the ten most worried regions about violent crime are Greek, as discussed by Zarafonitou (2009). Descriptive statistics of the estimates are shown in Table 6.5.

Although there is a very high correlation between the SEBLUP estimates of dysfunctional worry about burglary and worry about violent crime (ρ=0.95, p-value<0.001), dysfunctional worry about burglary is higher than worry about violent crime in most regions. 125 of the 192 regions are more worried about burglary than about violent crime. Particularly interesting is that most regions with higher observed worry about violent crime than worry about burglary at home are concentrated in certain countries. For example, the seven Norwegian regions show higher worry about violence than worry about burglary. This trend is also shown in Poland, where 13 of its 16 regions report higher observed worry about violent crime than worry about burglary at home; Sweden, where this is shown in 7 of its 8 regions; and Lithuania. On the other hand, every single region within 11 countries (Croatia, Cyprus, Estonia, Finland, Greece, Hungary, Ireland, Netherlands, Portugal, Slovakia and Slovenia) show higher dysfunctional worry about burglary than worry about violence. The observed gap between worry about burglary at home and worry about violent crime is usually small: only 10 regions display differences greater than 3%, and the seven of them belong to Greece, where dysfunctional worry about burglary is remarkably higher than worry about violent crime.

From a broader perspective, our estimates add evidence on research showing higher levels of worry about crime in Southern and Eastern/post-communist European countries and lower rates in Central and Northern Europe (H6.1) (Hummelsheim et al., 2011; Jackson and Kuha, 2014). Figure 6.1 and Figure 6.2 illustrate the geographical distribution of SEBLUP estimates of dysfunctional worry about burglary at home and dysfunctional worry about violent crime, respectively. Darker shades of grey represent higher estimates of worry and lighter tones show a lower worry, according to groups defined by the quantiles of the combined estimates of the two outcome measures.

Figure 6.1 SEBLUP estimates of dysfunctional worry about burglary.

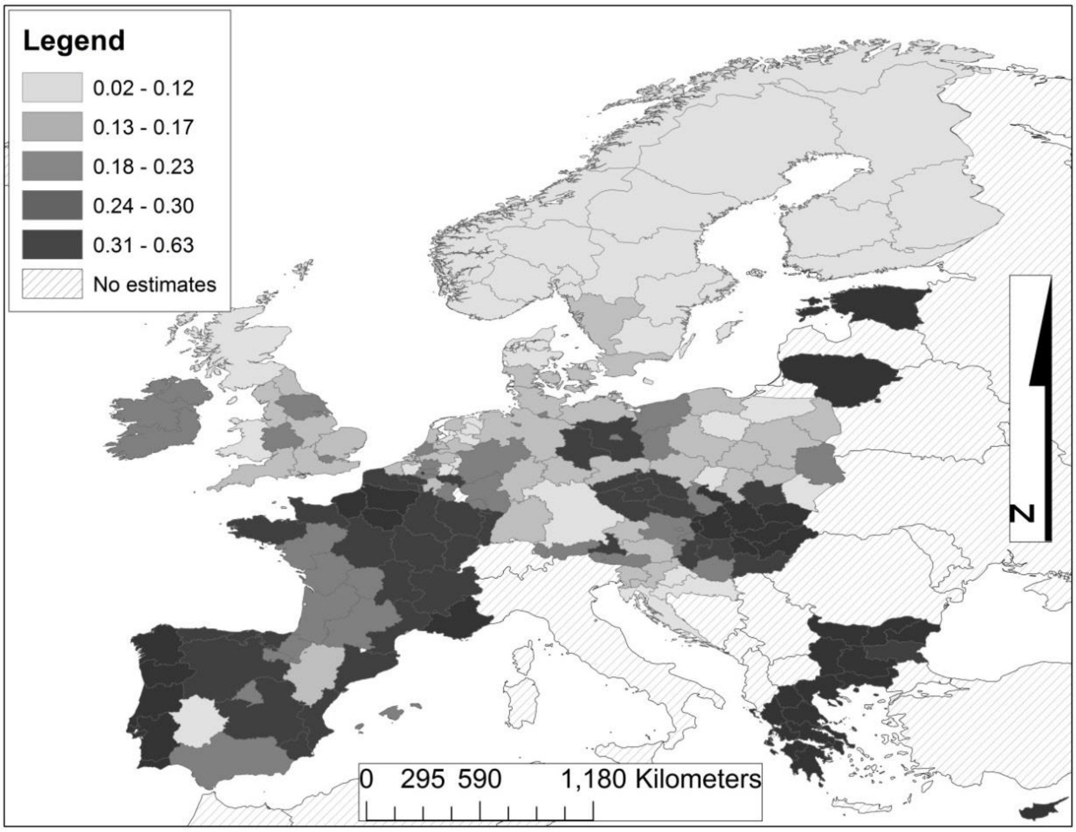
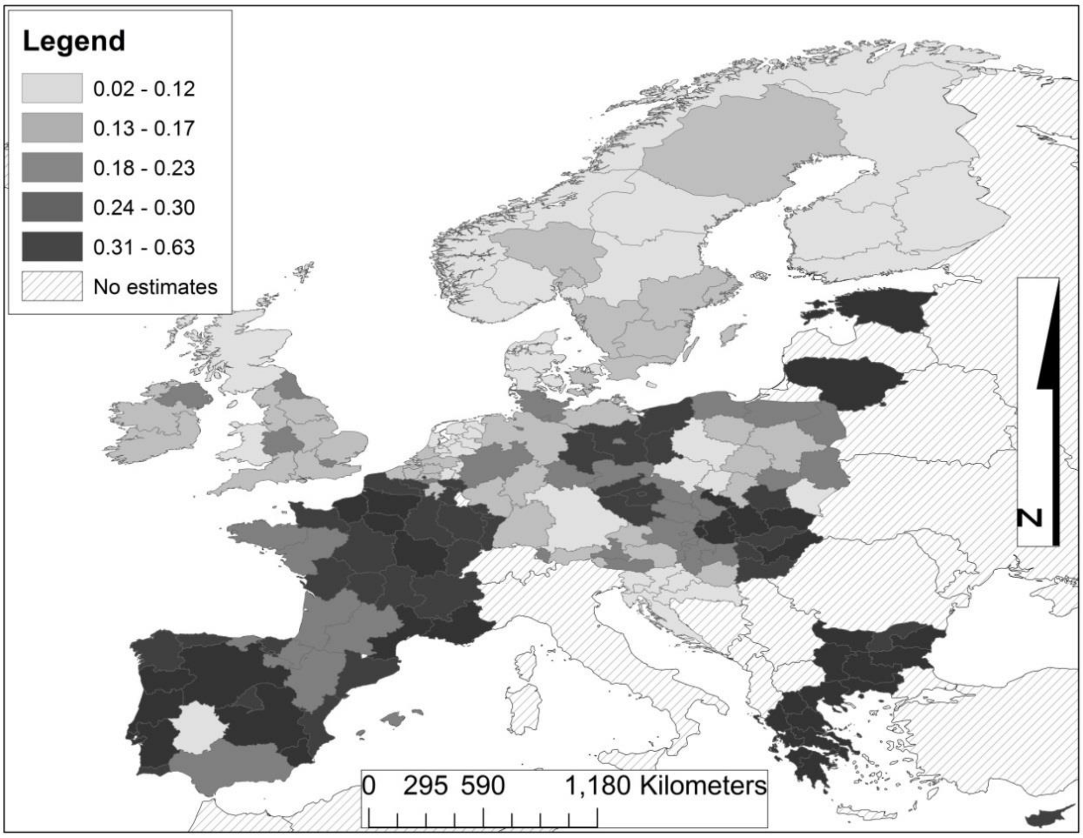


Figure 6.2 SEBLUP estimates of dysfunctional worry about violent crime.



6.4.3 Reliability checks

In order to check the reliability of the estimates, Figure 6.3 and Figure 6.4 show the estimated RRMSEs of the direct, EBLUP and SEBLUP estimates. RRMSEs are needed to check whether the reliability of the small area estimates is acceptable. As a rule, it is considered that small area estimates' RRMSEs should be lower than 25% to be accepted as reliable, estimates with RRMSEs higher than 25% should be used with caution and estimates with RRMSEs higher than 50% are regarded as unreliable (Commonwealth Department of Social Services, 2015). SEBLUP estimates are expected to be the most reliable ones (Petrucci and Salvati, 2006; Pratesi and Salvati, 2008).

Figure 6.3 RRMSEs of direct, EBLUP and SEBLUP estimates of worry about burglary (ordered by sample sizes).

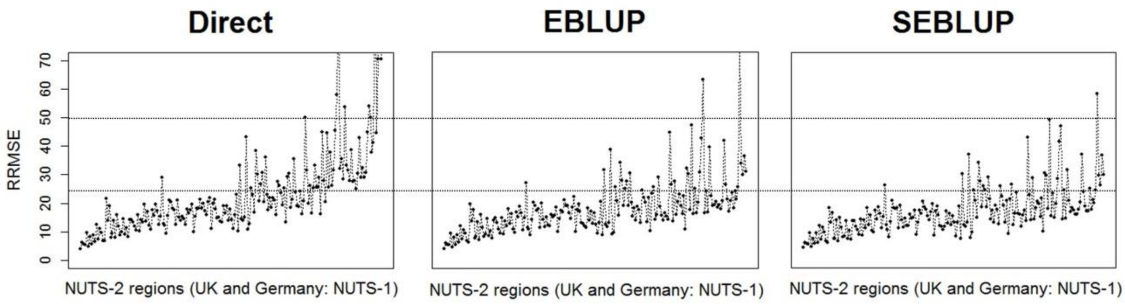
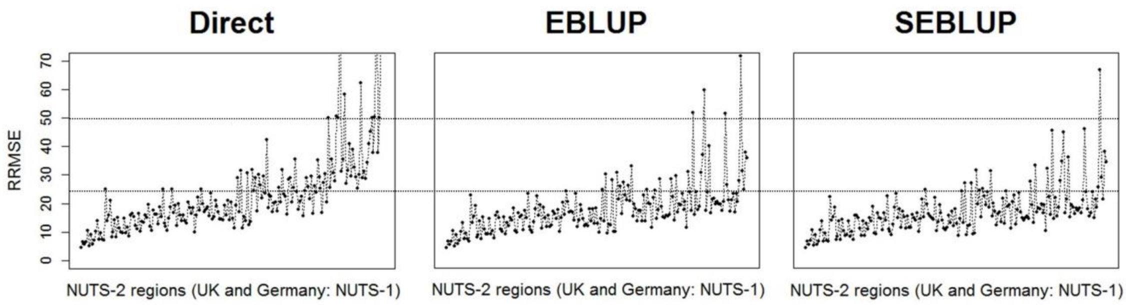


Figure 6.4 RRMSEs of direct, EBLUP and SEBLUP estimates of worry about violent crime (ordered by sample sizes).



First, as expected, the SEBLUP estimates' average RRMSE is lower than the EBLUP and direct estimates' RRMSEs (H6.7 and H6.8). In the case of dysfunctional worry about burglary, the average RRMSE is reduced from the 22.5% of direct estimates to 18.2% of EBLUPs and 17.2% of SEBLUPs. This reduction is also shown for worry about violent crime: from 22.6% of direct estimates, to 18.6% of EBLUPs and 16.9% of SEBLUPs. On average, the percentage relative difference (henceforth $\overline{RD\%}$) between the original direct estimates' RRMSE and the final SEBLUP estimates' RRMSE is $\overline{RD\%} = -10.07$ in the case of worry about burglary and $\overline{RD\%} = -10.09$ in the case of worry about violent crime; which show a large relative improvement of the estimates' measure of reliability. The maximum percentage relative difference between the RRMSEs of the direct and SEBLUP estimates is -67.24 in the case of worry about burglary and -68.34 in the case of worry about violent crime.

Second, it is important to focus on the area-specific RRMSE to assess the reliability of area-level estimates. While more than 60 areas have direct estimates' RRMSEs higher than 25% in both variables of interest, the number of small areas with SEBLUP estimates' RRMSEs higher than 25% is only 24 in the case of worry about burglary at home and 20 in the case of worry about violent crime. There is only one area whose SEBLUP estimates' RRMSEs are higher than 50%, whose sample size is n=25.

6.4.4 Model diagnostics

Diagnostics of the SEBLUP models are presented below to examine whether our estimates are biased by the models and to check the models' validity (Brown et al., 2001). We present the q-q plots of the estimates' standardised residuals in Figures 5 and 6 to check the normality of the residuals. Standardised residuals of small area estimates have been produced based on Pratesi and Salvati (2008:132). Figures 6.5 and 6.6 show that standardised residuals follow a normal distribution with slight variations at the tails. The Shapiro-Wilk statistic test for normality gives the value of *W*=0.99 (*p-value*=0.46) for worry about burglary and *W*=0.99 (*p-value*=0.59) for worry about violent crime, which suggests a failure to reject the null hypothesis of the normal distribution.

Finally, Figures 6.7 and 6.8 show the scatter plots of the direct estimates against the SEBLUP estimates. Regarding that direct estimates are design-unbiased, we expect a high linear correlation between direct and model-based estimates. As expected, regression model adjusted R-squared is very high (R^2=0.96 for worry about burglary and R^2=0.94 for worry about violent crime). Both plots show that SEBLUP estimates are less extreme than direct estimates, shrinking extreme values towards the mean.

Figure 6.5 and Figure 6.6 Normal q-q plots of standardised residuals of SEBLUP estimates.

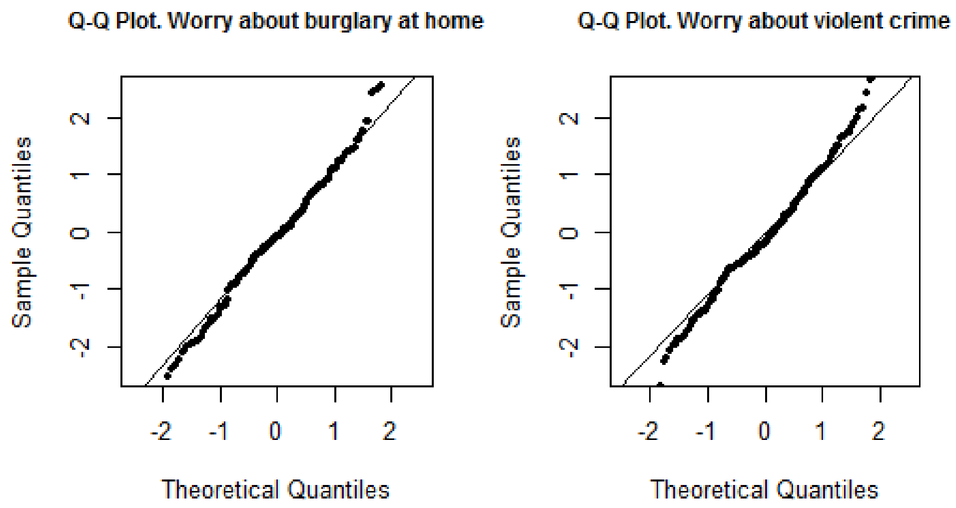
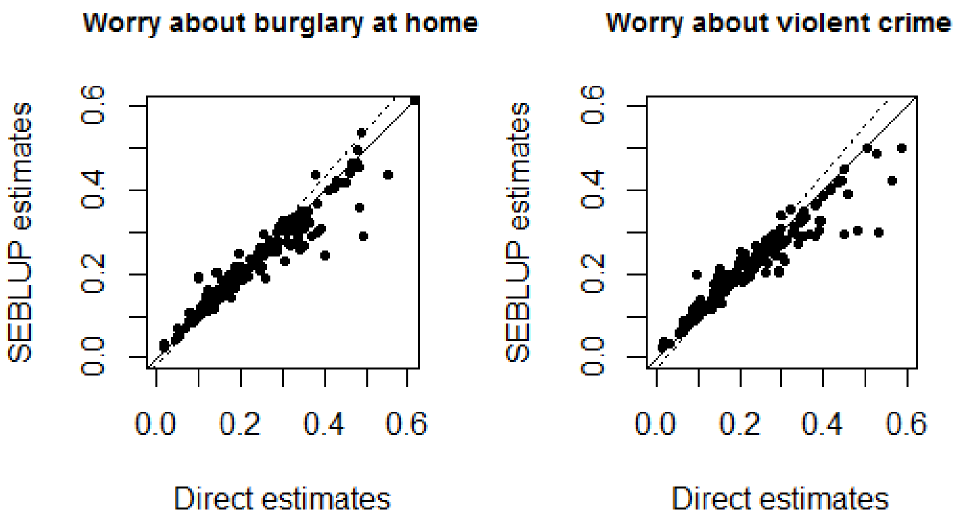


Figure 6.7 and Figure 6.8 Direct estimates versus SEBLUP estimates, x=y line (solid) and linear regression fit line (dash).



6.5 Conclusions

This research has produced estimates of dysfunctional worry about burglary at home and dysfunctional worry about violent crime for 192 regions across 24 European countries from ESS 5 (2010/11) data. We have produced direct, EBLUP and SEBLUP estimates. This paper illustrates that model-based SAE methods, and specifically the SEBLUP with spatially correlated random area effects, are potential tools to estimate and map variables of criminological interest at a small area level. SEBLUP estimates of dysfunctional worry about crime have shown to be more reliable than EBLUP and direct estimates. The models fitted in this research are limited by the availability of reliable auxiliary information (i.e. covariates): some variables explored in previous studies (e.g. income inequality, investment on health/education) could not be tested in this research.

Our estimates add evidence to research showing that Eastern and Southern European regions are the areas with highest proportions of citizens worried about crime (Jackson and Kuha, 2014). More specifically, our SEBLUP estimates show that Greek, Slovakian, Estonian, Lithuanian and Bulgarian regions have high proportions of citizens worried about crime, as well as certain regions in Portugal, Spain and South France. At the other end, most regions in Central Europe and Scandinavia show the lowest SEBLUP estimates of dysfunctional worry about crime, especially Dutch, Norwegian, Swedish, Danish and Finish regions, but also some exceptions in Poland, Croatia and Spain.

Our EBLUP and SEBLUP models suggest that unemployment is the best predictor (among the covariates included in our models) of dysfunctional worry about crime. Macro-level unemployment, as well as other variables such as inequality or low public investment on health and education, are known to be social signals of low public protection that increase concerns about the social and economic situation of one’s region, and these affect the worry about crime (Hummelsheim et al., 2011; Visser et al., 2013). Note that variables such as inequality and public investment on health and education could not be tested in our models due to lack of available data. Vieno et al. (2013) argue that feelings of unsafety, at a macro-level, can be interpreted as ‘umbrella sentiments’ that hide unspecific concerns about the area’s social and economic instability. Here we observe that regional estimates of worry about crime are most likely explained by joblessness (and thus socio-economic) insecurities, and therefore the conceptualisation of ‘umbrella sentiment’ might well apply also to the worry about crime at a regional level.

Ageing and less educated regions also show higher estimates of worry about crime in Europe. Both the age and the level of education are known to be good predictors for the citizens’ perceived vulnerability, and thus explain the increased worry about crime, both at individual and aggregated levels (Hale, 1996; Pantazis, 2000). Further research is needed to examine the hidden theoretical mechanisms that explain why the strength of the effect of the proportion of older adults on the worry about crime is reduced in our spatial models.

The crime rates and the population density show significant but smaller correlations with worry about crime (Breetzke and Pearson, 2014; Fitzgerald et al., 2012). Some argue that the relation between the crime rates and macro-level worry about crime might be influenced by the media, which reflects and reproduces reported crime rates (Liska et al., 1982). On average, people show a higher dysfunctional worry about property crimes than personal crimes (Jackson and Kuha, 2014).

Further research might explore in greater depth the particularly high worry about crime in Greece. Zarafonitou (2009) argued that high fear of crime in Greece between 2004 and 2005, and in particular in Athens, could be related to high social and economic insecurities and perceived decline in quality of life. The growth on unemployment experienced in Greece after 2009 might be interpreted as a signal for low social protection that increased concerns about the social and economic situation, and in turn the worry about crime.

