The Utility of Crime Harm Measurement in the Spatial Analysis of Police Reported Victim Based Crime

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Abstract

Crime rates and published statistics are usually calculated using the unweighted volume of crime as though offences have parity. The use of unweighted crime volume in the spatial and temporal study of crime has led to the understanding that crime is concentrated, non-random in its location and that this concentration is stable over time (Weisburd et al, 2017, Lee et al, 2017). Recently there has been an emergence of work that incorporates a weighted measure of crime to the spatial analysis. The most influential crime harm index was created by Sherman et al (2016). The Cambridge Crime Harm Index was developed with a UK focus using sentencing guidelines as the basis for the weighting. Numerous country specific iterations have developed since. However, despite this recent emergence of work on crime harm several research gaps remain.

This thesis has utilised the Cambridge Crime Harm Index, across three empirical papers to better understand the benefit that analysing crime weighted by harm in addition to unweighted crime volume can bring to the understanding of the geographical distribution of crimes, and therefore to policing. Crime data from two English police forces were analysed in addition to publicly available datasets and quantitative analytical methods employed. Analysis from both force areas indicates that, in line with previous findings, crime harm is more concentrated than volume. Crime volume and harm can be combined to identify areas for targeted police attention. The broad location of the offence has an influence on the level of crime volume and harm experienced with environmental factors having differing impact. Crime volume and harm may have a differing relationship with social frontiers which may be impacted by location. However, methodological decisions can influence the direction of those relationships. These findings have implications for policing and the use of harm in crime reporting and prevention.

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Chapter 1. Introduction

1.1 Introduction

When survey respondents are asked to rank crimes by their seriousness there is consensus of opinion across different social groups and nationalities regarding the ordering of crimes (Adriaenssen et al, 2020). Crimes involving violence are ranked as the most serious with theft offences placing lower and crimes without an immediate victim ranking lower still (ibid, Stylianou, 2003). It is recognised that some crimes are mere inconveniences, others may impact a victim financially, while a relatively small number can have life changing consequences for both the victim and those closest to them (Sherman, 2013). However, within published crime statistics the theft of someone's post and a person's murder are each counted as a single instance of crime within the summed total.

This notion, that crimes are not experienced as equal, forms the basis for the creation and growing adoption of crime harm indexes for use within criminological study (Sherman et al, 2016). These crime harm indices, using sentencing (actual sentences, or guidelines) try to capture the relative harmfulness of different offences and offer an alternative metric by which to analyse criminal activity.

While a relative measure of crime severity or harm is not yet used as an official measure of criminal activity for strategic or crime reporting within the UK the use of crime harm within criminology is growing. There is a greater awareness that raw counts of crime alone do not sufficiently provide a full understanding of the distribution of crime, how and where to allocate policing resources, or whether public safety is improving (Sherman et al, 2016, Andersen and Mueller-Johnson, 2018).

In terms of the distribution of crime, this area of criminology, crime and place, has seen considerable growth from the 1980s onward. Early work by Sherman et al (1989) and Pierce et al (1988) found crimes to be concentrated when viewed at a micro spatial scale such as addresses or street segments and this has been replicated to the point of being considered an axiom. It is also well established that these areas of concentration are stable over time (Lee et al, 2017). This is not to say that neighbourhood level criminology is passé but rather that the implicit assumption of uniformly distributed crime is no longer held (Walter et al, 2023). The relationship between crime concentration and areas of distinct neighbourhood borders (also referred to as social frontiers) is an emerging area of study. These examinations have been brought about by advancements in geographic information systems (GIS) and spatial analysis coupled with the growing availability of spatially specific police data. The addition of a crime harm measure extends the study of crime and place.

This thesis adds to the growing body of research concerning crime harm by examining the utility of using a crime harm index in tandem with the traditional measure of unweighted crime volume to the understanding of crime's geospatial distribution. As previous research has focused primarily on calls for service or crime volume when investigating the concentration and distribution of crime, it has left the amount of harm contained within these high crime areas as an unknown. This thesis, by examining both, will initially show how identifying areas of both high crime volume and harm can identify areas requiring priority policing, enabling efficient use of resources. It will then show how both measures can be incorporated within a time sensitive network routing analysis to increase police visibility along high crime and harm streets segments, appropriate to the day / shift.