Model-based SAE has shown to be a potential tool to produce reliable small area estimates of survey-recorded criminological phenomena, especially when sample sizes are not large enough to allow reliable direct estimates. However, estimates need to be produced meticulously and model-based approaches with spatially correlated area random effects seem to be the most promising. Further applications of SAE techniques to the worry about crime might focus on producing small area estimates from Jackson and Kuha’s (2014) composite measure of worry.

CHAPTER 7: Article 3 - The geographies of perceived neighbourhood disorder. A small area estimation approach[5]

7.1 Introduction

Signs of disorder, observed and inferred, criminal and noncriminal, play a vital role in understanding wellbeing in contemporary cities. For residents, rowdy teenagers, panhandlers and public drinking, and even deteriorated housing and graffiti, can be perceived as disorderly and threatening. However, perceiving disorder goes beyond observed cues of lack of order and is shaped by neighbourhood stigmas and reputations as dimensions of social inequality (Sampson, 2009; Taylor, 2001). Factors such as the concentration of minorities and neighbourhood poverty are bound up by social meanings frequently associated with disorder (Franzini et al., 2008; Sampson and Raundenbush, 1999; Wickes et al., 2013).

Perceived disorder erodes residential satisfaction and local commitment (Robinson et al., 2003) and is related to perceived powerlessness, fear and social mistrust (Ross and Mirowsky, 1999; Ross et al., 2000; Skogan, 2015). Moreover, Wilson and Kelling (1982) theorised that uncontrolled neighbourhood disorder causes an increase in serious crimes, leading to controversial zero tolerance policies (Skogan, 1990; Taylor, 2001).

Whether perceived disorder is seen as a cause of crime or as a socially damaging phenomenon itself, it is necessary to have an accurate picture of its geographical distribution. Maps of perceived disorder are useful to comprehend its causes and design evidence-informed policies and policing interventions. As shown by Braga and Bond (2008), policing interventions that target hot spots of disorder and crime are successful in reducing crime and antisocial behaviour. However, while police data record crimes at a detailed geographical scale and allow for micro-level crime maps, more advanced statistical techniques are needed to map the neighbourhood disorder. Perceived disorder is mainly recorded by surveys, which are

[5] *Full reference:* Buil-Gil, D., Medina, J., & Shlomo, N. (2019). The geographies of perceived neighbourhood disorder. A small area estimation approach. *Applied Geography, 109*, 102037.

usually designed to be representative of large areas. Thus, direct estimates drawn from these are unreliable at small area level (Rao and Molina, 2015).

Furthermore, Hipp (2010a) shows that the ecological connections between socioeconomic variables (e.g. concentration of minorities, poverty), crime and neighbourhood perceptions operate at the scales of small communities or micro-neighbourhoods, rather than larger geographical units. Neighbourhood perceptions are shaped by immediate societal and environmental features and crimes and disorders happening within the neighbourhood (Hipp, 2010a). Thus, we aim to reliably map the perceptions of disorder at small geographical level.

New methods have been explored to map disorder perceptions at low spatial levels, but these are limited by biases that could lead to unreliable maps. Crowdsourcing projects (Solymosi and Bowers, 2018) and records of requests for city services (O'Brien et al., 2015) might be limited by little and biased social participation. SSO may be limited by observer biases (Hoeben et al., 2016) and shows little consistency with perceptual measures of disorder (Yang et al., 2018).

In order to precisely map the perceived neighbourhood disorder, model-based small SAE techniques use existing survey data and introduce models to borrow strength across related areas (Rao and Molina, 2015). In 2008, the US Panel to Review the Programs of the Bureau of Justice Statistics indicated the need for using SAE to produce regional estimates from the NCVS (Groves and Cork, 2008). This work was started by Fay and Diallo (2012) using area-level models with temporal random effects, which account for the temporal stability of crime trends but do not take advantage from the (typically) high spatial autocorrelation of crime and disorder. Others have explored different model-based synthetic estimators to map various attitudes towards crime (Taylor, 2013; Wheeler et al., 2017); but synthetic estimators suffer from a risk of bias arising from the models (Rao and Molina, 2015).

In this work we suggest the application of the SEBLUP to estimate the residents' perceived disorder in their neighbourhoods. The SEBLUP accounts for the implicit spatial dimension of neighbourhood perceptions and is expected to provide better estimates than basic model-based estimators (Pratesi and Salvati, 2008). This method has been applied to study poverty and social exclusion, but this is the first SEBLUP application to analyse neighbourhood perceptions. Mooney et al. (2018)

suggest using a universal kriging, which also incorporates the spatial autocorrelation parameter and covariates in a model-based approach, to estimate physical disorder from Google Street View images. Although their approximation is innovative and incorporates the spatial dimension of disorder, it does not account for neither the neighbourhoods' stigmas experienced by residents in their areas nor the social disorder (observed or socially constructed), both of which have serious effects on residents' everyday life (Robinson et al., 2003; Ross and Mirowsky, 1999).

This article introduces the SEBLUP to examine the geographies of a latent score of perceived disorder in Manchester Local Authority District (Manchester LAD), England. The SEBLUP is expected to overcome the main limitations found by previous research and produce reliable small area estimates, and it provides evidence about significant covariates to predict the distribution of perceived disorder. This is also one of the first applications that combine latent factor models and SAE. Section 7.2 presents the theoretical background and hypotheses. Section 7.3 introduces the data and estimation approaches, followed by results shown in Section 7.4. Finally, Section 7.5 presents discussion and conclusions.

7.2 Theoretical background

7.2.1 Perceived neighbourhood disorder

Ross and Mirowsky (2001:265) define perceived neighbourhood disorder as "conditions and activities […] that residents perceive to be signs of the breakdown of social order". Disorder is frequently classified into social and physical. Social disorder refers to episodic human behaviours that trouble citizens and indicate lack of social control; while physical disorder relates to time-persistent cues showing that an area is not maintained properly (Ross and Mirowsky, 1999; Skogan, 2015). Some cues indicating social disorder are street fights and public consumption of alcohol and drugs; and physical cues that might be perceived as disorderly are graffiti and rubbish lying around.

However, some authors argue that this distinction is unnecessary. Even when physical and social disorders are different problems that require specific policies, both drive to the same human reactions: "disorders in questions usually engender the same reaction –be it fight or flight– from neighborhood residents" (Skogan, 1990:4).

Accordingly, Ward et al. (2017) examine perceived physical and social disorder from multilevel Structural Equation Modelling and argue that there is no utility in separating these when measuring perceived disorder at the neighbourhood level. This is the reason why we aim to produce estimates of a single latent score of perceived neighbourhood disorder.

7.2.2 Neighbourhood characteristics and perceived disorder

Even when neighbourhood perceptions are essentially individual, residents living in certain neighbourhoods perceive higher disorder than others. Perceived disorder has been associated with individual features such as age, ethnicity, victimisation and education level (Hipp, 2010b; Steenbeek et al., 2012). However, perceptions of disorder are known to be especially influenced by community-level variables that shape social structures and neighbours' perceptions at a small geographical level, such as the concentration of minorities, poverty, unemployment, residential instability and crime (Hipp, 2010b; Sampson and Raundenbush, 2004; Steenbeek and Hipp, 2011).

Sampson and Raudenbush (1999, 2004) analysed perceived disorder in Chicago from SSO and questionnaires and concluded that visual cues of lack of social and physical order partially predict perceived disorder, but the neighbourhood concentration of minorities, poverty and low social control have more explanatory power. Social cohesion and collective efficacy have shown a strong negative relation with both observed and perceived disorder (Sampson and Raudenbush, 2001; Steenbeek and Hipp, 2011; Taylor, 2001). The neighbourhood's residential instability, as measured by the population churn of residents who move in and out, has been repeatedly associated to perceived disorder (Ross et al., 2000; Sampson and Raudenbush, 1999; Steenbeek et al., 2012; Steenbeek and Hipp, 2011). High crime rates are also known to increase the neighbours' perceived disorder (Franzini et al., 2008; McCord et al., 2007; Skogan, 2015). With respect to the relation between minorities' concentration and perceived disorder, some argue that it is moderated by the neighbourhood's social cohesion (Wickes et al., 2013). Ross and Mirowsky (1999) found more perceived disorder in urban centres in Chicago, while citizens living in suburbs, villages and rural areas perceive less disorder; and Megler et al.

(2014) found more graffiti reports in the central/commercial (mixed land-uses) areas of San Francisco. Mixed land-uses correspond to areas that enable different land uses, such as residential, commercial and leisure activity (e.g. central urban areas).

Perceived disorder is known to be especially affected by the characteristics of the micro-neighbourhood (Hipp, 2010a). This paper introduces the SEBLUP to research on perceived disorder, to estimate its small geographies and analyse its predictors. The review of previous research provides essential information to decide which neighbourhood covariates should be fitted in SAE models.

7.2.3 Hypotheses

Based on the literature review, we expect to find higher perceived disorder in neighbourhoods characterised by:

H7.1 higher residential instability,

H7.2 lower income,

H7.3 higher crime rates,

H7.4 higher concentration of minorities,

H7.5 higher unemployment, and

H7.6 mixed land-uses.

Methodologically, we expect SEBLUP estimates to be more reliable than basic model-based estimates:

H7.7 SEBLUP estimates are more reliable than basic model-based estimates.

7.3 Methods

7.3.1 Manchester Resident Telephone Survey

This research is based on the MRTS, which recorded data between November 2012 and February 2014. The MRTS is a quota sample survey based on age, gender, ethnicity and employment, which is designed to measure general aspects of life in Manchester. After deleting households who refused to report their postcodes and respondents living outside Manchester LAD, our database has a sample of 7989 residents. Manchester is the major local authority of Greater Manchester Metropolitan County. The areas analysed in this research are the 282 Manchester

LSOAs. LSOAs are small areas in England and Wales that contain between 1000 and 3000 residents, and between 400 and 1200 households. The average sample size per LSOA is $\bar{n}$=28.3, but samples vary between 2 and 79. Only 11 areas have less than 10 respondents, while most areas (143) have sample sizes between 10 and 29.

Prior research has shown that smaller units of analysis (e.g. street blocks) are preferred over larger scales when examining neighbourhood perceptions (Hipp, 2010a). LSOAs are designed by grouping households which are physically and economically similar, show a good degree of overlap with urban communities, and are small enough to allow a close analysis of neighbourhood perceptions (Brunton-Smith et al., 2014). Furthermore, LSOAs are the smallest possible scales at which we are able to fit the area-level models and examine our hypotheses. Although MRTS data were recorded at a postcode level, some of the area-level covariates needed to fit the models are only available at LSOA level, and thus this research uses this unit of analysis.

7.3.2 Variable of interest: Perceived disorder

The MRTS includes questions about how much of a problem seven types of disorder are in one's local area (see Table 7.1). Respondents can answer 'Not a problem at all', 'Not a very big problem', 'A fairly big problem' and 'A very big problem'. 'No opinion' responses are recoded as missing. The measure with the lowest values is abandoned and burnt out cars, in which 93.3% of respondents reported that it was not a problem or not a very big problem; while rubbish lying around was reported as a fairly or very big problem by 44.2% of respondents.

Table 7.1 Frequencies of measures of perceived disorder.

		Not a problem at all	Not a very big problem	A fairly big problem	A very big problem	No opinion
Noisy neighbours and parties	*f*	5084	1651	840	383	31
	%	63.6%	20.7%	10.5%	4.8%	0.4%
Teenagers hanging around the streets	*f*	3939	1958	1315	730	47
	%	49.3%	24.5%	16.5%	9.1%	0.6%
Rubbish and litter lying around	*f*	2606	1827	1965	1569	22
	%	32.7%	22.9%	24.6%	19.6%	0.3%
Vandalism, graffiti and damage to property/vehicles	*f*	4436	1900	1093	511	49
	%	55.5%	23.8%	13.7%	6.4%	0.6%
People using or dealing drugs	*f*	4118	1248	1232	804	587
	%	51.5%	15.6%	15.4%	10.1%	7.3%
People drunk or rowdy in public places	*f*	4439	1937	1050	485	78
	%	55.6%	24.2%	13.1%	6.1%	1%
Abandoned and burnt out cars	*f*	6463	987	331	123	85
	%	80.9%	12.4%	4.1%	1.5%	1.1%

In order to produce a unit-level single measure of perceived disorder, and given that all pairwise correlations between the seven measures were significant and strong, we hypothesised that all measures were underlying a single latent variable and computed a single latent score from Confirmatory Factor Analysis (CFA). The goodness-of-fit indicators suggest that the one-factor model is the best fitting CFA solution compared to the two-factor model (see Table 7.2). Measures of *Root Mean Square Error of Approximation* (RMSEA) and *Root Mean Square of the Residuals* (RMSR) are slightly smaller for the one-factor solution than the two-factor model (social and physical disorder), and the *Tucker-Lewis Index* (TLI) of factoring reliability is higher for the one-factor solution. The sum of squared factor loadings, which is the amount of variance explained by the single factor, is 2.72 for the one-factor solution. And the proportion of variance associated with each factor that could be explained from the dataset is 0.39. Such measures are smaller for the two-factor solution. Moreover, the bivariate correlation between the two possible latent scores of social and physical disorder is very high (ρ=0.97, *p-value*<0.01) and these load together on the same factor.

Table 7.2 Goodness-of-fit indicators for one-factor and two-factor CFA solutions.

	One-factor solution	Two-factors solution
RMSEA	0.05	0.07
SMSR	0.02	0.03
TLI	0.97	0.95
Sum of squared factor loadings	2.72	2.54
Proportion of variance contributed by factors	0.39	0.36

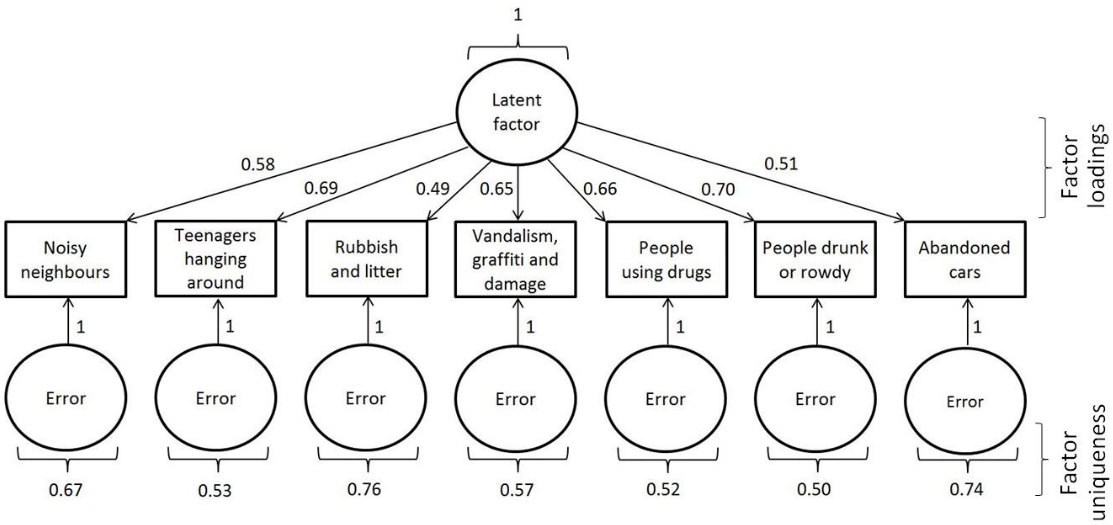
Single latent scores were computed based on the Full Information Maximum Likelihood estimator, which makes maximal use of all data available from every respondent and can handle missing values, borrowing information about missing values on the basis of non-missing values, to obtain unbiased latent score estimates (Schlomer et al., 2010). All scores were shifted to a positive 0-1 measure ($\frac{F_i - \min(F)}{\max(F) - \min(F)}$) to make results easier to interpret (see Table 7.3), where F_i is the latent score for unit *i*.

Table 7.3 Summary of latent scores and shifted latent scores of perceived disorder.

	Minimum	Lower quartile	Median	Mean	Upper quartile	Maximum
Latent scores	-0.99	-0.77	-0.19	-0.01	0.53	3.21
0-1 latent scores	0	0.05	0.19	0.24	0.36	1

Figure 7.1 shows standardised loadings of disorder measures, which represent how these are weighted at the latent factor, and uniqueness values, which show the proportion of the variable common variance not associated with the factor. Some physical disorder indicators (rubbish and abandoned cars) have the lowest loadings; while measures of teenagers hanging around, people drunk and people using drugs, three social disorder indicators, have the highest loadings. Although the latent score of perceived disorder is composed of all measures of disorder and fits the data well, it gives more strength to indicators of social disorder than physical disorder measures.

Figure 7.1 Loadings and uniqueness for each indicator of the latent score of perceived disorder.



7.3.3 Calculating survey weights

Due to the use of quota sampling, we calibrate the sample to the population of Manchester to minimise bias arising from the non-random sampling design and to reduce possible biases arising from the decreased use of landlines. We calculate survey weights by calibrating the proportion of respondents according to certain characteristics to such proportion in the population. Let N_d be the population count in class d and similarly n_d be the sample count. Then, the survey weight for respondents in class d is N_d/n_d. In our case, the survey weights were calibrated by cross-classifying age (18-34, 35-54, 55+), sex (male, female), ethnicity (white, others) and area (North, Central, South Manchester). The weights calculation is limited by the social-demographic variables recorded by the survey. Variables such as respondents' country of birth were not included in the questionnaire and could not be included in the survey weights calibration. Population data were obtained from the UK Census 2011. Although the original sample characteristics were already quite similar to the population parameters due to the use of quota sampling, the use of survey weights adjusts the sample to the population characteristics and reduces the risk of bias in the final model-based estimates (see Table 7.4).

Table 7.4 Socio-demographic characteristics of MRTS sample and Manchester population (aged 18+).

	MRTS sample (unweighted)	MRTS sample (weighted)	Manchester LAD population
Age			
18-34	47.3%	48.1%	48.2%
35-54	30.6%	30.1%	30.1%
55 or more	22.1%	21.7%	21.6%
Gender			
Male	49.9%	50.0%	50.2%
Female	50.1%	50.0%	49.8%
Ethnic origin			
White	79.3%	65.7%	66.7%
Black	4.6%	7.9%	8.5%
Asian	12.4%	19.5%	17.1%
Other	3.7%	6.8%	7.8%
Employment status			
Employed	52.7%	52.8%	52.9%
Unemployed	7.9%	8.0%	7.3%
Student	12.2%	13.1%	13.3%
Retired	12.7%	12.1%	12.3%
Other	14.6%	14.0%	14.3%

7.3.4 Auxiliary data

In area-level model-based SAE, estimates borrow strength from a set of area-level covariates fitted in a model. Covariates were selected based on the literature review and preliminary data analyses. Then, we fitted an LSOA-level model with: (1) proportion of black and minority ethnic (BME) citizens 2011, (2) crime per capita 2012, (3) proportion of unemployed 2011, (4) income deprivation 2012, (5) population churn since 2011, and (6) a dichotomous 0-1 variable for mixed land-uses (see Table 7.5).

Table 7.5 Summary of covariates and coefficients of correlation of each variable with direct estimates of perceived disorder.