In addition, it will examine the relationship between environmental factors and crime volume and harm, drawing out similarities and differences. This analysis offers further novel insight by examining crime volume and harm by the broad location in which the offence was committed which further highlights areas requiring focused policing. As work on social frontiers is in its infancy significant research opportunities exists. At the time of writing no analysis exploring social frontiers has included crime harm nor has this analysis been undertaken for crimes committed in differing locations. This is another area on which this thesis offers novel investigation, this time in relation to neighbourhood policing.

There is a need for additional work examining both crime volume and harm, as Curtis-Ham (2022) explains, if high crime volume places and high crime harm places were the same, there would not be a need for a separate harm measure, but as initial research is indicating they are very rarely found in the same locations.

The chapters in this thesis use data from two UK police forces before COVID. Over the past few decades, the increased availability of spatially specific geocoded crime data and the more extensive use of geographic information systems (GIS) within research and police practice have allowed more in-depth examination of the spatial patterns within available crime data (Chainey, 2021). As Chainey (2021) also states, in regard to any analysis outputs, if they are to be used effectively "…the interpretation of the analysis outputs must be based on clear theoretical principles." (p, 2). As it is focused on the location of crime volume and crime harm, this thesis is underpinned by theories making up the subset of criminology known as environmental criminology.

The remainder of this chapter will cover the overall research aims and specific questions explored in each of the three empirical studies. It will then discuss the spatially specific nature of the thesis and outline the data provided by two UK police forces. An overview of potential issues regarding the use of police data will also be given. The chapter closes with a fuller expression of the contribution of the thesis and a description of the remaining chapters.

1.2 Overall research aim and questions

The overall aim of this thesis is to better show the utility of crime harm as a metric in spatial criminology. In order to do so, it will further the growing body of work using measurements of crime harm to more effectively and efficiently police areas of concentrated crime, often identified as 'hot' in terms of crime volume and crime harm. In addition, a further aim of examining offences by the broad location in which they occur (outside crime locations and locations in and around residential properties), rather than by offence type, will add a new dimension to the manner in which areas are identified as locations of concentrated crime and harm.

Q1: Acknowledging both day of week and police shift, to what extent is it useful to combine police reported crime volume and crime harm to police patrol routing?

Chapter 3 addresses this initial question by creating a road network for the policing district of Rotherham (South Yorkshire Police) in a Geographic Information System (GIS) that contains street segments with not only the summed crime volume and Cambridge Crime Harm Index (CCHI) score of the incidents closest to them by their z scores. Utilising the 5 level classification proposed by Weinborn et al (2017) allows this information to be used as the basis for route selection for police patrol. The network analysis uses a cost weighting based on the classification to prioritise street segments that contain both the highest crime volume and crime harm (combined hot and harm spots), then street segments of high crime volume (hot spots) and then harm spot street segments. This allows the routing of police vehicles (or foot patrols) to be along the street segments of the high crime volume and harm. Underpinned by routine activity theory and the crime preventative actions of guardians, and hot spot policing as a policing strategy, this routing allows officers to identify areas of concentrated crime and harm for visible patrol. This route planning was also broken down by day of the week (weekday / weekend) and policing shift (morning / afternoon / night) to highlight the changing crime volume and harm distributions, and the need to acknowledge temporal changes in crime and harm locations when targeting areas for visible policing.

Q2: To what extent are variables pertaining to situational crime theory associated with police reported victim based crime volume and harm? Does this association differ when crime volume and harm are subset by broad location and does this have implications for policing?

The analysis in Chapter 4 approaches this question by examining crime attractors and generators in addition to guardian features and motivated offenders. It also adds to the exploration of crime location by sub-setting the police reported victim based crime by broad location. These locations are based on scene location data provided with each offence entry in data provided by West Midlands Police for the city of Coventry. This allows crime volume and harm to be examined in terms of offences occurring in outside locations (overt crime taking place in public) and in and around residential properties (covert crime taking place out of view) (Felson and Eckert, 2017). Street segments are again the micro scale unit of analysis with, in addition to summed crime volume and harm scores, environmental features relating to crime pattern theory located on the nearest segment and summed within buffers. Negative binomial regressions are used to model the association of these features on both crime volume and harm for comparison of effect as well the data subset by location.