	Min	First quartile	Median	Mean	Third quartile	Max	Spearman coeff
Proportion BME	0.03	0.15	0.25	0.31	0.42	0.89	0.31**
Crime per capita	0.04	0.11	0.16	0.17	0.23	6.04	0.29**
Proportion unemployed	0.06	0.28	0.36	0.35	0.43	0.69	0.29**
Income deprivation	0.01	0.12	0.24	0.24	0.34	0.52	0.35**
Population churn	0.21	0.33	0.39	0.39	0.44	0.68	0.13*
Mixed land-uses	0	0	0	0.19	0	1	0.10*

**p-value<0.01, *p-value<0.05

The income deprivation score, which is recorded by the English Index of Multiple Deprivation 2015, measures the proportion of population with low salaries or without income. The proportion of BME and unemployed citizens were recorded by the UK Census 2011. Crimes per capita are computed from Greater Manchester Police (GMP) data. Population churn is an estimate provided by the Consumer Data Research Centre which shows the proportion of households that changed its occupier between 2011 and 2016. The dichotomous variable of mixed land-uses is calculated based on the Classification of Multi-Dimensional Open Data of Urban Morphology, which describes the typology of each area based on its environmental and urban morphology attributes (Alexiou et al., 2016). Neighbourhoods defined as 'old town', 'high street and promenades' and 'central business district' are classified as mixed land-uses (coded as 1), while other categories are coded as 0. This measure accounts only for morphological features and future research will explore the use of better measures of the level of mixed land-uses.

We also explored other variables, but their bivariate correlations with perceived disorder (as measured by direct estimates) were small or non-significant, so we did not include them in our models: mean age (ρ=0.04, *p-value*>0.1), proportion of citizens not staying in school after 16 (ρ=0.01, *p-value*>0.1), difference between the workday population and residents (ρ=0.11, *p-value*>0.1), population density (ρ=0.03, *p-value*>0.1) and premises licenced to sell alcohol (ρ=0.07, *p-value*>0.1). Certain variables emphasised by literature, mainly social control and collective efficacy, could not be tested in our model, as we found no available data.

7.3.5 Methodology

We produce small area estimates of perceived disorder based on three SAE approaches: Horvitz-Thompson (HT) direct estimation, area-level EBLUP estimator, and EBLUP estimator with spatially correlated random effects (SEBLUP).

First, the HT estimator uses data recorded by the original survey for each area and makes use of survey weights to produce design-unbiased direct estimates (Horvitz and Thompson, 1952). Direct estimates might suffer from high variance and unreliability in areas with small sample sizes.

Second, the EBLUP estimator, which is based on the FH model (Fay and Herriot, 1979), combines HT estimates with synthetic estimates produced from a linking model with area-level covariates to borrow strength from related areas (Rao and Molina, 2015). Since the true values of the variable of interest are unknown, we use the HT estimates as our data, whose errors are different in each area because sample sizes vary between areas. We assume our direct estimates to be linearly related to a set of area-level covariates, fit a model and predict from it to compute the synthetic estimates. EBLUP estimates are produced from combining the HT estimates with synthetic estimates, with more weight attached to direct estimates when their error is small, and more weight given to synthetic estimates when direct estimates' error is large (Rao and Molina, 2015). The EBLUP is an optimal combination between direct and synthetic estimates, and thus reduces the estimates' bias and is preferred over synthetic estimators. The fitting method chosen in this research is the restricted maximum likelihood, which takes into account the loss in degrees of freedom derived from the model (Rao and Molina, 2015).

Third, the SEBLUP estimator adds spatially correlated random area effects to EBLUP estimates and borrows strength from neighbouring areas through a simultaneous autoregressive process (Pratesi and Salvati, 2008). The SEBLUP has shown to provide more reliable estimates than basic model-based estimators when the variable of interest shows medium-high levels of spatial autocorrelation, as is the case of neighbourhood perceptions (Hipp, 2010a; Steenbeek et al., 2012). By borrowing strength from contiguous areas, we expect neighbouring areas to be more related than areas that do not share borders. The proximity matrix used in this research follows a standardised Queen Contiguity approximation, which defines as neighbouring areas not only polygons that share borders, but also areas that share at least one vertex. Queen Contiguity matrices are recommended in SAE when the number of areas under study is large (144 or more) (Asfar and Sadik, 2016).

The main advantage of model-based SAE over other approaches to estimate population attributes at small area level, such as spatial microsimulation, is that extensive research has been devoted to the development of precise methods to examine the estimates' reliability (i.e. RRMSE). We note, however, that novel approaches are being explored to estimate uncertainty in spatial microsimulation approaches (Whitworth et al., 2017).

In SAE, estimates' RRMSEs are examined to analyse their level of reliability (a function of the variance and bias). Smaller RRMSEs indicate more reliable estimates. We expect a RRMSE reduction in EBLUP estimates in comparison to HT estimates. Furthermore, we expect RRMSEs to be reduced when producing SEBLUP estimates. RRMSEs are obtained by the method of bootstrapping adapted to account for variations arising from the CFA (Moretti et al., 2019) as follows:

For HT estimates, we draw $b = 1, \ldots, 500$ simple random samples with replacement (SRSWR) from the sample based on the original sample sizes. In each sample we fit the CFA to predict factor scores. We then calculate survey weights and HT estimates in each sample. Finally, we calculate their average and bootstrap standard error. Dividing the bootstrap standard error by the average of direct estimates provides us with a bootstrap Coefficient of Variation, which is equivalent to the RRMSE for unbiased estimates.

The RRMSEs of EBLUP and SEBLUP estimates are produced using the parametric bootstrap procedure by Molina et al. (2009) adapted to account for the CFA (Moretti et al., 2019). We follow the steps described above: draw $b = 1, \ldots, 500$ SRSWR, fit a CFA to predict factor scores, and calculate survey weights. Then, the parametric bootstrap is implemented on each sample according to steps described in Molina et al. (2009). We obtain a Monte Carlo unbiased approximation of the RRMSE of EBLUP and SEBLUP bootstrap estimates, which accounts for the variance arising from the CFA.

As a general rule, RRMSEs need to be lower than 25% to be regarded as reliable, RRMSEs ranging from 25% to 50% should be used with caution, and RRMSEs higher than 50% are unreliable (Rao and Molina, 2015:40). Estimates have been produced using the `'sae'` package for `R` software.

7.4 Results

In Subsection 7.4.1 we discuss the model results. Subsection 7.4.2 presents the map of SEBLUP estimates. Subsection 7.4.3 checks the estimates' reliability and model diagnostics.

7.4.1 The model

Although the main objective of SAE is to produce estimates of increased reliability, the models fitted to produce such estimates provide relevant information about the covariates' explanatory capacity for understanding the distribution of the outcome measure. It is common practise in SAE applications to discuss their results. Table 7.6 shows the results of EBLUP and SEBLUP models used to produce the small area estimates of perceived disorder. AIC and BIC measures are slightly smaller in SEBLUP model than in EBLUP model, and SEBLUP estimates show the highest reliability measures (see Subsection 7.4.3). Thus, SEBLUP model results are slightly preferred over EBLUP results.

Table 7.6 EBLUP and SEBLUP models of perceived disorder.

	EBLUP				SEBLUP			
	Coeff.	SE	t-value	p-value	Coeff.	SE	t-value	p-value
(Intercept)	-0.114	0.04	-2.9	0.003	-0.096	0.04	-2.3	0.021
Proportion BME	0.065	0.02	2.7	0.005	0.067	0.02	2.4	0.018
Crime per capita	0.144	0.03	4.3	0.000	0.153	0.03	4.5	0.000
Proportion unemployed	0.086	0.04	2.0	0.042	0.058	0.05	1.2	0.047
Income deprivation	0.178	0.04	4.8	0.000	0.193	0.04	4.8	0.000
Population churn	0.281	0.05	5.1	0.000	0.261	0.06	4.5	0.000
Mixed land-uses	0.012	0.02	0.8	0.048	0.008	0.01	0.6	0.048
AIC	-700.11				-702.39			
BIC	-669.62				-670.97			
Spatial correlation					0.49			

Both models show that population churn, the measure of residential instability, is the variable with the most predictive power of distribution of perceived disorder (β^{EBLUP}=0.281 / β^{SEBLUP}=0.261, *p-value*<0.001). These coefficients provide strong evidence to accept our first hypothesis (H7.1). Income deprivation has the second strongest coefficient (β^{EBLUP}=0.178 / β^{SEBLUP}=0.193, *p-value*<0.001). Thus, this variable needs to be considered when predicting perceived disorder (H7.2). The number of crimes per capita also shows a significant positive relationship with perceived disorder (β^{EBLUP}=0.144 / β^{SEBLUP}=0.153, p-value<0.001) (H7.3). Finally, the concentration of BME (H7.4), unemployment (H7.5) and the measure of mixed land-uses (H7.6) have significant but smaller positive relations with neighbourhood perceived disorder.

We observe very little variations between EBLUP and SEBLUP model coefficients. However, the measure of unemployment shows a clear smaller coefficient in the SEBLUP than in the EBLUP model. Non-spatial models can thus be seen to be overstating the contribution of unemployment to the explanation of the geographies of perceived disorder. T-values show lower values for the proportion of BME, population churn and mixed land-uses in SEBLUP than in EBLUP model. Non-spatial models might overestimate their effect to explain the distribution of perceived disorder. The spatial correlation coefficient is $\hat{\rho}$=0.49, which shows medium-high levels of spatial concentration.

7.4.2 Mapping perceived disorder

Direct, EBLUP and SEBLUP estimates have been produced (see Table 7.7). Since SEBLUP estimates are the most reliable estimates (see Subsection 7.4.3), we analyse these and use them to produce the map in Figure 7.2.

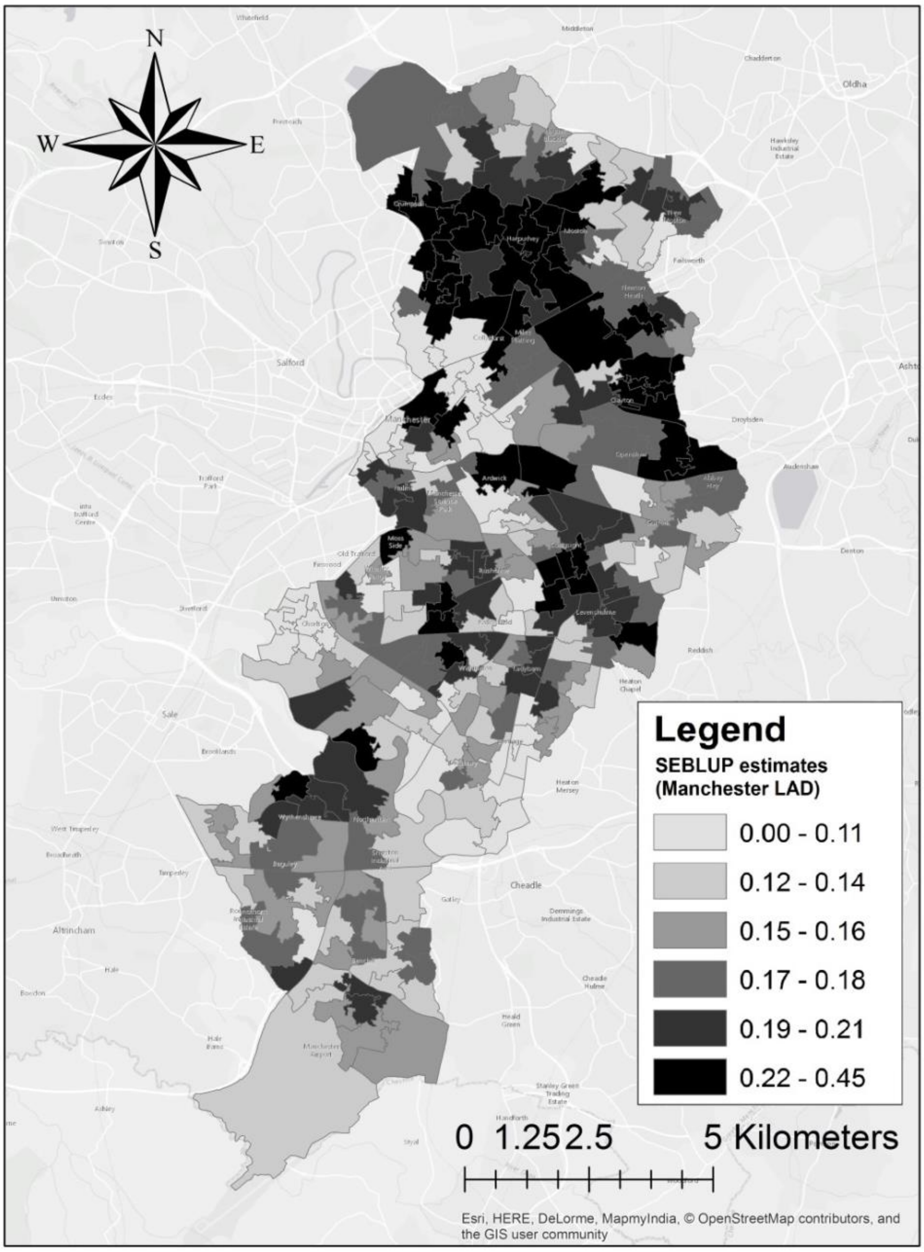
Table 7.7 Summary of small area estimates and average RRMSEs.

	Minimum	Lower quartile	Median	Mean	Upper quartile	Maximum	Average RRMSE
Direct	0.001	0.124	0.175	0.184	0.235	0.629	28.50
EBLUP	0.001	0.131	0.166	0.166	0.204	0.437	20.41
SEBLUP	0.001	0.133	0.167	0.166	0.201	0.447	18.37

Figure 7.2 shows SEBLUP estimates at LSOA level in Manchester. Lighter shades of grey indicate lower estimates of perceived disorder, while darker areas correspond to higher perceptions. SEBLUP estimates show higher perceived disorder in most areas in Northern and Central-Eastern Manchester, while most Southern areas have lower estimates. The highest estimate is located in the western area of the city centre ($\hat{\delta}^{SEBLUP}$=0.45), where we find the central shopping mall (Arndale), Victoria train station, Manchester Arena concerts stadium and tourist attractions such as the John Rylands Library and National Football Museum. The second highest estimate is found in the southern area of the city centre ($\hat{\delta}^{SEBLUP}$=0.35), where Piccadilly Gardens (main green area in city centre), Manchester Central coach station and the Gay Village are located. Manchester city centre is not only characterised by a very high population churn and crimes rate, but also by a large proportional difference

between the usual residents and the workday population and a buoyant night-time economy. Large amounts of retail shops, business activity, historic buildings, green areas and main streets are characteristic of mixed land-uses. Most areas surrounding the central business and shopping hub in Manchester city centre have very low levels of perceived disorder, corresponding to neighbourhoods with lower crime and less poverty.

Figure 7.2 SEBLUP estimates of perceived disorder in Manchester (division in 6 quantiles).



7.4.3 Checking the estimates' reliability and bias diagnostics

RRMSE is the measure used in SAE to check the estimates' reliability, as a function of the variance and bias. SEBLUP estimates have the lowest average RRMSE (i.e. are the most reliable) (H7.7). Average RRMSE is reduced from $\overline{RRMSE}$=28.50% of direct estimates to $\overline{RRMSE}$=20.41% of EBLUPs and $\overline{RRMSE}$=18.37% of SEBLUPs. Figure 7.3 shows that RRMSEs have greatly decreased from direct to SEBLUP estimation in most areas: RRMSEs have only increased in two areas. Figure 7.4 shows that most estimates were also improved from EBLUP to SEBLUP estimation: only 42 areas increased their RRMSEs, and none of such increases were greater than 3%. While 172 direct estimates have RRMSEs higher than 25%, only 39 areas have SEBLUP's RRMSEs greater than 25%. Thus, RRMSEs of SEBLUP estimates are lower than 25% in most areas (243 out of 282), while a few number of LSOAs show values between 25 and 35% (31 out of 282), and only eight areas suffer from very low reliability (larger than 35%). In general, these estimates show high reliability measures according to SAE standards (Rao and Molina, 2015) and can be used for policy-making purposes. New methods for statistical testing are needed to examine whether differences between estimates in neighbouring areas (with their measures of error) are significant since the estimates are highly correlated due to the SAE spatial model. Such methods would evidence the utility of SAE for producing statistically distinguishable estimates but are currently out of scope of this paper.

In relation to the model diagnostics, the Shapiro-Wilk test to check the normality of SEBLUP's standardised residuals suggests no rejection of the null hypothesis of normal distribution (W=0.99, *p-value*=0.78). The analytic validity of model-based estimates is examined by comparing these with the direct estimates, which are model-unbiased. We expect a high linear correlation between direct and SEBLUP estimates to show that model-based estimates are not biased by the model. The Spearman coefficient of correlation is ρ=0.87 (*p-value*<0.001), showing little bias coming from the model.

Figure 7.3 RRMSEs of direct and SEBLUP estimates.

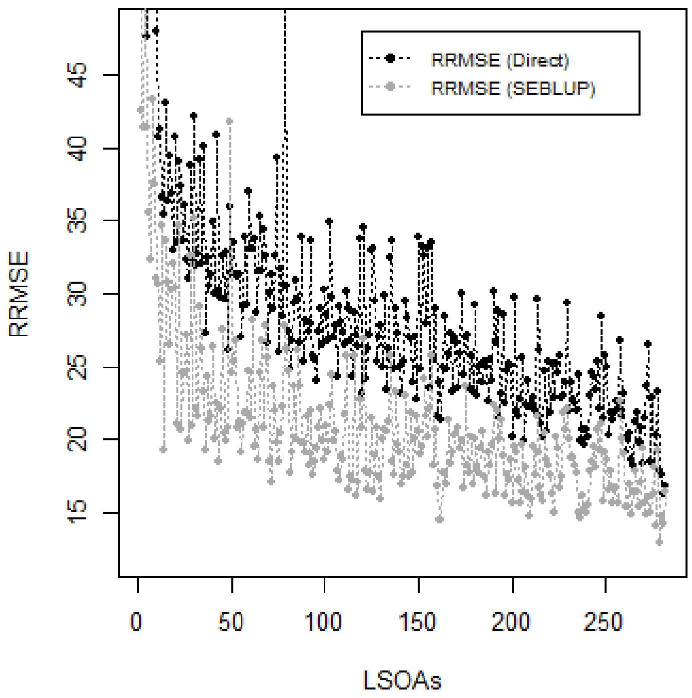
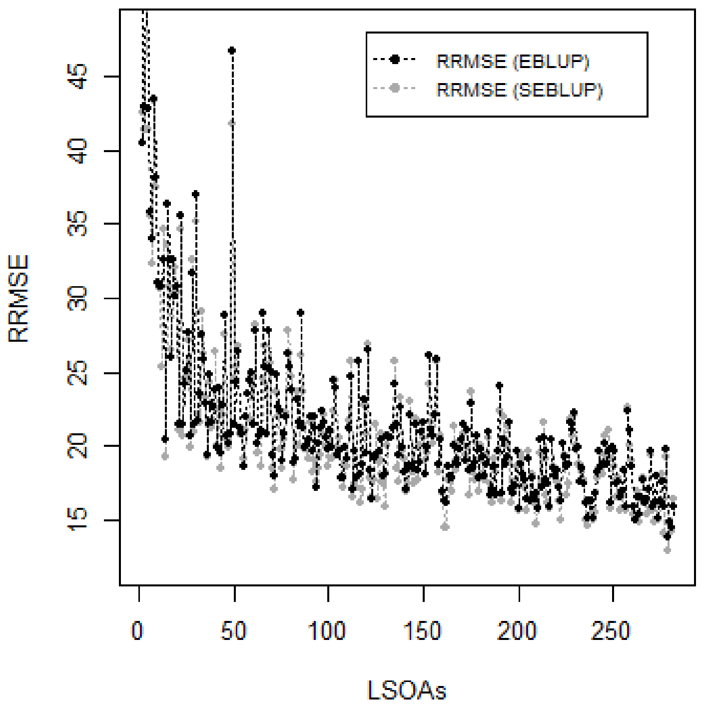


Figure 7.4 RRMSEs of EBLUP and SEBLUP estimates.