Q3: *To what extent is crime harm, in addition to crime volume, associated with social frontiers? Does this association differ when crime volume and harm are subset by broad location and does this have implications for policing?*

The final analysis presented in Chapter 5 combines the meso-level neighbourhood with smaller areal units (100m by 100m grids) to investigate the impact of social frontiers, areas of sharp social difference between adjacent neighbourhoods, on crime volume and harm (Dean et al, 2019). This analysis is also subset by broad location as in the previous chapter. Social frontiers were generated for Coventry using 2011 census data at Lower Super Output Area (LSOA) level and analysis at both LSOA level and the finer grid square scale were undertaken. Previous work highlighted differing methodological options for analysis and regression modelling was conducted under different conditions to assess the effect on any associations.

1.3 Research Design and Data Sources

The approaches and analysis undertaken in this work are spatially explicit. The data provided by both SYP and WMP contain easting and northing coordinates input during the formation of the crime entry and these point locations are the starting point for any aggregation and analysis. Initial data cleaning ensured complete coordinates that fell within the boundaries of the respective force areas.

Secondary variables and administrative data used in the analysis are also spatial in composition, whether as point variables such as addresses, urban fixtures and places of interest; polyline features comprising a road and path network, or larger administrative data aggregated to LSOA polygons.

That the analysis is interpreted through the lens of theories making up environment criminology also highlight the spatial nature of the work. The analysis is not focused on the reasons why an individual may choose to commit a criminal act beyond their appraisal of their immediate surroundings as part of a rational decision process (wider explanation of theoretical underpinning is found in chapter 2).

Spatially specific police reported crime data was made available for analysis. Crime and incident data provided by South Yorkshire Police (SYP) is used in Chapter 3 and West Midlands Police (WMP) data in Chapters 4 and 5. Both datasets offer point specific data for incidents reported and uncovered within the force areas with additional date and time information. In the case of data provided by WMP the dataset also included scene location information. Having access to data which has not undergone geographic anonymisation for public release allows greater accuracy within the spatial analyses conducted.

Stipulations about the use and storage of the data were made by each police force. South Yorkshire Police provided access via their secure network on their premises at Carbrook Headquarters, Sheffield. West Midlands Police required their data be held on a university server and accessed through a virtual machine on a password protected personal computer. In both cases Non Police Personnel vetting at Level 2 was required to access the data. As personal information was included within each dataset ethical approval was required and obtained through the University of Sheffield. This thesis uses quantitative methods throughout the three papers and supplements the police data provided by SYP and WMP with open secondary data or data provided by a third party under licence conditions.

1.3.1 South Yorkshire

A snapshot of crime data from South Yorkshire Police was taken in October 2019 for a period of 22 months, from January 2018 to October 2019. The geocoded data contained single row entries of crimes and incidents reported to and by SYP. This data contained the offence category with corresponding Home Office code classification, the 3 levels of Her Majesty's Inspectorate of Constabulary (HMIC) Crime tree subgrouping, the date and time (where known) and easting and northing coordinates. This initial dataset included incidents classified as non-crime and non-notifiable offences (those offences not included in crime outcome statistics) ONS (2017). As SYP is policed as four separate districts the decision was made in conjunction with SYP to focus on Rotherham. Initial data cleaning excluded any entry with incomplete coordinates and those with locations falling outside of the Rotherham policing area.

In addition to crime data from SYP, the analysis in Chapter 3 used the initial 2016 Cambridge Crime Harm Index supplied by the University of Cambridge Institute of Criminology and completed it for the offences within the dataset. Ordnance Survey Open roads roadlink data was downloaded and cropped to Rotherham using the SYP neighbourhood policing boundary shapefile supplied by SYP. Descriptive statistics were generated for crime and harm at street segment level and the data subset by day by weekday or weekend and then by shift. The 5 point classification was used to 'sort' each segment by level of crime and harm at 2 standard deviations (Weinborn et al, 2017). This classification was converted into an impediment layer within a network analysis routing procedure to produce visible police vehicle or foot patrol routes.