7.5 Discussion and conclusions

This research has introduced the SEBLUP to research on neighbourhood perceptions and has produced estimates of a single latent measure of perceived disorder for 282 LSOAs in Manchester. Goodness-of-fit indicators show that the single latent factor model is the best fitting solution and it allows for a single map of perceived disorder. Although geographical units smaller than LSOAs would be preferred to analyse neighbourhood perceptions (Hipp, 2010a), LSOAs show a good degree of overlap with urban communities and are small enough to capture neighbourhood perceptions (Brunton-Smith et al., 2014), allowing to research our hypotheses. Our results illustrate that SEBLUP estimates are more reliable compared to other survey estimates, so we draw our discussion on their results. SEBLUP estimates have been used to examine the explanatory mechanisms and spatial distribution of citizens' perceived disorder in their own neighbourhoods, showing that residents' neighbourhood perceptions are related to the characteristics of their area of residence. App-based and crowdsourcing measures (Solymosi and Bowers, 2018) might be appropriate for future research aiming to examine citizens' perceptions in areas other than their own neighbourhoods, but new methods are needed to overcome potential biases due to non-random sampling.

The main methodological contribution of our research to previous research on perceived disorder is introducing the SEBLUP to analyse and map neighbourhood perceptions at a detailed geographical level. The SEBLUP takes advantage of the implicit spatial dimension of neighbourhood perceptions and produces more precise small area estimates than the EBLUP estimator (Pratesi and Salvati, 2008). Such estimates allow for reliably mapping and targeting the hot spots of (perceived) disorder, leading to more accurate environmental explanations of neighbourhood perceptions. Reliable maps of perceived disorder are needed by crime analysts and police departments to develop strategic and intelligence-led tools, and to design and implement evidence-based micro-targeted policing practices and urban policies (Braga and Bond, 2008).

The main substantive contribution of our research is adding compelling evidence about the relevance of residential instability, poverty and crime to explain the geographies of perceived disorder. Our models show that population churn and income deprivation are the two most important predictors of perceived neighbourhood disorder, and the correlation coefficient between these is very low ($\rho=0.03$, p-value>0.5). Thus, the joint effect of poverty and residential instability largely explains the spatial distribution of perceived disorder in Manchester. Crime rates are also positively related to perceived neighbourhood disorder (Franzini et al., 2008; McCord et al., 2007); though some of the original measures of perceived disorder in the MRTS are regarded as crimes (e.g. drug dealing), and thus we expected some level of association (Skogan, 2015).

Sampson and Raudenbush (1999, 2001) argue that residential instability might function as a structural condition that reduces social cohesion and collective efficacy, and in turn fosters disorder and crime. Furthermore, Ross et al. (2000) show that residential instability increases perceived disorder more in poor neighbourhoods with high crime rates than it does in wealthy areas: stability provides more advantages in affluent neighbourhoods. However, longitudinal data show that residential instability and disorder might be related in the opposite direction: disorder perceptions might encourage residents to move out, thus increasing residential instability (Sampson and Raudenbush, 2001; Steenbeek and Hipp, 2011). Further research and longitudinal data are needed to deepen the causal mechanisms between these, to examine whether perceived disorder is a direct consequence of poverty, residential instability and crime, as three independent constructs; or whether it functions as a mediator variable between the neighbourhood poverty, residential instability and crime.

Small but significant regression coefficients also indicate higher levels of perceived disorder in neighbourhoods with high concentration of minorities and unemployment and mixed land-uses (Ross and Mirowsky, 1999; Sampson and Raundenbush, 1999; Steenbeek et al., 2012). Mixed land-uses shows low model coefficients, partly due to the local nature of this study, and may show a larger effect in research analysing disorder at a supralocal level. Further research will seek better measures of the level of mixed land-uses, which might increase the models' explanatory power and estimates' reliability. Moreover, more research is needed to unmask the effect of the neighbourhood social cohesion on biased prejudices towards the presence of minorities, which may increase perceived disorder (Wickes et al., 2013). The use of alternative data sources should be explored to analyse the distribution of perceived disorder at lower spatial levels (e.g. output areas), which is expected to capture hidden internal heterogeneity in neighbourhood perceptions and result in less sharp boundaries –less dissimilar estimates– between neighbouring areas.

In conclusion, by introducing the SEBLUP to estimate the geographies of perceived disorder we are able to produce precise maps at a detailed spatial level and examine its main social organisation predictors. These findings allow local administrators and police departments to better understand neighbourhood perceptions and to design evidence-based micro-targeted interventions aimed to reduce crime and disorder and increase community safety.

Acknowledgments

The authors would like to thank the Manchester City Council for providing the survey data used in this research. Population churn data have been provided by the Consumer Data Research Centre, an ESRC Data Investment, under project ID CDRC 260, ES/L011840/1; ES/L011891/1. We thank Angelo Moretti and Reka Solymosi for comments that improved the manuscript.

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CHAPTER 8: Article 4 - The measurement of the dark figure of crime in geographic areas. Small area estimation based on the Crime Survey for England and Wales

8.1 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 (Biderman and Reiss, 1967; O'Brien, 1996). 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 generalisation of the use of crime mapping techniques in police departments, the adoption of place-based and hot spots policing, and the more recent focus on predictive policing. Geocoded police-recorded crimes constitute the basis for all of these. Yet certain social groups are more likely to report crimes to police than others (Carcach, 1997; Hart and Rennison, 2003), and police forces are more effective in recording crimes in certain areas (Baumer, 2002; Goudriaan et al., 2006; Xie, 2014). The dark figure of crime is thus unequally distributed across geographic areas, and crime maps based uniquely on police records are likely to be imprecise and biased by the police effectiveness in documenting crimes in each area. 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.

Crime reporting rates are larger for female victims than males, elderly citizens report less than young people, and married report more than singles (Carcach, 1997; Hart and Rennison, 2003; Jackson et al., 2013; Tarling and Morris, 2010). However, there are also contextual factors that explain why the dark figure of crime is 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 the crime reporting rates (Baumer, 2002; Berg et al., 2013; Goudriaan et al., 2006; Jackson et al., 2013; Slocum et al., 2010; Xie, 2014; Xie and Baumer, 2019; Zhang et al., 2007). The dark figure of crime also varies between crime types. While the dark figure of police records tends to be small for thefts of vehicles and burglaries, other crimes (e.g. vandalism, theft from vehicle) suffer from a large proportion of unknown offences (Baumer and Lauritsen, 2010; Carcach, 1997; Gibson and Kim, 2008; Gove et al., 1985; Hart and Rennison, 2003; Hough and Mayhew, 1983; Jansson, 2007; 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 consist on visualising offences known to police with maps and examining their spatial patterns. Advanced spatial techniques are applied to produce crime maps at small spatial scales to enable targeted policing strategies (Chainey and Ratcliffe, 2005; Weisburd et al., 2004), while the potential sources of error arising from the dark figure of crime are usually left touched upon as a limitation, warning or area for future work: "[a]n easy solution to this trail of error potential is to add a caveat that a map shows only those locations of crimes reported to and recorded by the police" (Ratcliffe, 2002:216). Crime mapping techniques are used not only by academics but also by police departments targeting hot spots of crime, and therefore have serious impacts on residents' everyday lives (Brantingham, 2018; Hall et al., 1978). We believe that greater efforts should be invested in accounting and correcting for measurement errors in crime data.

Victim surveys were developed to address the limitations of police statistics as a source of information about crime (Skogan, 1977). Nevertheless, surveys have limitations to produce estimates of crime at the increasingly smaller focus of the new criminology and policing of place. Most surveys are designed to record representative samples for large geographical areas (i.e. countries, regions), and direct estimates of target parameters are unreliable for most small unplanned areas. This paper produces the first estimates of crimes unknown to police at a local and neighbourhood level in England and Wales, to map the dark figure of crime and serve as basis for future research aiming to correct for the measurement error in police records and increase the validity of crime maps. We suggest the use of model-based SAE to produce estimates of the dark figure of crime. SAE makes use of 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 exemplar study we produced estimates of crimes unknown to police from six editions of the CSEW.

Section 8.2 introduces the implications of the dark figure of crime for crime analyses. Section 8.3 presents a literature review about contextual conditions affecting the geographical inequality of the dark figure of crime. Section 8.4 presents data and methods. Section 8.5 shows model results and estimates, and Section 8.6 checks the estimates' reliability and model diagnostics. Finally, Section 8.7 presents conclusions and limitations.

8.2 Mapping police records: Assuming an unassumable assumption

Maps produced solely from police records could only be assumed to be a reliable representation of the geographical distribution of crime rates if the dark figure of crime was not conditioned by variables affecting some areas more than others. However, research tends to show that the propensity of crimes to be missing in police statistics is related to social conditions unequally distributed across areas (e.g. income deprivation). Thus, police records are likely to be biased and crime maps may show an unreliable representation of crime rates. In other words, the dark figure of police records needs to be considered and accounted for when representing crime rates on the map. This puzzle is at the very heart of crime mapping methodologies and it explains whether these techniques succeed or fail to produce valid crime maps.

Some argue that maps produced from police records and crime surveys show similar results, and therefore assume that police-recorded crimes show true crime levels (e.g. Gove et al., 1985). In 1979, Rob Mawby published the Sheffield Study on Urban Social Structure and Crime, in which police records were compared with other data sources (victimisation surveys, self-report studies) in nine areas. He concluded that all data showed similar results of contrasting areas: "it is evident that recorded information shows no indication of area differences being radically altered due to the different actions of the police (or indeed the public) in different areas" (Mawby, 1979:182). Bottoms and Wiles (1997) argue that such results must not be overstated and cannot be overgeneralised, and criticise that these findings cannot be used to establish a working presumption that official statistics are always valid indicators of area crime rates. Bottoms et al. (1987) conducted a similar study in seven areas in Sheffield and concluded that police data may provide valid crimes rates for comparisons across areas with similar housing types and within the same police force jurisdiction. However, police records underestimated crime rates in two high-rise areas and authors warned that caution is necessary when comparing statistics across different police forces.

Others show evidence that residents from certain areas are more likely to report crimes to police than others, which increases crime rates in some places. Goudriaan et al. (2004) examined cross-national survey data and concluded that victims are more likely to report property crimes in countries where police forces are perceived to be more competent. Xie (2014) examined crime reporting trends in large metropolitan areas in the US and observed that there was a national trend towards higher reporting rates (also shown in large cities such as Philadelphia, Chicago, Detroit and Los Angeles), but data showed no significant change 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 economically deprived neighbourhoods are less likely to report certain crime types (Berg et al., 2013; Goudriaan et al., 2006; Slocum et al., 2010). Baumer (2002) shows that citizens living in deprived neighbourhoods, but also those living in wealthy areas, are less likely to inform the police; and argues that there is a curvilinear relationship between neighbourhood poverty and crime reporting rates. Although public reporting is not the unique pathway through which the police become aware of crimes (police can observe crimes in action, observe environmental cues of crimes, be informed by private law enforcers, offenders may surrender), it is arguably the main source of data for most crime types and have a very large impact on crime rates (Brantigham, 2018; Mawby, 1979).

The assumption that maps produced from police statistics show reliable representations of the geographies of crime is fraught with danger, and crime mapping techniques that put police records on the map without further investigation may suffer from a high risk of producing biased spatial analyses. It should always be checked whether other variables are conditioning crime records in geographic areas, and surveys provide data to correct for the measurement error in official statistics.

The next section reviews variables that may affect the unequal distribution of the dark figure of crime in geographic areas.

8.3 Factors affecting the geographical inequality of the dark figure of crime

Researchers have found several contextual conditions affecting the unequal geographical distribution of crimes unknown to police. Factors can be aggregated in variables that affect victims' reporting rates (i.e. demographic, economic, social, environmental and crime-related conditions and perceptions about the police), unequal police surveillance in different areas and differences in police counting rules. In England and Wales, the latter has been scrutinised and all 43 police forces follow common counting rules (i.e. Home Office Counting Rules for Recorded Crime, National Crime Recording Standard). We will thus focus on the other factors. It must be noted, however, that a 2014 inspection into police-recorded data reported a series of practices that need improvement to increase police records' comparability (HMIC, 2014), and research conducted in the US shows that county-level measurement error in police data is likely affected by non-response from police agencies, instrumental errors and stochastic variation (Maltz and Targonski, 2003).

Economically deprived areas tend to suffer from lower reporting rates than middle-class neighbourhoods (Berg et al., 2013; Black, 2010; Goudriaan et al., 2006; Slocum et al., 2010; Zhang et al., 2007). Social identities in disadvantaged areas may develop legal cynicism that reduces the public cooperation with police, 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 anti-police views play a less important role. Baumer (2002) shows that neighbourhood socioeconomic 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, aggravated assault). Moreover, while victims of simple assault living in disadvantaged neighbourhoods were less likely to report to police than elsewhere, the lowest reporting rates were found in the wealthiest areas. Baumer (2002) argues that deprived and wealthy areas are characterised 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. Gibson and Kim (2008) find statistically significant correlation coefficients between countries' inequality and crime reporting rates of theft from car, attempted burglary and robbery.

Research examining the effect of social cohesion on the residents' willingness to report crimes to police show contradictory results. Some argue that areas characterised by high social cohesion are also those where crime reporting rates are lower, due to residents' higher social resources to cope with crime through social mechanisms alternative to 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 in the neighbourhood are related to a higher likelihood of reporting crimes to police. According to these results, the more cohesive a neighbourhood is, the greater the cooperation with police and the larger the crime reporting rates. Measures of residential instability tend not to show significant relationships with victims' reporting rates (Jackson et al., 2013; Schnebly, 2008).

Residents living in suburban areas are known to be less likely to report crimes to 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 a decreased likelihood of victims' reporting to police (Carcach, 1997; Hart and Rennison, 2003; Jackson et al., 2013; MacDonald, 2001; Tarling and Morris, 2010), and therefore areas characterised by a larger proportion of these groups are expected to suffer from lower crime reporting rates. For example, reporting rates are expected to be larger in ageing areas, but also in neighbourhoods with more females, singles and uneducated 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 police is the area crime rates: those who live in areas with high crime are less likely to notify the police. The relationship between crime levels and crime reporting rates is likely to be mediated by the public perceptions of police effectiveness. The crimes' level of seriousness also affects crime reporting rates (Black, 2010), and offenders are less likely to report their own victimisation when they live in areas marked by high crime and structural disadvantage (Berg et al., 2013). Other research shows not significant effects of crime rates on citizens' cooperation with police services, while the perceived neighbourhood disorder reduces the willingness to call the police (Jackson et al., 2013).

The public perceptions about the police, which vary between neighbourhoods, are known to be a good predictor of crime reporting rates. Low perceptions of police effectiveness were related to smaller crime reporting rates in New York regardless of victims' characteristics (Xie, 2014). Several studies have shown that perceptions of police legitimacy and trust in police fairness are the most important predictors of citizens' willingness to report and cooperate with the police (Jackson et al., 2013; Myhill and Quinton, 2011). Citizens' perceptions of police legitimacy are highly related to their contact with the police, but these are also explained by neighbourhood social identities shaped by the neighbourhood's economic and social conditions (Bradford, 2014).

Finally, unequal policing strategies may impact the proportion of crimes unknown to police, both through affecting the victims' willingness to report and the police probability to witness incidents. Braga (2007) reveals that hot spot policing strategies reduce the citizens' calls for services in treatment places relative to control areas. Schnebly (2008) shows that police notification is higher in cities with larger proportions of police officers trained in community-oriented policing, but victims are less likely to call the police in cities with larger proportions of full-time 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, groups or crime types might increase their recorded number, which has been named as ‘deviancy amplification spiral’ (Hall et al., 1978). Thus, the police would serve as ‘amplifiers of deviancy’ (Young, 1971). However, others argue that over-policing areas and targeting stop and search practices in specific locations contribute to alienate residents from the police and decrease the residents’ willingness to cooperate with police services (Jackson et al., 2013; Rengifo et al., 2019). Police-initiated encounters may have strong negative effects on citizens’ cooperation with the police (Jackson et al., 2013).

Previous research about contextual variables that explain the geographical inequality of the dark figure of crime is necessary when selecting area-level covariates in SAE. We will examine available area-level auxiliary information about these variables and fit optimal models to produce reliable estimates of crimes unknown to police.

8.4 Data and methods

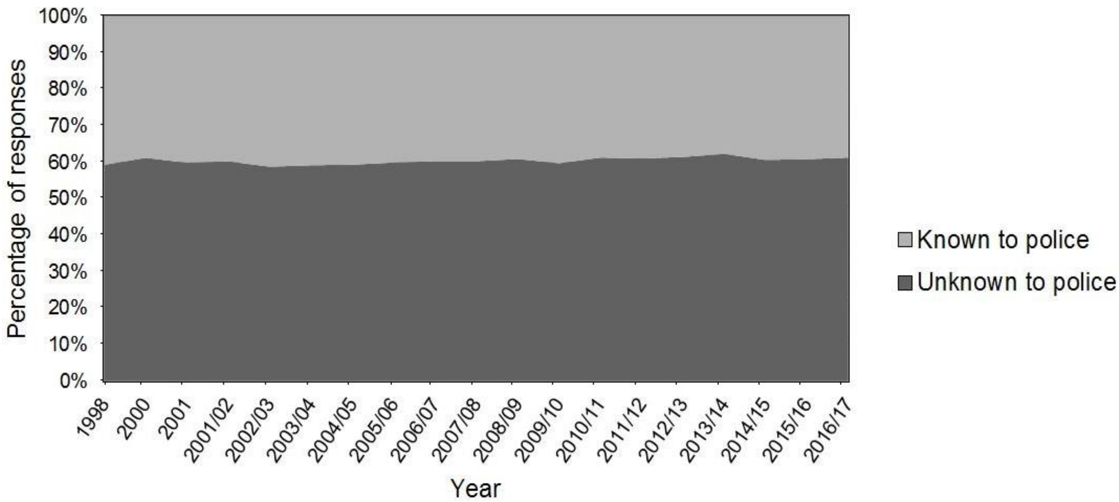
First, we present the survey used to produce estimates of crimes unknown to police. Second, we introduce SAE methods. Third, optimal area-level covariates are selected to fit the SAE models.

8.4.1 Data

Data from the CSEW is used to produce small area estimates of crimes unknown to police. The CSEW, previously named BCS, is an annual victimisation survey conducted since 1981. The sampling design consists on a multi-stage 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 victim of a crime in the last 12 months. The questionnaire includes a range of questions about perceived safety and attitudes towards the police, among others. The main part of the questionnaire is completed face-to-face in participants’ houses, but a series of questions (alcohol and drugs use, domestic abuse) are administered with computer-assisted personal interviewing. Some modules are asked to a sample of 10 to 15 years 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 victimisation for a range of crimes. In case of positive answer, respondents are asked about details of each victimisation, with a cap of five incidents per person. Although this cap allows cross-sectional comparisons, it reduces the amount of information in an arbitrary way and is being reviewed by survey administrators. Sample sizes of recorded crimes, whose data will be used in this research, 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 will be used to estimate the percentage of crimes unknown to police. At a national level, the percentage of crimes unknown to police remains stable around 60% (see Figure 8.1).

Figure 8.1 Percentage of crimes known and unknown to police (unweighted valid cases)



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 victim's report (around 64% of crimes), followed by a report by another person (around 32%). The percentage of crimes known to police by another way (police were there or found out by another way) is small (around 4%). These percentages remain stable over time (see Table 8.1).

Table 8.1 Descriptive statistics about how the police come to know about crimes (unweighted valid cases)

		CSEW 2011/12	CSEW 2012/13	CSEW 2013/14	CSEW 2014/15	CSEW 2015/16	CSEW 2016/17
Police told by	*f*	3445	2352	2147	1935	2004	1902
respondent	%	63.2	63.2	65.0	63.4	64.0	65.5
Police told by	*f*	1759	1214	1032	974	978	872
another person	%	32.3	32.6	31.2	31.9	31.3	30.0
Police were	*f*	127	79	65	65	84	58
there	%	2.3	2.1	2.0	2.1	2.7	2.0
Police found	*f*	121	76	60	77	65	70
out by another way	%	2.2	2.0	1.8	2.5	2.1	2.4
Total	*f*	5452	3721	3304	3051	3131	2902

Table 8.2 shows the percentage of crimes unknown to 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 (Carcach, 1997; Hart and Rennison, 2003; MacDonald, 2001). The percentage of crimes unknown to police by victims' ethnicity and age show inconsistent results across years due to small sample sizes in certain categories. With regards to the victim's relationship to offender, the percentage of unknown crimes is larger when the offender is a stranger. The crime type which is most likely to be known to police is theft of motor vehicle, but a small dark figure is also observed for burglary (Gibson and Kim, 2008; Jansson, 2007; Tarling and Morris, 2010). The largest proportions of crimes unknown to police are observed for robbery, criminal damage and threat or intimidation.