1.3.2 West Midlands Police

The crime data used in chapter 3 and 4 was provided by WMP for use during the latter stages of the COVID pandemic. Investigation into overt and covert crime locations was made possible by the location information contained within this dataset. It allowed for subsetting by location, residential crime and crime occurring outside. Ordnance Survey MasterMap Highways Network - Roads product was used for residential offences and Ordnance Survey MasterMap Highways Network - Roads with the addition of MasterMap Highways Network - Paths was used for outside crime. An updated 2020 Cambridge Harm Index was available from the University of Cambridge Institute of Criminology and again completed for the victim based offences which were determined using the Counting Rules for Recorded Crime from the Home Office. The Ordnance Survey Points of Interest product in addition to Ordnance Survey AddressBase data were used to create the independent variables. Four deprivation domains were included to account for social context using The Index of Multiple Deprivation from the Office for National Statistics. Coventry City Council helpfully provided the location of the lighting products in use as of May 2022. Again, descriptive statistics were produced, and negative binomial regression models were estimated to ascertain association of these situational variables to crime and harm.

The final paper, Chapter 4, used WMP crime data and the CCHI cleaned for Chapter 3. Ethnicity, country of birth and religion census variables were used at LSOA level for Coventry, taken from the 2011 census. Social frontiers were generated for each of these variables using the publicly available socialFrontiers R package (Zhang, 2021). Brief descriptive statistics were produced, and a negative binomial fixed effects model tested the association between crime, harm (all, outside and residential) and the differing frontiers. Figure 1.1 shows a summary of research questions, the scale of analysis with connections to datasets and analysis methods.

Non-crimes and non-notifiable offences were excluded from both datasets generated from SYP and WMP. Notifiable crimes are reported monthly to the Home Office to generate the unweighted crime statistics used by the government and are also used as a measure of the demand on the police (ONS, 2017).

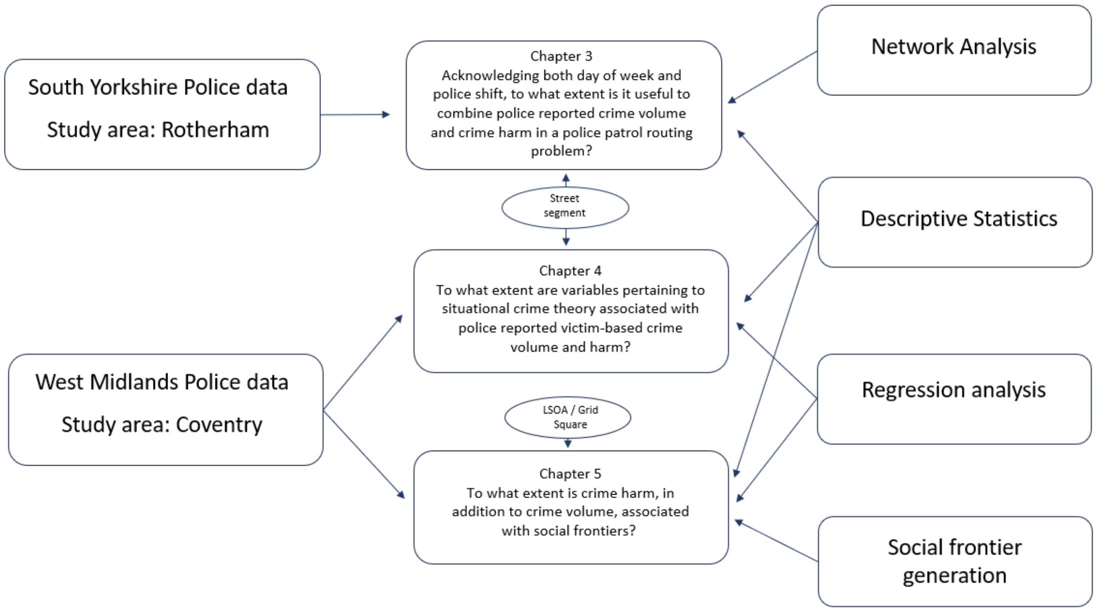


Figure 1.1: Summary diagram of chapters 3 to 5

1.3.3 Use of Police Data

Police forces collect and collate a range of data such as, but not limited to, calls for service, stop and search, offences as well as offender and victim information. Supplementary information is also recorded such as date / time and location. A status variable will also signify the stage or outcome of the record.

As Curtis-Ham et al (2024) note, police data is collected to be operationally useful and may not be research ready. It is collected and recorded by officers and is therefore subject to human error. Unstructured free data entry can include mistakes or omissions and alphabetised drop down menus may not be fully utilised. Issues of accuracy also extend to date and times as well as location data where a default location maybe entered (a police station for example). As a result decisions taken throughout the data cleaning and spatial processing were recorded.