Table 8.2 Descriptive statistics about crimes unknown to police by characteristics of victim, relationship to offender and crime type (unweighted valid cases)

		2011/12	2012/13	2013/14	2014/15	2015/16	2016/17
Total	*f*	8874	6205	5669	4868	5038	4753
	%	61.0%	61.5%	62.3%	60.6%	60.8%	61.3%
Gender							
Male		62.2%	62.6%	63.5%	61.6%	62.1%	62.3%
Female		59.9%	60.5%	61.2%	59.7%	59.8%	60.4%
Ethnicity							
White		60.8%	61.5%	62.3%	60.7%	60.5%	61.1%
Black		61.9%	62.9%	58.8%	53.9%	68.4%	63.5%
Asian		63.3%	60.0%	61.6%	61.0%	59.4%	60.2%
Other		61.9%	62.9%	67.6%	64.1%	68.0%	67.0%
Age							
16-29		62.5%	63.6%	63.7%	63.1%	59.3%	59.5%
30-49		60.2%	60.2%	61.6%	59.5%	59.4%	61.1%
50-64		62.2%	62.3%	61.7%	60.6%	65.1%	62.9%
65 or older		58.7%	59.9%	63.2%	59.7%	59.8%	61.4%
Marital status							
Never married		62.8%	62.7%	62.0%	61.9%	59.9%	62.1%
Married		60.2%	60.8%	61.6%	59.6%	61.4%	61.8%
Other		59.8%	60.2%	64.1%	60.8%	61.1%	60.0%
Employment status							
Employed		62.0%	62.6%	62.9%	61.4%	61.6%	62.0%
Unemployed		61.6%	59.2%	62.8%	61.3%	64.6%	57.0%
Economically inactive		59.0%	59.4%	60.9%	58.8%	59.1%	60.3%
Household income							
Under £20.000		60.0%	59.8%	62.0%	61.3%	59.7%	60.3%
£20.000-£49.999		63.0%	63.6%	62.9%	61.2%	61.9%	61.2%
£50.000 or over		61.7%	62.2%	63.3%	58.6%	62.7%	63.0%
Relationship to offender							
Knew well		50.9%	52.5%	50.8%	50.5%	49.0%	49.4%
Casual		49.7%	53.2%	52.2%	47.8%	51.7%	51.4%
Stranger		63.4%	63.5%	64.7%	63.2%	63.3%	63.9%
Crime type							
Violent/sexual offences		55.5%	55.7%	51.4%	49.4%	48.2%	53.9%
Robbery and theft		66.8%	66.8%	68.7%	68.6%	67.1%	68.0%
Burglary		40.4%	38.4%	39.7%	37.9%	39.4%	38.5%
Theft of motor vehicle		7.8%	10.0%	3.1%	7.8%	5.0%	4.7%
Theft of cycle		54.1%	58.0%	54.5%	51.8%	50.6%	51.8%
Criminal damage		67.6%	68.8%	70.2%	69.1%	70.4%	68.9%
Threat/intimidation		63.0%	67.4%	69.1%	64.4%	66.6%	67.0%

Table 8.3 shows descriptive analyses of the percentage of crimes unknown to police by respondents' area of residence. Crimes suffered by victims from rural areas are more likely to be known to police than crimes to victims living in urban areas. The

dark figure of crime tends to be larger among respondents living in inner parts of cities. When comparing the dark figure of crime by deciles of the Indices of Multiple Deprivation, which rank every area according to a relative measure of multi-dimensional deprivation in England or Wales, respectively, we observe that the dark figure of crime tends to be larger in the least deprived areas, but this is not consistent across years.

Table 8.3 Descriptive statistics about crimes unknown to police by type of area (unweighted valid cases)

	2011/12	2012/13	2013/14	2014/15	2015/16	2016/17
Rural or urban						
Urban	61.3%	61.8%	62.5%	60.8%	60.8%	61.9%
Rural	59.7%	59.8%	61.3%	59.5%	60.7%	58.1%
Inner city or not						
Inner city	62.9%	61.9%	60.0%	64.4%	62.5%	64.3%
Not inner city	60.8%	61.4%	62.6%	60.2%	60.6%	60.9%
Index of Multiple Deprivation 2010/2015 (England)						
30% most deprived	60.9%	60.4%	61.7%	62.2%	59.3%	60.8%
40% between most and least deprived	61.3%	61.6%	63.3%	60.4%	61.8%	60.8%
30% least deprived	62.1%	62.9%	62.2%	57.8%	60.6%	63.0%
Index of Multiple Deprivation 2008/2011/2014 (Wales)						
30% most deprived	52.5%	58.2%	56.3%	59.3%	60.3%	53.9%
40% between most and least deprived	59.3%	63.3%	62.7%	65.4%	65.7%	63.6%
30% least deprived	59.5%	64.3%	64.0%	65.1%	65.3%	65.8%

Small area estimates will be produced for LADs and MSOAs. LADs represent local governments and MSOAs are small geographic 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 Isles of Scilly. London is composed of 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 (e.g. LSOAs) would allow for more precise spatial analyses of the dark figure of crime. However, the main available area-level SAE techniques require that the assumption of normal distribution of the direct estimates is met at the target spatial scale. Such assumption is only met when aggregating CSEW victimisation data at the LAD level or at

MSOA level after merging more than five editions together. We note that new methods are being developed in SAE to deal with zero-inflated data and distributions skewed towards zero for agricultural data (Dreassi et al., 2014), but further research is needed before these can be applied in the social sciences and this is topic of future research. Instead, the aggregation of data at the LAD and MSOA scales allow for the use of extensively researched SAE methods for which there is evidence about their performance in the social sciences.

To produce estimates at LAD level, we will explore SAE techniques based on spatial, temporal and spatial-temporal models. To produce estimates at MSOA level, all six CSEW editions will be merged to increase effective area sample sizes and only spatial models will be used. Thus, estimates will be produced at the LAD level for six time periods (April 2011 to March 2012, April 2012 to March 2013, April 2013 to March 2014, April 2014 to March 2015, April 2015 to March 2016 and April 2016 to March 2017) and at MSOA level for all editions together (April 2011 to March 2017). The main limitation of producing one single estimate per MSOA is that such estimates are likely to hide variability across years. At the LAD level, average area sample sizes are 41.8 in 2011/12 (min = 0, max = 235), 29.0 in 2012/13 (min = 0, max = 137), 26.1 in 2013/14 (min = 0, max = 133), 23.3 in 2014/15 (min = 0, max = 117), 23.8 in 2015/16 (min = 0, max = 160), and 22.3 in 2016/17 (min = 0, max = 139). At the MSOA level, after merging all editions, the average sample size per area is 8.0 (min = 0, max = 53), and there is a large amount of zero sample sizes (544 out of 7201 areas).

8.4.2 Small area estimation methods

At the LAD level, estimates will be produced using six SAE methods (one design-based and five traditional, spatial, temporal and spatial-temporal model-based approaches), and the most reliable estimates will be used to describe the geographies of the dark figure of crime. At the MSOA level, only traditional and spatial model-based approaches are used due to the merging of all data in a single dataset. See Rao and Molina (2015) for derivations of small area estimators and measures of uncertainty used in this research.

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

$$\hat{\bar{Y}}_d = \hat{N}_d^{-1} \sum_{i \in s_d} w_{di} Y_{di}, \tag{8.1}$$

where w_{di} is the adjusted individual weight for unit/crime i in area d, Y_{di} is the value of crime reporting for unit/crime i in area d, and $\hat{N}_d$ is approximated as the sum of adjusted individual weights in area d (i.e. estimated number of individuals who were victims of crime). Note that each respondent can be represented up to five times as a unit in the CSEW dataset of crimes, and thus we adjusted individual weights by dividing the 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 groups 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. Thus, model-based approaches are needed.

Second, regression-based synthetic estimates are produced by fitting a linear model with the area-level direct estimates as dependent variable and relevant area-level auxiliary information as covariates, and then computing regression-based predictions (i.e. synthetic estimates). Regression-based 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 are likely to be biased by 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 both the direct and synthetic estimates are used for areas with at least two respondents.

Third, the area-level EBLUP, which is based on the Fay and Herriot (1979) model, obtains an optimal combination of direct and regression-based synthetic estimates in each area. 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 the optimal combination of these in each area.

Fourth, the Rao-Yu model (Rao and Yu, 1994) is an extension of the area-level EBLUP for time series or cross-sectional data. It adds temporally autocorrelated random effects to the EBLUP estimator and the estimates borrow strength over time. Rao-Yu model has shown to provide better estimates than the area-level EBLUP when the between-time variation relative to sampling variation is small.

Fifth, the SEBLUP adds spatially autocorrelated random effects to the EBLUP and borrows strength from neighbouring areas (Pratesi and Salvati, 2008). It has shown to improve small area estimates when the variable of interest has medium/high levels of spatial autocorrelation (i.e. when values cluster together in a map), as is typical in criminological studies. 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 border or vertex.

Sixth, the STEBLUP is also an extension of the EBLUP, but this time it accounts for both temporally and spatially autocorrelated random effects (Marhuenda et al., 2013). It is expected to improve small area estimates when the variable of interest is stable across time and shows medium/high levels of 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 suffer from inadequate reliability. Note that SAE methods can produce reliable estimates in some areas but not others. In this research, a parametric bootstrap approximation has been used to compute the RRMSEs of EBLUP, Rao-Yu, SEBLUP and STEBLUP estimates (for details see González-Manteiga et al., 2008; Marhuenda et al., 2013). The measure of uncertainty of direct estimates is the Coefficient of Variation, which is the corresponding measure to the RRMSE for direct estimators. Small area estimates and their RRMSEs have been computed in R software with `‘sae’` (Molina and Marhuenda, 2015) and `‘sae2’` (Fay and Diallo, 2015b) packages.

8.4.3 Covariates selection

Area-level covariates are needed in area-level SAE to fit models and produce estimates. Existing literature is used to select covariates associated to our outcome measure. In order to allow for the use of temporal SAE models to produce estimates at the LAD level, only covariates with available information for all years between 2011 and 2017 are included. These are selected from reliable and administrative sources of data such as ONS and Consumer Data Research Centre (CDRC). The same covariates and additional non-cross-sectional covariates recorded by the UK Census are used at the MSOA level.

Estimates on area percentages of males/females, average age, unemployment, house prices, income, population density and urban/rural classification are provided by ONS (www.ons.gov.uk). Three categories are used to classify areas based on the urban/rural classification: urban conurbations (major and minor), urban cities/towns (henceforth small urban areas) and rural areas. Urban conurbations classify the largest cities in England and Wales, which are characterised by a large population density and an urban morphology. It mainly includes the urban areas of Birmingham, Leeds, Liverpool, London, Manchester, Newcastle, Nottingham and Sheffield. Urban areas outside these large cities are classified within the group 'small urban areas', while the rest of areas are defined as rural. The population density is calculated as the population estimate in each area (provided by ONS) divided by its land area in square kilometres. The absolute standard score (henceforth 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 police (Baumer, 2002). It is calculated as $ASS(x_d) = \left|\frac{x_d - \bar{x}}{s}\right|$, 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 across areas. Estimates of ethnic groups and population churn are provided by CDRC (www.cdrc.ac.uk) under a user agreement for safeguarded data. Police-recorded crimes and stop and search data are provided by the Home Office (data.police.uk). The crime rate is calculated as the total amount of police-recorded incidents divided by the population times 100. Stop and search data is only published since 2015 and cannot be used to model cross-sectional data. The UK Census 2011 provides additional data that may be used to fit non-temporal models at the MSOA level, such as the workday population, language skills, marital status, country of birth, social grade and education level. No available data were found to measure social cohesion, collective efficacy, perceptions about police services and policing strategies. These measures will be examined in future research.

Across all survey editions, at the LAD level, the strongest bivariate coefficients of Spearman correlation (henceforth ρ) with crimes unknown to police (as measured by direct estimates) are found for the measure of small urban areas ($\rho = 0.05, p - value < 0.05$), crime rate ($\rho = -0.04, p - value < 0.05$), large conurbations ($\rho = -0.03, p - value < 0.05$) and rural areas ($\rho = -0.03, p - value < 0.05$). However, for the 2015/16 and 2016/17 editions, the stop and search rate shows the strongest significant coefficient ($\rho = 0.07, p - value < 0.05$). At MSOA level, the following covariates show the strongest significant ρ with crimes unknown to police: small urban areas ($\rho = 0.03, p - value < 0.01$), workday population density ($\rho = 0.03, p - value < 0.01$), crime rate ($\rho = -0.03, p - value < 0.01$), population density ($\rho = 0.02, p - value < 0.05$), rural areas ($\rho = -0.02, p - value < 0.05$), percentage of males ($\rho = 0.02, p - value < 0.05$) and ASS of income ($\rho = 0.02, p - value < 0.05$).

In case of using repeated cross-sectional survey data in SAE, as is our case, van den Brakel and Buelens (2014) examine different model selection approaches for identifying the optimal set of covariates across all 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 over all editions. Then the option with the best averaged optimization criteria is selected and used to model all editions. The preferred selection criterion is the conditional Akaike Information Criterion (cAIC). We follow this procedure to select the model with an optimal set of covariates across the six editions at LAD level (i.e. the lowest averaged cAIC), and then 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 (i.e. Model 5 in Table 8.4).

Table 8.4 Averaged cAIC across six years for five models with best optimization criteria (LAD level)

	Model 1	Model 2	Model 3	Model 4	Model 5
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	x
Rural					
Whites (%)	x	x	x	x	x
Blacks (%)	x				
Asians (%)	x	x	x		x
Others ethnic groups (%)		x			
Population churn					
Crime rate	x	x	x		x
Burglary rate					
Averaged cAIC	2836.01	2835.89	2835.87	2834.37	2834.01

At MSOA level, the same covariates are averaged across years and used to fit non-temporal SAE models, but additional covariates are included to increase the model's explanatory capacity: percentage without any qualification, percentage of citizens with higher/intermediate managerial, administrative or professional occupations, percentage born in UK and workday population density. The latter covariates were only recorded by the Census 2011 and therefore could not be included in temporal models fitted at 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 standard deviations of the variable. Gelman and Hill (2007) suggest dividing by two standard deviations instead of one in order to maintain coherence when considering binary variables. By rescaling the covariates we obtain standardised model coefficients not affected by the covariates' natural scales (e.g. dummy variables vs. percentages vs. rates) without affecting the final small area estimates, estimates' measures of error and the rest of SAE parameters (spatial and temporal autocorrelation, standardised residuals). Then, models are fitted for all years and model-based estimates (synthetic, EBLUP, Rao-Yu, SEBLUP and STEBLUP) are produced.

8.5 Small area estimation of crimes unknown to police

First, we present the model results to obtain information about the area-level predictors of the dark figure of crime at the different scales. Although the main objective of SAE is to increase the estimates' reliability, SAE models provide valuable information to understand the distribution of our variable of interest and it is common practise to discuss the model results. Second, we will represent the map of small area estimates.

8.5.1 Explaining the geographies of the dark figure of crime

Table 8.5 shows the temporal and spatial-temporal models' results used to produce small area estimates at the LAD level for six time periods. Not only STEBLUP estimates are the most reliable ones (see Section 6.1), but also the log-likelihood estimate indicates that the STEBLUP model has the best goodness-of-fit. We thus analyse the STEBLUP model results. The STEBLUP accounts for spatial ($\hat{\rho}_1 = 0.21$) and temporal ($\hat{\rho}_2 = 0.09$) autocorrelation parameters. Although these show small scores of spatial and temporal clustering, their incorporation increases the estimates' reliability and model's explanatory capacity.

Table 8.5 Rao-Yu and STEBLUP models of crimes unknown to police at LAD level (standardised coefficients)

	Rao-Yu				STEBLUP			
	Beta	SE	t-value	p-value	Beta	SE	t-value	p-value
(Intercept)	59.920	0.3	181.83	0.000	60.96	2.1	28.37	0.000
ASS income	1.447	0.8	1.90	0.042	1.558	0.8	2.04	0.031
Conurbation	0.361	1.1	0.32	0.555	0.496	1.1	0.44	0.461
Small urban	2.455	1.0	2.46	0.013	2.246	1.0	2.24	0.025
Employed (%)	-0.317	0.8	-0.38	0.503	-0.493	0.8	-0.58	0.459
Whites (%)	-1.927	3.2	-0.59	0.349	-0.374	3.3	-0.11	0.511
Asians (%)	-1.040	2.9	-0.36	0.521	-0.025	2.9	-0.01	0.593
Mean house price	-0.572	1.0	-0.55	0.119	-1.071	1.1	-0.99	0.041
Crime rate	-0.809	0.9	-0.95	0.341	-0.543	0.9	-0.63	0.128
Males (%)	0.291	0.8	0.37	0.510	0.514	0.8	0.64	0.517
Spatial autocorrelation							0.21	
Temporal autocorrelation			0.11				0.09	
Log-likelihood			-8161.9				-8171.1	
Number of areas			331				331	

At the LAD level, three covariates show significant standardised coefficients with the percentage of crimes unknown to police. The strongest coefficient is found for the measure of small urban areas, as opposed to conurbations and rural areas. The dark figure of crime is significantly larger in small urbanities, while the measure of large conurbations also shows a positive but not significant coefficient. The second largest coefficient is found for the ASS of income, which is positive. LADs whose average income is far from the average income in England and Wales (i.e. wealthy and deprived municipalities) have larger percentages of crimes unknown to police, while middle-class LADs show a lower dark figure of crime (Baumer, 2002). Finally, the area mean house price shows a significant negative coefficient: the percentage of crimes unknown to police is slightly smaller in expensive LADs.

Results of non-temporal EBLUP and SEBLUP models fitted at the MSOA level are shown in Table 8.6. The log-likelihood estimate shows that SEBLUP model results are slightly preferred over EBLUP results, and thus we will focus on these. The spatial autocorrelation parameter is small ($\hat{\rho}_1 = 0.13$), showing that the level of spatial clustering of the dark figure at MSOA scale is small.

Table 8.6 EBLUP and SEBLUP models of crimes unknown to police at MSOA level (standardised coefficients)

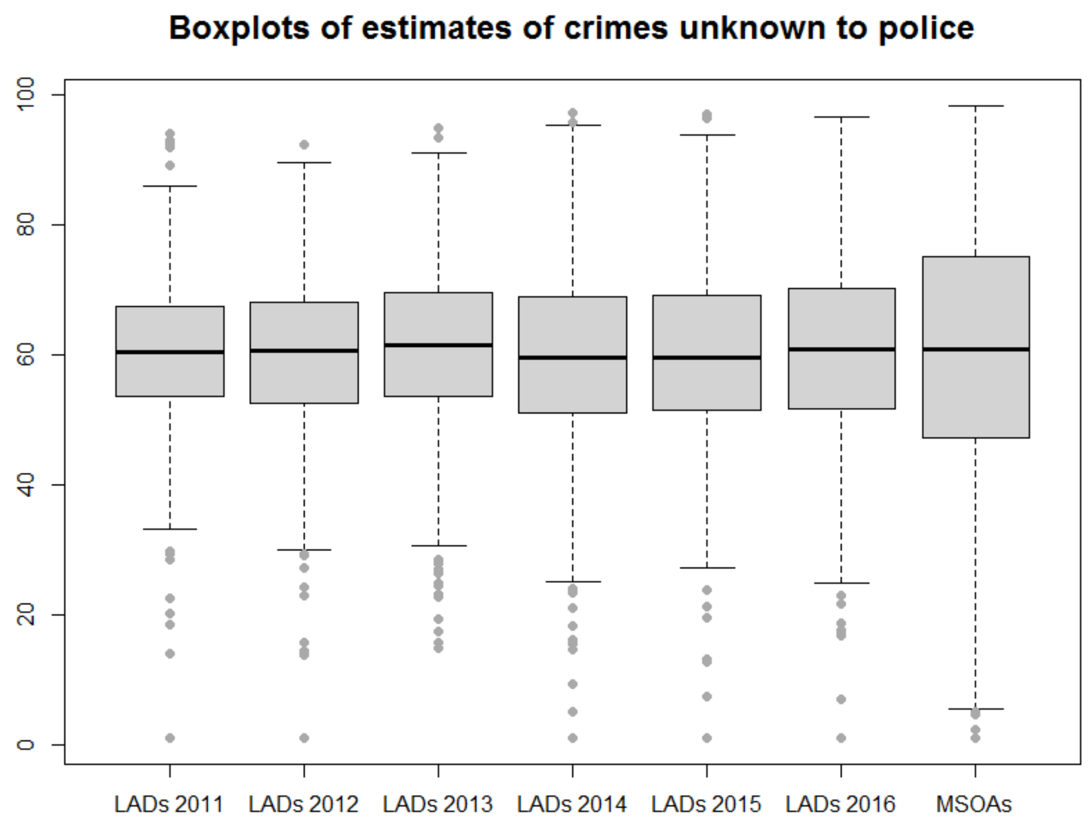
	EBLUP				SEBLUP			
	Beta	SE	t-value	p-value	Beta	SE	t-value	p-value
(Intercept)	59.961	0.3	205.10	0.000	59.965	0.3	198.05	0.000
ASS income	1.227	0.7	1.74	0.083	1.257	0.7	1.71	0.048
Conurbation	-0.830	0.9	-0.84	0.403	-0.814	1.0	-0.81	0.419
Small urban	2.156	0.9	2.39	0.017	2.127	0.9	2.33	0.019
Employed (%)	-0.651	0.8	-0.83	0.408	-0.639	0.8	-0.81	0.420
Whites (%)	-2.621	4.3	-0.61	0.544	-2.747	4.4	-0.62	0.532
Asians (%)	-5.533	2.9	-1.86	0.063	-5.614	3.0	-1.85	0.044
Mean house price	-4.312	1.2	-3.59	0.000	-4.322	1.2	-3.56	0.000
Crime rate	-1.141	0.8	-1.33	0.183	-1.091	0.9	-1.27	0.204
Males (%)	0.633	0.7	0.87	0.387	0.616	0.7	0.84	0.401
No qualification (%)	4.530	1.7	2.70	0.006	4.453	1.7	2.63	0.008
High/int. occupations (%)	-6.050	1.9	-3.24	0.001	-5.989	1.9	-3.18	0.001
Born UK (%)	-5.726	2.3	-2.46	0.013	-5.666	2.4	-2.41	0.016
Workday pop. density	1.292	0.9	1.47	0.141	1.237	0.9	1.39	0.094
Spatial autocorrelation							0.13	
Log-likelihood			-30554.82				-30556.88	
Number of areas			6657				6657	

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

8.5.2 Mapping the geographies of the dark figure of crime

Model-based small area estimates are then produced at the LAD and MSOA levels. Figure 8.2 shows the boxplots of the distribution of estimates produced for different spatial scales and years. The median of the percentage of crimes unknown to police remains stable around 60% at both scales, but the variation between small area estimates is very large. In other words, the dark figure of crime is unequally distributed across geographic areas. The variation of the dark figure of crime is particularly large at the lower spatial scales, thus showing the need to develop new methods to account for crimes unknown to police in crime mapping.

Figure 8.2 Boxplots of model-based estimates of crimes unknown to police at LAD and MSOA levels



Model-based estimates of the dark figure of crime produced at the LAD level are shown in Figure 8.3. STEBLUP estimates are produced for 331 out of 348 municipalities, while regression-based synthetic estimates are used for areas where STEBLUP estimates could not be produced due to zero and one sample sizes. Darker shades of grey represent a larger dark figure of crime and lighter tones show a lower percentage of crimes unknown to police, according to groups defined by five equal intervals. The level of spatial clustering is small/medium and the temporal variability is large in many local authorities.

Estimates show that the dark figure of crime has increased in 180 out of 348 LADs (51.7%) between 2011 and 2017. The largest increase is observed in towns such as Teignbridge, South Riddle, Gravesham and Harlow; while Test Valley, Conwy and Warrington have the largest decrease in the percentage of crimes unknown to police. Nine out of the ten most populated LADs show important decreases in the dark figure of crime, with the only exception of Liverpool, where the observed percentage of crimes unknown to police increased by 4.3% between 2011 and 2017. Such reduction was very large in Sheffield (-15.0%), Bristol (-9.8%), Manchester (-9.5%) and Birmingham (-7.0%). In Greater London, the dark figure of crime increased in 23 out of 33 LADs. On average, the Police Force Areas (PFAs) with the largest dark figures of crime are West Midlands, which is among the ten PFAs with the largest dark figure in four out of the six years (it tends to be larger than 63%), and Gwent, Staffordshire, Lancashire, Surrey, Hertfordshire and Lincolnshire, which are among the seven PFAs with the largest percentages of unknown crimes in three out of six years. At the other end, the City of London is among the five PFAs with the lowest dark figure of crime in four out of six editions. Low estimates are also found in Cumbria, West Yorkshire, Nottinghamshire and Thames Valley, which are among the ten PFAs with the lowest dark figures of crime in three out of six editions. Besides from West Midlands, the other two largest police forces (Metropolitan Police Service and Greater Manchester Police) maintain the dark figure of crime stable around 58%.

Figure 8.4 shows the model-based estimates produced at the MSOA level, according to groups defined by equal intervals. SEBLUP estimates are used in 6657 of the 7201 MSOAs, while regression-based synthetic estimates are used for the areas with zero or one sample sizes. On average, the PFAs with the largest dark figure of crime are Sussex (the percentage of crimes unknown to police is larger than 65% in 100 of its 202 MSOAs), Staffordshire (larger than 65% in 66 out of 143 areas), Hertfordshire (larger than 65% in 78 of 153 MSOAs), Lincolnshire (larger than 65% in 39 of 88 areas), Lancashire (larger than 65% in 92 of 191 areas) and Gwent (larger than 65% in 34 of 77 neighbourhoods). The PFAs with the lowest dark figures of crime are the City of London (50% of crimes are known to police), Cumbria (only 19 of 64 areas have dark figures larger than 65%) and West Yorkshire (larger than 65% in 84 of 299 MSOAs). In Greater London, 441 of 982 MSOAs show dark figures of crime larger than 65%.

Figure 8.3 Model-based estimates of crimes unknown to police at the LAD level

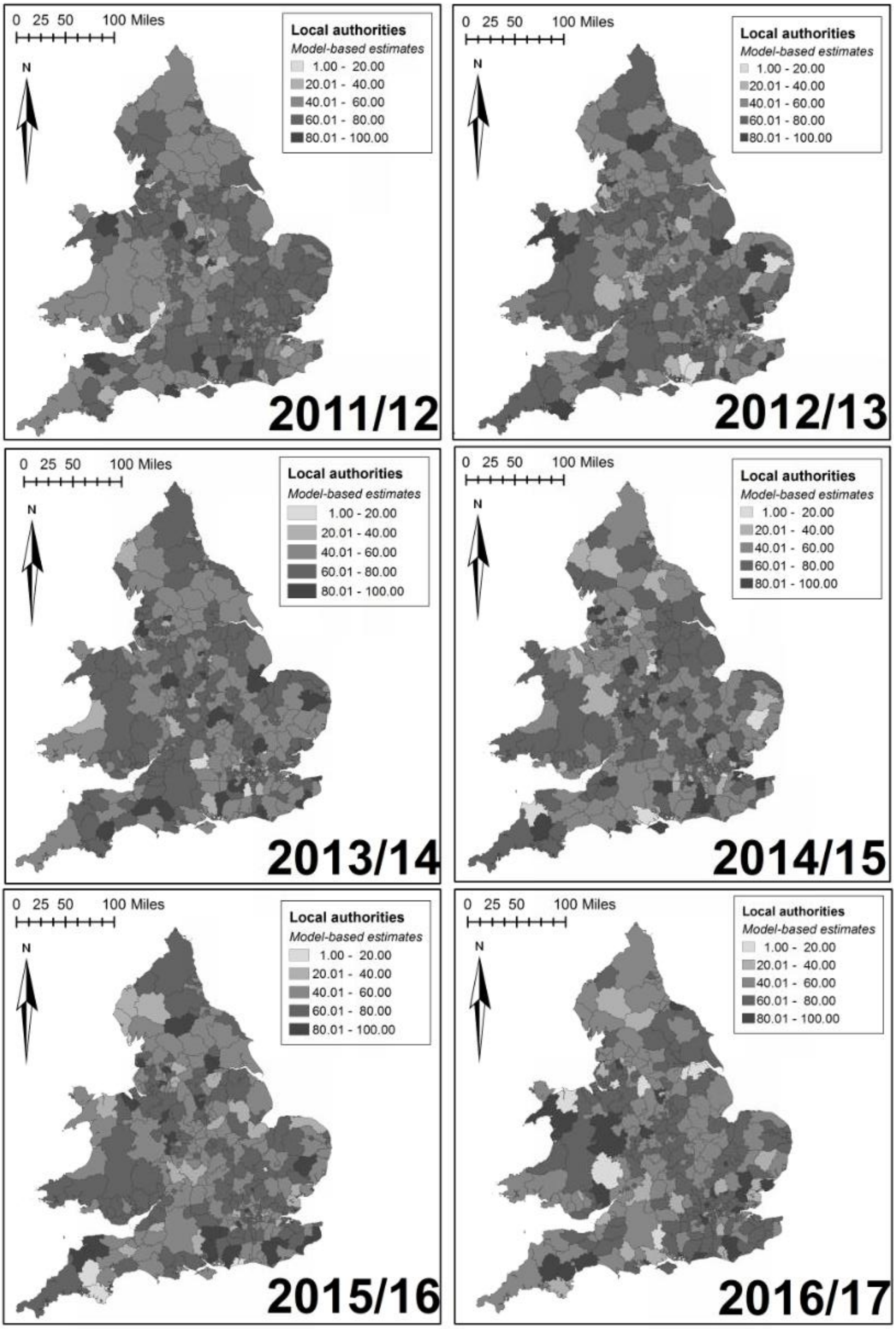
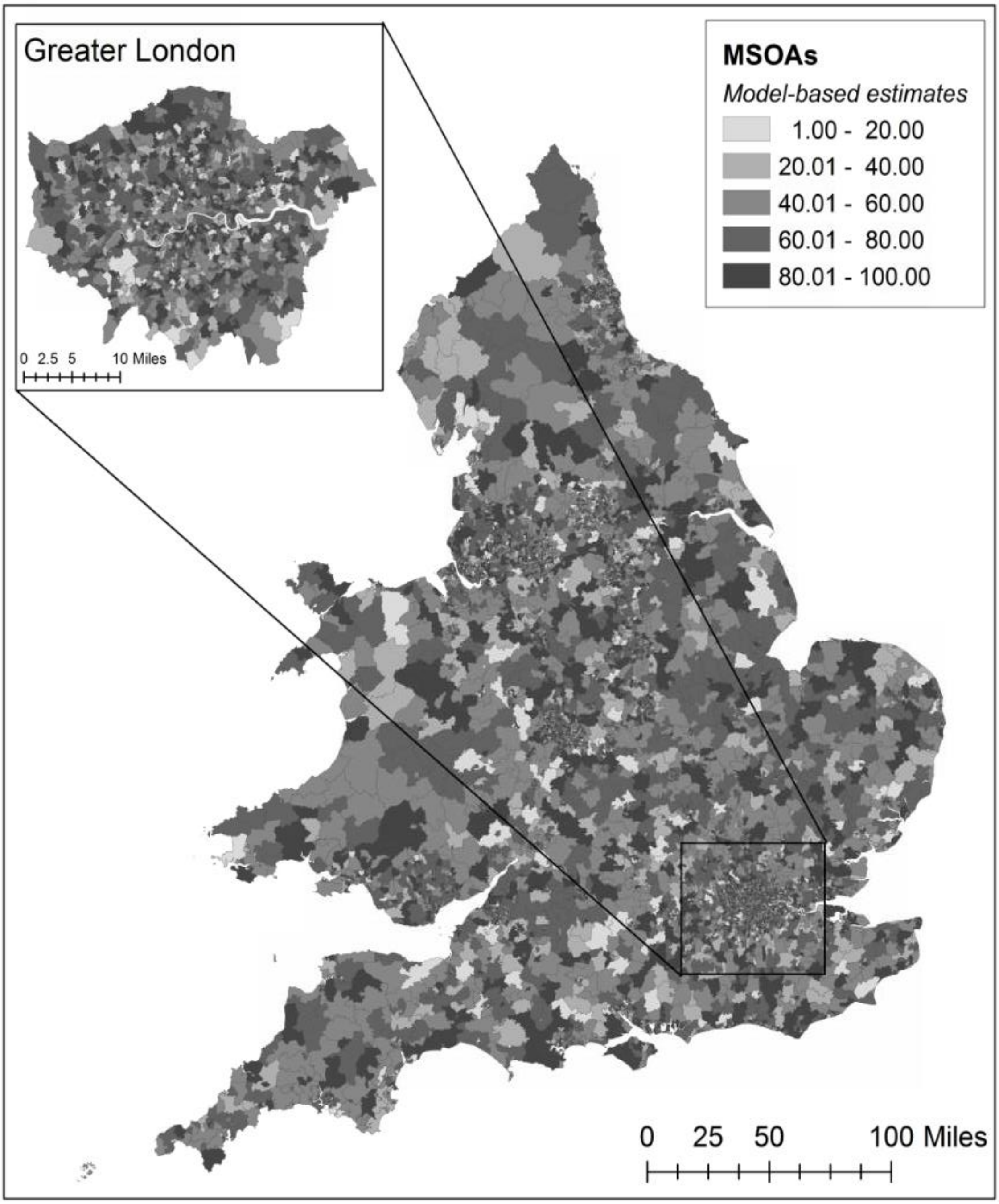


Figure 8.4 Model-based estimates of crimes unknown to police at the MSOA level (2011-2017)



8.6 Reliability checks and model diagnostics

Small area estimates' RRMSEs need to be checked to assess their reliability. Model diagnostics are also presented.

8.6.1 Reliability checks

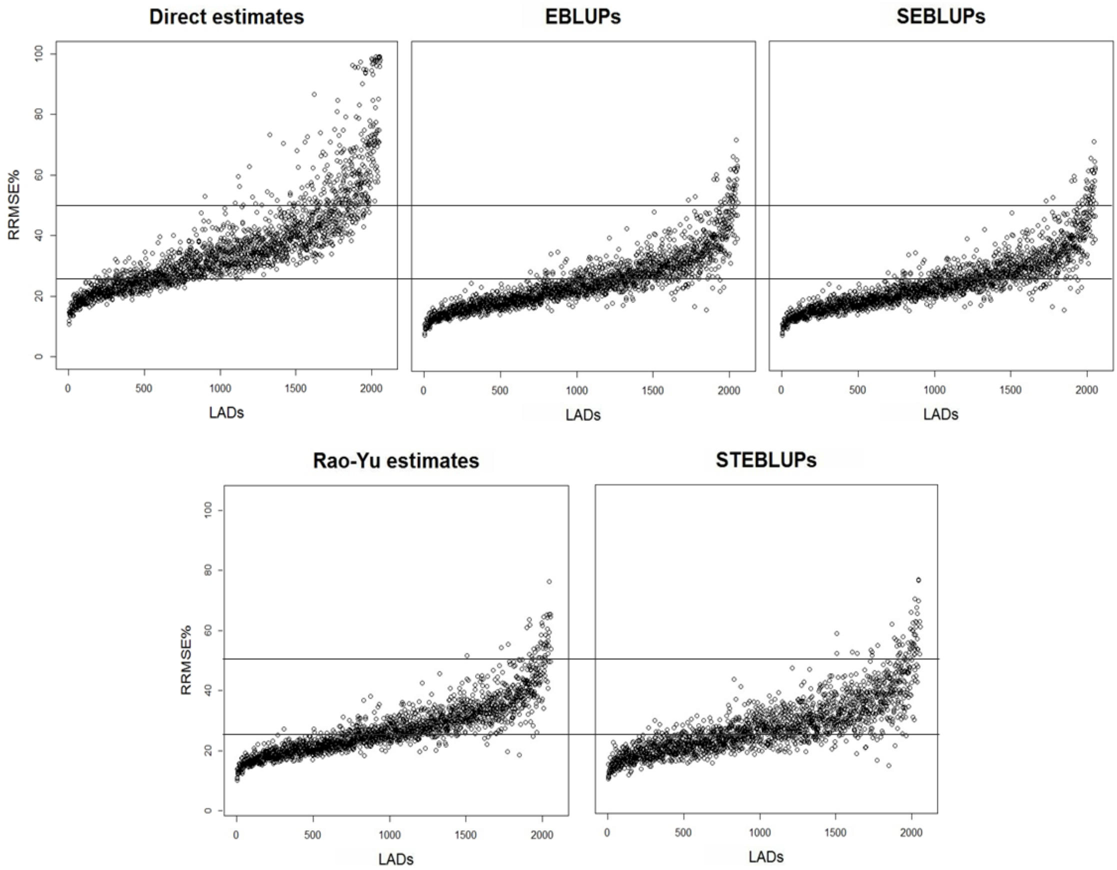
Table 8.7 shows the averaged estimates' RRMSE for all SAE methods. As expected, direct estimates have the largest RRMSEs, showing the need for model-based estimates. At the LAD level, the STEBLUP produces the most reliable estimates (i.e. the lowest RRMSEs) for four survey editions out of six, while Rao-Yu estimates are slightly more reliable than STEBLUPs in 2013/14 and 2016/17. The inclusion of temporal and spatial random effects tends to provide a slight improvement in the estimates' reliability, and thus STEBLUP estimates are examined. The SEBLUP produces the most reliable estimates at the MSOA level.

Table 8.7 $\overline{RRMSE}\%$ of small area estimates and number of areas with an estimate (all methods)

		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		
Areas with an estimate	LADs 2011/12	342	342	342	331	331
	LADs 2012/13	342	342	342	331	331
	LADs 2013/14	344	344	344	331	331
	LADs 2014/15	345	345	345	331	331
	LADs 2015/16	341	341	341	331	331
	LADs 2016/17	341	341	341	331	331
	MSOAs 2011/17	6657	6657	6657		
D	LADs			348		
	MSOAs			7201		

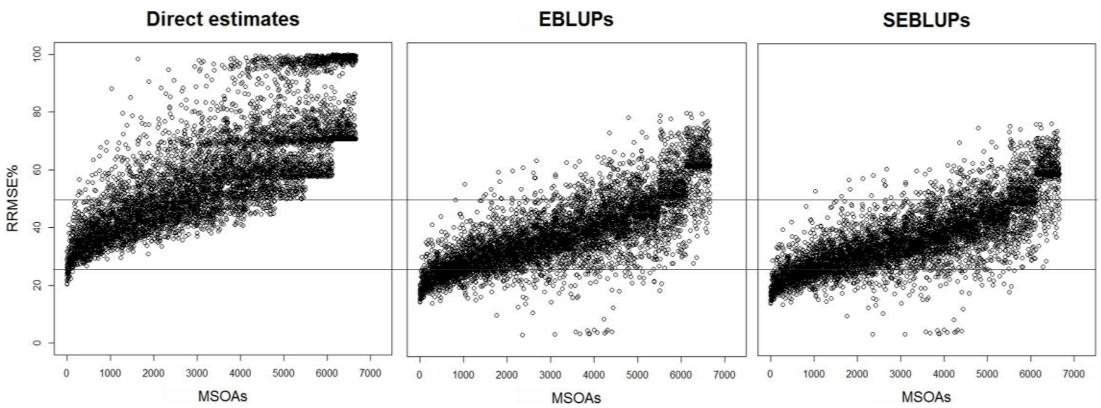
At the LAD level, 1548 out of 2055 (75.3%) direct estimates suffered from RRMSEs larger than 25%, while this number is reduced to 1000 out of 2055 (48.7%) EBLUPs, 849 out of 2055 (41.3%) SEBLUPs, 792 out of 1986 (39.9%) Rao-Yu estimates, and 759 out of 1986 (38.2%) STEBLUPs (see Figure 8.5). The percentage of estimates with RRMSEs larger than 50% is reduced from 14.5% direct estimates, to 3.2% EBLUPs, 2.2% SEBLUPs, 1.5% Rao-Yu estimates and 1.4% STEBLUPs.

Figure 8.5 $RRMSE\%$ of small area estimates produced at LAD level (ordered by area sample size)



In the case of the estimates produced at the MSOA level, whereas 6633 out of 6657 (99.6%) direct estimates suffered from a RRMSE larger than 25%, this proportion is reduced to 5725 out of 6657 (85.9%) EBLUPs and 5467 out of 6657 (82.1%) SEBLUPs (see Figure 8.6). The percentage of estimates with RRMSEs larger than 50% is reduced from 60.9% direct estimates to 17.9% EBLUPs and 13.6% SEBLUPs. Although model-based estimates have lower RRMSEs than direct estimates, the estimates' unreliability measures are very large in many areas and therefore these estimates must be used with caution.

Figure 8.6 $RRMSE\%$ of small area estimates produced at MSOA level (ordered by area sample size)



8.6.2 Model diagnostics

Model diagnostics are presented for the STEBLUP model fitted at LAD level and the SEBLUP model fitted at MSOA level. The Shapiro-Wilk test is used to check the normality of the estimates' standardised residuals. It fails to reject the null hypothesis of normal distribution of STEBLUP estimates produced at LAD level ($W = 0.981, p - value = 0.210$) and SEBLUP estimates produced at MSOA level ($W = 0.975, p - value = 0.112$).

In order to check the analytic validity of model-based estimates, these are compared to design-unbiased direct estimates. A high linear correlation is expected to show that model-based estimates are not biased by model misspecification. We observe a high Spearman coefficient of correlation between STEBLUP and direct estimates produced at LAD level ($\rho = 0.942, p - value = 0.000$) and between SEBLUP and direct estimates produced for MSOAs ($\rho = 0.935, p - value = 0.000$). The bias arising from the models is thus very small.

8.7 Discussion and conclusions

This research has produced the first map of the dark figure of crime at a local and neighbourhood level in the UK and elsewhere, and has provided evidence about which geographic areas require further efforts to increase the police effectiveness to register offences. Our estimates show the large geographical inequality of the dark figure of crime and demonstrate the need to account for the dark figure of crime in crime mapping studies and evidence-based policing. Moreover, although the main objective of SAE is to produce estimates of increased precision, SAE models provide a significant set of information for advancing criminological understanding of the explanatory mechanisms of the dark figure of crime. We thus discuss model results to gain evidence about the area-level predictors of the dark figure of crime. At the LAD level, the STEBLUP model has the largest explanatory capacity and produces, on average, the most reliable estimates. At the MSOA level, all survey editions were merged to meet model assumptions, and thus only non-temporal models were used. The SEBLUP model shows the best goodness-of-fit and produces the most reliable small area estimates, but many estimates suffer from low precision and these must be used with caution. We examine STEBLUP model results at LAD level and the SEBLUP model at MSOA level.

At the local level, the main predictor of the dark figure of crime is the measure of small urban areas, as opposed to larger conurbations and rural areas. This covariate is also significant and positive at the MSOA scale, showing that the percentage of crimes unknown to police is larger in small urban municipalities, and in particular in suburban neighbourhoods outside the main conurbations. This adds evidence to previous research results (Hart and Rennison, 2003; Langton et al., 2012). Urban areas in Britain are characterised by a lower sense of community/feeling of belonging than rural areas (Office for National Statistics, 2016). 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, either by letting the police know about the need to prevent future crimes in the area or by hoping that the police will stop a specific offender, rather than an actual hope or need for restoration of harm (Hart and Rennison, 2003; Tarling and Morris, 2010). Moreover, data from the Community Life Survey 2016/17 shows that citizens from small urban areas tend to live in these places less times than residents from rural areas and conurbations and thus feelings of belonging may also be lower, and perceived measures of social harmony (as measured by ‘people from different backgrounds getting on well together’) are the lowest in small urban areas (Department of Culture, Media and Sport, 2017). The dark figure of crime is likely to be lower in areas where citizens live for longer periods of time, neighbours perceive that people cohabit in a peaceful way and residents have a larger sense of community.

The ASS of income also has explanatory capacity to interpret the spatial-temporal distribution of the dark figure at the LAD level. Both wealthy and deprived municipalities suffer from a larger percentage of crimes unknown to police, while crimes that occur in medium-class LADs with average incomes are more likely to be known by the police. Baumer (2002) showed that the relationship between the area’s wealth and the crime reporting rates in the US is curvilinear, as shown in our analyses. He argued that it was likely to be explained by the area’s levels of social cohesion and the residents’ capacity to cope with victimisation (especially minor offences) by alternative non-police ways. Nevertheless, research conducted in the UK has shown that measures of collective efficacy are positively related to cooperating with the police: “the more cohesive a community the greater the cooperation” (Jackson et al., 2013:194). Similar results were observed in other research conducted in Europe (e.g. Netherlands; Goudriaan et al., 2006). Moreover, complementary analyses conducted from the CSEW 2016/17 show that the main reason for not reporting to police among residents living in the 20% most deprived neighbourhoods in England is the low level of confidence in police work (41.7% believe that police would do nothing, would not be bothered or would not be interested). Instead, the most common reason for not reporting in the 30% least deprived areas was that the crime was too trivial or not worth reporting (answered by 28.7% of victims 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%). Therefore, while the large dark figure of crime in deprived areas is likely affected by low levels of confidence in policing (Berg et al., 2013; Jackson et al., 2013; Xie, 2014), many minor crimes in wealthy areas are unreported due to their small effect on resident’s lives. The mean house price also shows a negative significant relationship with the dark figure at both spatial levels. The sense of belonging tends to be large in expensive areas with low levels of deprivation (Brodsky et al., 1999), and therefore residents from cities and neighbourhoods with higher mean house prices are expected to cooperate more with police services and have higher crime reporting rates.

At the neighbourhood 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 percentages of citizens with higher/intermediate occupations, born in UK, Asians and without any qualification. Most of these could not be included in the temporal models fitted at the local level due to lack of cross-sectional information. The relationship between the percentage of higher/intermediate occupations and the dark figure is negative, showing that the dark figure of crime is smaller in areas where citizens have a higher social grade. Neighbourhoods with larger proportions of citizens with high occupations are typically more expensive areas, where the sense of community is larger and neighbours develop proactive roles to maintain their areas safe (in this case by reporting crimes to police). Previous research had already shown that crime reporting rates tend to decrease in neighbourhoods with a large proportion of immigrants, especially within new immigrants' destinations (Xie and Baumer, 2019). Areas with larger percentages of whites and Asians, as opposed to blacks and other ethnic groups, have smaller dark figures of crime, although only the proportion of Asians is significant. This result seems to oppose previous US-based research, which showed that black minorities tend to report crimes to police more often than whites (Hart and Rennison, 2003). In the UK, however, Asian communities are known to have the highest levels of sense of belonging to their neighbourhoods, followed by white citizens (Department of Culture, Media and Sport, 2017). Therefore, Asian communities are expected to have a more active contribution to their neighbourhoods' safety. Contrarily, black, mixed and other ethnic groups tend to show lower values of sense of community (Department of Culture, Media and Sport, 2017). Moreover, complementary analyses conducted from the CSEW 2016/17 show that trust in the police is the lowest among black citizens in the UK. Further research should analyse the impact of perceptions about police services on different ethnic communities, as well as the composite effect of the ethnic concentration and income deprivation, as certain minorities are overrepresented in deprived areas (Goudriaan et al., 2006; Jackson et al., 2013). Uneducated citizens are also overrepresented in deprived areas and therefore we expected the dark figure of crime to be larger in areas with lower levels of education.

There are significant limitations to the results presented here that need to be considered and accounted for in future research:

- Estimates are produced at large geographical levels, which cannot be considered micro places. Smaller geographical units suffer from zero-inflated data and distributions skewed towards zero. New methods are needed to allow for estimates from zero-inflated data, and this will be a topic for future research.
- The cap of five crimes recorded per respondent reduces the amount of data in an arbitrary way. This is being reviewed by CSEW administrators.
- We produce estimates of all crimes unknown to police and obtain a single dimensional picture of the dark figure of crime. It would be more appropriate to produce estimates for each crime type, but we would encounter a zero-inflated dataset that cannot be modelled by using existing SAE methods.
- Our estimates produced at MSOA level suffer from low reliability in many areas, and these must be used with caution.
- Crime surveys have their own methodological issues and measurement error may arise from victims' non-recall, lying or underestimation of situations. Moreover, not all crimes are included in the CSEW questionnaire, and thus no information is recorded about reporting rates for so-called victimless crimes (drug-related offences, corporate crimes) and homicides.
- Our estimates show crimes unknown to police for area victimisation rates, rather than area offence rates. The first measures offences committed against a defined population who lives in an area, regardless where the incidents happened, while the second measures crimes that happened in each area. This last limitation might complicate efforts to combine estimates of the dark figure and police records. It may be addressed by selecting only offences that took place within the survey respondents' area of residence, but new methods would be needed to deal with zero-inflated data.

Acknowledgments

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 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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CHAPTER 9 - Conclusions

This doctoral dissertation has presented theory and exemplar studies for the use of SAE in criminological research. Particularly, several applications have been developed to show the potential for the use of area-level SAE techniques with spatially correlated random area effects (i.e. the area-level SEBLUP and STEBLUP) in criminological research and practise. The contributions of this thesis are:

a. rigorously motivating the use of SAE in criminological research, and in particular those SAE techniques that incorporate the spatial autocorrelation parameter;
b. providing a clear methodological framework for the application of these techniques in criminology;
c. conducting simulational assessments of the SAE methods' performance under different spatial conditions; and
d. applying SAE techniques in four criminological case studies in order to:
    i. produce small area estimates of confidence in police work in Greater London and obtain information about its spatial predictors;
    ii. produce small area estimates of worry about crime in Europe and obtain information about its macro-level spatial predictors;
    iii. produce small area estimates of perceived neighbourhood disorder in Manchester and obtain information about its spatial predictors; and
    iv. produce small area estimates of the dark figure of crime in England and Wales and obtain information about its spatial predictors.

The main contribution is thus providing compelling evidence about the benefits of using SAE in criminology to produce precise maps of crime (known and unknown to police) and other criminological phenomena and to gain evidence about the significant area predictors of these measures. This contribution is framed within the theoretical body of geographic criminology and the criminology of place (Bruinsma and Johnson, 2018; Weisburd et al., 2012; Wortley and Townsley, 2017), and more specifically within the move in criminological research towards the study of small geographic areas and micro places. Criminological research and evidence-based policing and criminal policy making have required for decades the development and use of refined methods to produce reliable estimates of criminological parameters (e.g. crime rates, worry about crime, confidence in policing, perceived disorder) at small spatial scales, and SAE has shown to be a very strong candidate to address this need.

The four exemplar studies presented in this thesis have been used to identify potentials and limitations for the use of SAE in criminology, which are discussed in Section 9.1; to obtain a series of substantive findings to explain the distribution of the different outcome measures, which are summarised in Section 9.2; and to point towards potential areas of future research, some of which are presented in Section 9.3. Section 9.4 presents the thesis' final remarks.

9.1 Potentials and limitations for the use of small area estimation in criminological research

A list of potentials and limitations for the use of SAE in criminology has been identified throughout the previous chapters. Although the term SAE is used to define all those methods whose objective is to produce precise estimates of characteristics of interest for areas for which only small samples are available (Pfeffermann, 2013), there are notable differences between the assumptions of each of the many existing SAE techniques. Therefore, the potentials and limitations for using SAE in criminology should be specified for every estimator, as some techniques may be preferred (and produce more reliable estimates) when applied to certain outcomes but not others. The extent to which existing SAE techniques may be used for producing valid maps of criminological parameters depends on how each SAE method adjusts to each topic of interest (RQ1). Here we detail the potentials and limitations for applying the SAE techniques that have been discussed in this dissertation. Moreover, there are a series of limitations that may affect all available SAE methods, which are also discussed below.

Unit-level SAE approaches, and in particular the basic unit-level EBLUP (Battese et al., 1988), may be used in criminology to examine and map criminological variables explained mainly by individual conditions. Previous research shows that unit-level SAE approaches tend to produce less reliable estimates than area-level SAE in the case of outcome measures highly conditioned by contextual measures (Namazi-Rad and Steel, 2015). Many variables of interest in criminology are known to be dependent on the social, demographic and environmental characteristics of the immediate environment, and this is the reason why area-level model-based SAE techniques have been prioritised in this thesis. However, unit-level SAE approaches should also be examined in future research analysing criminological variables determined by individual characteristics.

Among area-level SAE techniques, regression-based synthetic estimators are not based on a direct measurement of the outcome on target areas, and previous research shows that these suffer from a high risk of producing biased estimates due to model misspecification (Levy, 1979; Rao and Molina, 2015). The area-level EBLUP based on the FH model (Fay and Herriot, 1979) and its extensions are thus preferred to improve the reliability of small area estimates of those criminological variables conditioned by the area characteristics. Synthetic estimators may be used to produce estimates in areas with zero and one sample sizes.

Several simulational examinations of the temporal Rao-Yu model (Rao and Yu, 1994) have shown that this approach tends to produce better estimates than the basic area-level EBLUP when the between-time variation relative to the outcome measures' sampling variance is small (Rao and Molina, 2015). The temporal Rao-Yu model and its extensions, which are the dynamic model presented in Fay and Li (2011) and Fay and Diallo (2012) and the multivariate dynamic model presented in Fay et al. (2013), have been used to produce estimates of crime rates for states and large counties in the US using data recorded by the NCVS (Fay and Diallo, 2015a). Crime rates are known to be stable over time and thus temporal SAE models are a potential option to produce estimates with increased precision. The dynamic and multivariate dynamic models are preferred over the Rao-Yu temporal model when the assumption of stationarity is unclear. Nevertheless, area-level temporal SAE approaches are likely to produce estimates of inadequate precision when analysing specific crime types –instead of general crime rates– at detailed spatial scales. The assumption of normality of individual effects and area effects is rarely met when examining most crime types (e.g. rape and sexual assault, homicide, burglary) at detailed geographical levels. At small scales, the distributions of the counts and rates of specific crime types tends to resemble zero-inflated Poisson rather than normal.

Thus, new estimators designed to model zero-inflated data are needed in criminological research. Temporal SAE techniques are not designed to estimate binary and count data either.

Two SAE techniques that incorporate the temporal autocorrelation parameter (i.e. the Rao-Yu model and STEBLUP) have been used in this thesis to estimate the dark figure of crime at the local authority level (Chapter 8). Temporal SAE models have not been used in the other applications due to the lack of repeated cross-sectional data. In Chapter 8, those area-level SAE approaches that incorporate the temporal autocorrelation parameter produced better small area estimates than non-temporal estimators.

The main SAE technique used in this dissertation is the SEBLUP. In Chapter 5, the SEBLUP's performance was examined under different scenarios of number of areas and spatial autocorrelation parameters, and results showed that the SEBLUP outperforms the EBLUP when the spatial autocorrelation parameter moves away from zero and when the number of areas under study is large. Instead, the EBLUP produces more reliable estimates than the SEBLUP when the measure of spatial autocorrelation is close to zero and the number of domains is small. The SEBLUP was then applied to produce estimates of four variables that are known to be spatially concentrated: confidence in police work (Chapter 5), worry about crime (Chapter 6), perceived neighbourhood disorder (Chapter 7) and the dark figure of crime (Chapter 8). The number of areas under study is large in all cases. As expected, the SEBLUP outperformed the EBLUP, in terms of estimates' RRMSE, in every one of the four case studies. This shows that SAE techniques that incorporate the spatial autocorrelation parameter are preferred to produce estimates of spatially aggregated criminological parameters that are affected by area characteristics (RQ2). As in the case of the temporal SAE models, the SEBLUP was not designed to deal with binary and count data, cannot be used for areas with zero and one sample sizes, and assumes the normality of area and individual effects. It is thus not suitable for estimating criminological phenomena at very detailed spatial scales (risk of zero and one sample sizes) or to estimate outcomes with zero-inflated distributions.

Although multivariate SAE approaches have not been directly used in this thesis, these are expected to increase the estimates' reliability when estimating multiple intercorrelated outcomes (Datta et al., 1991; Fay et al., 2013; Moretti, 2018). HB and EB estimators tend to be preferred to produce estimates of binary outcomes and count data, but require intensive computation and highly advanced expert skills (Pfeffermann, 2013; Rao and Molina, 2015). New SAE techniques are needed to deal with zero-inflated Poisson distributions in criminological research.

In summary, there are significant potentials for the use of SAE to produce estimates on many topics of criminological interest (RQ3):

- Unit-level SAE may be used to produce estimates and obtain information about individual predictors of variables highly conditioned by individual characteristics.
- Temporal extensions of the area-level EBLUP may be used to produce estimates and obtain information about area predictors of stationary variables affected by area characteristics.
- Spatial extensions of the area-level EBLUP may be used to produce estimates and obtain information about area predictors of spatially aggregated variables affected by area characteristics.
- Spatial-temporal extensions of the area-level EBLUP may be used to produce estimates and obtain information about area predictors of spatially aggregated and stationary variables affected by area characteristics.
- Multivariate extensions of the area-level EBLUP may be used to produce estimates obtain information about area predictors of multiple intercorrelated variables affected by area characteristics.
- Area-level EB and HB estimators may be used to produce estimates and obtain information about area predictors of binary and count variables affected by area characteristics.

There are, nevertheless, important limitations for the use of SAE in criminology. Some of these limitations are intrinsic to all SAE methods and some may be corrected in future research:

- Model-based SAE techniques can only be used when existing sample surveys with explicit -and adequate- measures of our variable of interest are available.

- Model-based SAE techniques can only be used when existing sample surveys with explicit spatial information at our target geographical scale is available.
- The ability of model-based SAE to produce reliable small area estimates partly depends on the randomisation of the original sampling design.
- The ability of model-based SAE to produce reliable small area estimates partly depend on the ability of sampling weights to adjust for sample selection and non-response biases.
- The ability of model-based SAE to produce reliable small area estimates partly depends on the availability of reliable area-level covariates related to our outcome measure.
- The ability of model-based SAE to produce reliable small area estimates partly depends on original sample sizes. The increased precision obtained from using SAE may not be enough for areas with very small sample sizes (e.g. two, three or four) and only regression-based synthetic estimates can be produced for areas with zero and one sample sizes.
- Existing SAE techniques are not adequate to produce estimates of parameters with zero-inflated Poisson distributions.

9.2 Key substantive findings

The exemplar applications of SAE techniques presented in this thesis not only demonstrate the value of these methods for producing reliable small area estimates of parameters of criminological interest, but also provide relevant substantive information for advancing criminological understanding of four key criminological variables: confidence in police work, worry about crime, perceived disorder and the dark figure of crime. Some of the main substantive findings of this dissertation are discussed below. The following subsections show the large extent to which SAE techniques may be used for advancing theoretical explanations of four exemplar criminological parameters (RQ4).

9.2.1 Small area estimation of confidence in police work in London

Chapter 5 presented the results of the first application of the SEBLUP in criminological research. Small area estimates of the confidence in police work in Greater London were produced and examined, and the neighbourhood conditions that affect the citizens' confidence in policing were discussed. The measures of unemployment, concentration of minorities, concentration of immigrants and poverty were all significant predictors of the confidence in police services (Bradford et al., 2017; Jackson et al., 2013; Wu et al., 2009), while crime rates did not show a significant relation with the confidence in police work.

The two covariates with the strongest coefficients were the unemployment rates and concentration of minorities. Different studies have shown that communities exposed to ethnic and class segregation and economic deprivation tend mistrust not only police forces but all government agencies (Dai and Johnson, 2009; Sampson and Bartusch, 1998). In this context, the unemployment and concentration of minorities are interpreted as indicators of social and economic subjugation that shape local identities in a way that the mistrust in police forces becomes generalised (Kwak and McNeeley, 2017).

Others argue that communities exposed to poverty and ethnic segregation are also subject to an excessive police control and use of force that negatively affect their confidence in the police (Dai and Johnson, 2009). Although we could not directly test this in our SAE models due to the lack of available auxiliary information about stop and search practices in 2012 (year of the survey data), we conducted additional analyses and observed that our model-based estimates of confidence in police work in 2012 show a significant negative correlation with the distribution of the use of stop and search practises in 2017. This shows that the confidence in police work is likely to be significantly lower in over-policed areas. However, stop and search practices and priorities are known to vary over time in each borough (Tiratelli et al., 2018), and thus newer research should analyse this relationship using data for same time periods.

Similarly, immigrants and citizens with low incomes cluster in communities exposed to multiple measures of deprivation, where negative perceptions about police forces are likely to arise due to cynicism about a perceived government negligence of their citizen rights or an excessive exposure to police control.

9.2.2 Small area estimation of worry about crime in European regions

The SEBLUP was also applied to produce estimates of the proportion of residents dysfunctionally worried about violent crime and dysfunctionally worried about burglary at home at a regional level in 24 European countries (see Chapter 6). Besides from producing the first European map of the worry about crime at a subnational level, the macro-level predictors of the worry about crime were also examined.

Our models suggest that the unemployment rate is the most significant predictor of both types of worry. Previous research had already shown that the macro-level distribution of the worry about crime is mainly associated with signals of low social protection, which affect not only general concerns and worries about the social, political and economic situation in one’s region, but also the worry about crime-related risks (Hummelsheim et al., 2011; Visser et al., 2013). Unemployment rates are known to be an indicator of the area’s socio-economic insecurity, and thus the worry about crime is interpreted here as an ‘umbrella sentiment’ that hides general concerns about the region’s social and economic instability (Vieno et al., 2013).

We also found that ageing and poorly educated European regions suffer from a significantly higher worry about violence and burglaries. At the unit level, senior citizens and low educated respondents tend to show higher measures of perceived vulnerability, which are related to a larger perceived risk of victimisation and more emotional reactions of worry about crime (Hale, 1996; Pantazis, 2000). It was thus expected that regions with a larger proportion of third-age and low educated citizens have also larger proportions of residents worried about crime.

The crime rates also showed significant correlations with both forms of worry about crime (Breetzke and Pearson, 2014; Fitzgerald et al., 2012), but their coefficients were very small. Liska et al. (1982) argue that the media reflects and reproduces crime rates and therefore are likely to positively affect the macro-level measures of worry about crime.

9.2.3 Small area estimation of perceived neighbourhood disorder in Manchester

In Chapter 7, the SEBLUP was used to produce small area estimates of a latent score of perceived disorder in Manchester neighbourhoods. It allowed producing estimates with a high reliability, visualising the perceptions of neighbourhood disorder on the map of Manchester, and examining the spatial predictors that explain its distribution. Here we detail the main substantive conclusions of this study.

The population churn, a measure of residential instability, and the income deprivation are the two most significant covariates to explain the spatial distribution of perceived neighbourhood disorder. The joint effect of these two covariates largely explains the ecological distribution of perceptions of disorder in Manchester. Crime rates were also positive correlated to the perceptions of disorder (Franzini et al., 2008; Skogan, 2015).

The causal mechanisms by which these four constructs (i.e. population churn, poverty, crime and perceived disorder) are associated are not clear, and literature gives conflicting arguments regarding the directionality of their relations. On one hand, the population churn may be understood as a structural condition that reduces social cohesion and the ability of communities to control individuals' behaviour, and in turn increases the risk of crimes and disorders happening in the area (Sampson and Raudenbush, 1999, 2001). Moreover, previous research has shown that the effect of residential instability on the perceptions of disorder is more severe in deprived neighbourhoods than wealthy areas (Ross et al., 2000). Others argue, however, that the relational connection between residential instability and perceptions of disorder may be the opposite one: perceived disorder might be one cause for residents to move out from the neighbourhood, which in turn is reflected on higher measures of population churn (Sampson and Raudenbush, 2001; Steenbeek and Hipp, 2011). Further examinations using longitudinal data are needed to explain the causal connections between residential instability, poverty, crime and perceptions of disorder.

Smaller but still significant coefficients were also observed for measures of concentration of minorities and unemployment (Ross and Mirowsky, 1999; Sampson and Raundenbush, 1999; Steenbeek et al., 2012). Ethnic minorities and unemployed citizens are overrepresented in economically deprived areas affected by multiple forms of social and economic subjugation, areas in which social cohesion measures tend to be lower and in turn the perceived disorder is likely to increase (Wickes et al., 2013). The prejudices against BME citizens may also explain why areas with a larger population of minorities are perceived as more disordered (Wickes et al., 2013).

The measure of mixed land-uses, which classifies areas that enable different uses of land (e.g. residential, commercial, business and leisure activities), showed significant but small positive coefficients to explain the perceptions of neighbourhood disorder. Small coefficients are explained by the local nature of this research, while larger effects are expected to be found in research examining perceptions of disorder for more than one local authority.

9.2.4 Small area estimation of the dark figure of crime in England and Wales

Chapter 8 used different model-based approaches to produce estimates of the proportion of crimes unknown to police, as a measure of the dark figure of crime, at the local and MSOA scales in England and Wales. At the local authority level, the STEBLUP produced most reliable estimates, while temporal models could not be used at the MSOA scale and the SEBLUP estimates were the most reliable ones. Thus, below are the main substantive conclusions obtained from the STEBLUP model fitted at the local level and from the SEBLUP model for MSOAs.

At the local authority scale, the most important predictor of the dark figure of crime was the measure of small urban areas –a dummy variable that differentiates small urban areas from larger conurbations and rural areas. This covariate was also positive and significant at the MSOA level. The dark figure of crime is thus larger in suburban neighbourhoods within small urban local authorities (Hart and Rennison, 2003; Langton et al., 2012). Communities living in small urban areas in the UK are characterised by low levels of sense of community and feeling of belonging (Office for National Statistics, 2016) and very low levels of social harmony (Department of Culture, Media and Sport, 2017). Moreover, on average, residents from suburban areas tend to live in these areas less time than citizens from rural and large conurbations (Department of Culture, Media and Sport, 2017). Based on previous research we know that citizens with a larger sense of community tend to take a more active role in keeping their areas safe, cooperating with police services and reporting crimes to the police (Aiyer et al., 2015; Goudriaan et al., 2006; Jackson et al., 2013). In addition, one may expect that residents who believe that, in their neighbourhoods, people from different backgrounds cohabit in a peaceful way are keener to maintain the security in their areas. Several reports have noticed that the main reason for letting the police know about crimes is the will the keep the area safe from crime (Hart and Rennison, 2003; Tarling and Morris, 2010). Thus, the large dark figure of crime in small urban areas is explained by the low levels of feeling of belonging and social harmony, that discourage residents from taking part in activities (in this case, reporting crimes to police) to maintain security in their areas. The feeling of belonging is also used to explain the relation between the areas' mean house price and the dark figure of crime: the sense of community is larger in more expensive areas where residents are expected to cooperate more with the police (Brodsky et al., 1999).

At the local level, the ASS of income, which measures the distance of the area's income from the average income in the UK, is also positively related to the dark figure of crime. In other words, wealthy and deprived areas have a larger proportion of crimes unknown to police. Other researchers argue that the curvilinear relationship between poverty and crime reporting may be due to the high levels of social cohesion and residents' capacity to cope with crimes by alternative non-police ways in very poor and very rich areas (Baumer, 2002). However, previous research conducted in the UK and Europe has shown that the most cohesive communities have the highest levels of cooperation with the police (Goudriaan et al., 2006; Jackson et al., 2013). The large dark figure of crime is believed to be particularly large in deprived communities due to their low levels of confidence in police work (Berg et al., 2013; Jackson et al., 2013; Xie, 2014), while the dark figure of crime is also large in wealthy areas because many petty crimes or misdemeanours have a small effect on residents' lives. This has been supported by complementary analyses conducted from CSEW data, which are presented in Section 8.7.

At the MSOA scale, the covariates with the most explanatory capacity are the measure of social grade (proportions of citizens with high or intermediate occupations), the percentage of born in UK, the percentage of Asians and the percentage without qualifications.

The relation between the neighbourhood's social grade and the dark figure of crime is negative: the number of crimes unknown to police is larger in areas with more citizens with higher and intermediate occupations. High social grade areas are also more expensive, where the sense of community thrives and residents take active contributions to maintain the security in the area.

Previous research had already observed that communities characterised by large populations of immigrants suffer from lower crime reporting rates (Xie and Baumer, 2019). However, while research based in the US had shown that BME citizens report crimes more often whites and other ethnic groups (Hart and Rennison, 2003), our results show that the dark figure of crime is smaller is neighbourhoods with more whites and Asians (although only the coefficient of Asians is significant). In the UK, Asian communities have the largest measures of feeling of belonging in their neighbourhoods, while the sense of community is the lowest among black communities (Department of Culture, Media and Sport, 2017). Moreover, the trust in the police is the lowest among black UK residents. Finally, poorly educated residents are overrepresented in deprived neighbourhoods and thus we expected the dark figure of crime to be larger in areas with larger populations of citizens without any qualification.

9.3 Where next?

A series of areas for future research have been detected throughout this dissertation. SAE has shown to be a potential source of information for criminological theory and practise, but further research is needed to construct a more robust framework for the use of SAE in criminology. Three areas for future research are discussed in the following subsections: the application of SAE to other measures of interest in criminology (Subsection 9.3.1), the development of new SAE methods -or adjusting of existing techniques- to advance understanding of criminological phenomena (Subsection 9.3.2), and the combination of crowdsourcing and SAE techniques to map sporadic context-dependent emotions about crime, such as the fear of crime events (Subsection 9.3.3).

9.3.1 Applying small area estimators to other criminological outcomes

Further than the applications presented in this dissertation, SAE may be used for advancing understanding of many other topics of interest in criminology.

First, the SEBLUP may be used to explain and produce small area estimates of criminological phenomena with similar characteristics to the variables analysed in previous chapters. For example, following results of Chapter 5, future research may examine the spatial distribution of satisfaction with police services, police legitimacy and procedural justice at detailed spatial scales. This work has been started in partnership with the Barcelona Institute of Regional and Metropolitan Studies (IERMB) with the objective of analysing the Barcelona residents' attitudes and perceptions about police services at a neighbourhood level using data from the Barcelona Metropolitan Area Victimisation Survey (EVAMB). Following Chapter 6 results, further research may also use the SEBLUP to examine the regional predictors of the worry about new types of crimes, such as cyber security risks, in Europe. The Eurobarometer includes specific questions to measure worries about cybercrimes that may be used for this. This research will be conducted as part of the Digital Trust and Security theme at the University of Manchester. The SEBLUP may also be used to examine crime reporting rates and the dark figure of crime in other geographical contexts, following results from Chapter 8. Data from the Catalan Crime Victimisation Survey (ESPC) has been granted by the Catalan Directorate General for Security Administration to conduct these analyses in Catalonia.

Second, the use of unit-level SAE approaches, starting with the basic unit-level SAE model (Battese et al., 1988), should also be examined in criminological research. Existing studies show that area-level models are preferred when the outcome measure is highly affected by contextual measures that vary between geographic areas (Namazi-Rad and Steel, 2015), as it is the case of many social phenomena of criminological interest. Nevertheless, other influential topics in criminological research are highly determined by individual characteristics. One example is the study of desistance from crime (e.g. Laub et al., 1998). Therefore, the use of unit-level SAE may be especially beneficial to examine criminological variables highly determined by individual conditions.

Third, multivariate SAE approaches are used to produce small area estimates of multiple area characteristics that are correlated between them, such as multidimensional indicators (Rao and Molina, 2015). For example, Datta et al. (1991) developed a multivariate extension of the area-level EBLUP and produced estimates of median income for four-person families, five-person families and three-person families. Multivariate SAE is also available for unit-level approaches (Moretti, 2018). In criminological research, area-level crime rates of different crime types tend to be correlated (e.g. cities with more drug crimes also have more robbery and homicides; Baumer et al., 1998), and therefore the use of multivariate SAE approaches might be beneficial to produce small area estimates of crime rates.

Fourth, EB and HB approaches may be used to overcome many of the limitations and assumptions of the frequentist EBLUP and its extensions. EB and HB techniques tend to be preferred for handling models for binary and count data, as well as for dealing with normal linear mixed models and non-normality of random effects (Rao and Molina, 2015). However, Bayesian approaches are criticised due to requiring specification of the prior distribution, and these techniques require intensive computation, advanced expert knowledge and advanced computing skills (Pfeffermann, 2013). EB and HB approaches are available for area-level and unit-level SAE models. In criminological research, EB and HB could be used to produce small area estimates of count data, such as the number of crimes at large spatial scales (e.g. regions or counties). Moreover, Bayesian approaches in SAE may also incorporate the use of spatial and temporal random effects.

9.3.2 Developing new small area estimators for criminological research

Besides from existing SAE techniques, criminological research would arguably benefit from the development of new methods adjusted to deal with specific needs of criminological variables. Three areas of research are highlighted here: the development of the unit-level SEBLUP, the advancement of SAE techniques for zero-inflated datasets and distributions skewed towards zero, and the development of techniques that allow linear combinations of police statistics and survey estimates.

The area-level SEBLUP has been widely researched and applied to examine many social issues (Pratesi, 2016; Pratesi and Salvati, 2008). It has also been applied to analyse four topics of criminological interest in this dissertation. However, some variables of interest in criminology are conditioned mainly by individual conditions but also show spatial concentration patterns, and therefore model-based SAE approaches could benefit from including the spatial autocorrelation parameter into unit-level SAE models. Although references to the unit-level SEBLUP have been included in published reports (see Best et al., 2008), to the extent of my knowledge there has been no publication including a neither detailed description nor examination of the unit-level SEBLUP. The specifications of the unit-level SEBLUP are not included in the main SAE handbooks and software either. Thus, further research should develop and publish specifications and a detailed examination of the unit-level SEBLUP, to analyse the extent to which it may provide better estimates than the area-level SEBLUP in criminological research and practise.

Most existing model-based area-level SAE techniques assume the normality of area and individual effects (Rao and Molina, 2015). However, the distributions of crime counts and rates at small area level usually resemble zero-inflated Poisson rather than normal. This is the case especially when data are aggregated at very detailed spatial scales and when the outcome measure is a specific crime types instead of general crime rates. New SAE techniques are being developed to deal with zero-inflated distributions (e.g. Dreassi et al., 2014), but these have been only applied for agricultural data and thus new research is needed to assess their applicability in the social sciences and criminological research. This may allow for small area estimates of specific crime counts at detailed spatial scales, which would have tangible impacts for understanding the spatial nature of crimes and designing advanced evidence-informed policing strategies. The development of new SAE methods to deal with zero-inflated data and distributions skewed towards zero is likely to be conducted within a research project that is currently being planned along with researchers from University of Surrey, University of Leeds and University of Manchester.

Another potential area of future research is the development of techniques that allow producing small area estimates from a linear combination of police statistics and crime survey estimates. Although the geographical distribution of police records is likely to be affected by the conditions of each area (see Section 8.2), these may provide valid measures of certain crime types in some areas. In this thesis we have used the police records of crimes as covariates in model-based SAE to help increasing the reliability of survey-based estimates. However, further research may seek to combine police and survey statistics to increase the construct validity of the outcome measure (crime rates) before fitting SAE models. The Multitrait-Multimethod Matrix (MTMM), which is an approach to assess the construct validity of a set of measures recorded by different data collection approaches, may be a way of addressing this combination of police and survey data, but there are many other methodological solutions that need to be evaluated.

9.3.3 Combining crowdsourcing methods and small area estimation

Social scientists are increasingly using crowdsourcing techniques to record open data about many social issues, some of which are of interest for criminologists, such as perceived safety or fear of crime events (Salesses et al., 2013; Solymosi and Bowers, 2018; Solymosi et al., 2017). Crowdsourcing techniques refer to those methods designed for obtaining information by enlisting the services of large crowds of people into one collaborative project (Howe, 2008).

Crowdsourced data offer many advantages over survey data: reduced cost of data collection and precise spatial information to map social issues at a detailed scale (Haklay, 2013). However, the unique mode of production of these data generates self-selection biases and non-representative information. For example, men tend to be overrepresented, and middle-aged, employed and educated residents are all more likely contributors to crowdsourcing platforms (Solymosi and Bowers, 2018). Moreover, crowdsourced data tend to suffer from participation inequality, and a small group of users are usually responsible for most observations. In turn, the biases introduced by the mode of production of crowdsourcing platforms may be too large to allow for precise direct estimates. Unit-level model-based approaches are being used to weight responses and reduce biases in non-probability samples obtained from crowdsourcing (see Elliott and Valliant, 2017). However, many crowdsourcing platforms do not record individual information besides from the outcome measure and spatial data, and thus unit-level modelling may not be used to reduce biases in these cases.

New approaches that combine crowdsourced data and area-level SAE may be deployed to increase the precision and accuracy of small area estimates of perceptions and emotions about crime. These methods may allow for renewed and more efficient research into the explanations of these criminological constructs. This work has been started using a two-step method consisting of a non-parametric bootstrap followed by an area-level EBLUP (Buil-Gil et al., 2020). The non-parametric bootstrap is used to estimate pseudo-sampling weights and produce area-level bootstrap weighted estimates from crowdsourced data. This is done to reduce the data's implicit bias and allow for more reliable estimates. Second, by fitting an area-level EBLUP model with available area-level covariates the estimates borrow strength from related areas and increase their precision. The results of the simulation study and application presented in Buil-Gil et al. (2020) show that this two-step method improves the precision and reduces the bias of small area estimates produced from crowdsourced data, but further simulation studies and applications are needed before this method can be used for policy making.

Other researchers are using open and crowdsourced data as covariates in model-based SAE to estimate outcome variables recorded by surveys, such as income and poverty rates (see Marchetti et al., 2015).

9.4 Concluding summary

This dissertation has provided a cohesive set of substantive and methodological theory and exemplar studies to show the utility of applying SAE to map and explain different topics of interest in criminological research. It has also been shown that SAE may be of use for police administrations and criminal policy makers. SAE techniques had been previously used to analyse social issues such as poverty and unemployment, and there had been some isolated applications of SAE techniques to analyse criminological phenomena. Nevertheless, a unified, detailed examination of their applicability to analyse criminological data was still needed. I believe that this dissertation bridges the gap between criminological research and SAE techniques –or at least some of them– and sets a starting point for further developing SAE in criminology and evidence-based policing and criminal policy making.

SAE may be used by police forces to map certain phenomena at a detailed spatial scale and allow for refined evidence-led place-based policing strategies. Moreover, SAE methods have also proven to be a valuable source of information for advancing criminological theoretical explanations about the effect of space and area conditions on crime and perceptions and emotions about crime and the police. Although existing SAE approaches provide very valuable information both for criminological research and crime prevention practise, the development of new SAE techniques is arguably needed to adjust for the modelling needs of many criminological parameters. This thesis has also been used to spot potential areas for future research. Since the study of small area is likely to dominate criminological research agendas during the next years and police administrations are more and more interested in advancing methods for mapping crime at detailed scales, it is important to expand the body of research using SAE in criminology and to design new SAE methods adjusted to the needs of criminological data.

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