Measurement error in police reported crime data is an area recently discussed by Buil-Gil et al (2024). Buil-Gil presented their work examining areas of possible bias in linear regression results using crime rates created from UK police data. The underreporting of crime was described as a systematic form of measurement error given that recorded crime rates are always smaller than all crime occurring.

Measurement error was also said to be random and multiplicative (greater error in areas with more crime). While not available for use within this analysis emerging work and statistical packages are being developed to enable sensitivity testing on the results of regressions using police data (Buil-Gil et al., 2024).

1.4 Contribution

This thesis is spatially explicit and uses geospatial analysis techniques in the analysis of crime volume and applies them to crime harm. The geospatial analysis of crime has for most part been based on calls for service or the unweighted volume of crime which, as mentioned previously, gave no indication of the amount of harm contained in the areas of concentrated crime.

By examining crime harm in tandem with crime volume this thesis contributes not only to the traditional environmental criminology literature using unweighted crime data but expands the growing literature concerning crime harm. It is the first to propose combining crime volume and crime harm in order to route non-emergency police vehicles through a road network. As chapter 3 will show it is possible to use police data to identify priority street segments. These are segments that are both high volume and high harm and can be further identified by day of week (weekday / weekend) and policing shift (as used by SYP). With this information there is scope for targeted policing at appropriate times allowing for greater efficiency.

To date no previous work has combined volume and harm and also incorporated offending location within the analysis undertaken. Chapters 4 and 5 make the case for analysis to acknowledge the location of the crime to again better direct policing resource. By portioning the data by offending location, namely residential and outside locations, the influence of environmental factors on volume and harm on a street segment can be better understood (chapter 4). This is also beneficial as it allows the full cohort of offences to be included in the analysis rather than being restricted to crime types bound to a particular geography.

By virtue of being an emerging area of study chapter 5's analysis of street segments makes a huge contribution to a research focus in its infancy.

1.5 Conclusion

This introductory chapter has outlined the main aim of the thesis and the research questions that will be addressed over the course of three empirical studies forming chapters 3 to 5. The COVID pandemic occurring midway through the work resulted in data from two police forces being used in the analysis. This data along with publicly available datasets have been briefly discussed here. The remaining 5 chapters are set out as follows. Chapter 2 will outline the variety of theoretical perspectives that fall under the broad umbrella of environmental criminology that the thesis draws from and site the study within the existing literature of crime concentration and crime harm. Chapters 3 to 5 contain the individual studies, and the thesis will be concluded in the final chapter with an overview of the thesis, contributions, policy implications, limitations and closing points.

References

Adriaenssen, A., Paoli, L., Karstedt, S., Visschers, J., Greenfield, V.A. and Pleysier, S., 2020. Public perceptions of the seriousness of crime: Weighing the harm and the wrong. *European Journal of Criminology*, *17*(2), pp.127-150.

Andersen, H.A. and Mueller-Johnson, K., 2018. The Danish Crime Harm Index: how it works and why it matters. *Cambridge Journal of Evidence-Based Policing*, *2*, pp.52-69.

Buil-Gil, D., Pina-Sánchez, J., Brunton-Smith, I. and Cernat, A., (2024) Measurement error in criminological research using police recorded crime data, Paper presented at Three decades of quantitative criminology at Manchester, Manchester, March 2024

Chainey, S., 2021. Understanding crime: Analyzing the geography of crime. *(No Title)*.

Curtis-Ham, S., 2022. Measuring harm with crime harm indices. In *The Crime Analyst's Companion* (pp. 177-192). Cham: Springer International Publishing.

Curtis-Ham, S., Tompson, L. and Czarnomski, S., 2024. Forewarned is forearmed: the hidden curriculum of working with police crime data. *The Crime Data Handbook,* p.9.

Dean, N., Dong, G., Piekut, A. and Pryce, G., 2019. Frontiers in residential segregation: Understanding neighbourhood boundaries and their impacts. *Tijdschrift voor economische en sociale geografie*, *110*(3), pp.271-288.

Felson, M. and Eckert, M.A., 2017. *Introductory criminology: The study of risky situations*. Routledge.

Lee, Y., Eck, J.E., O, S. and Martinez, N.N., 2017. How concentrated is crime at places? A systematic review from 1970 to 2015. *Crime Science*, *6*, pp.1-16.

Office for National Statistics, 2017, *Crime in England and Wales: year ending September 2017*. [Online].[Accessed 01 September 2023] Available at: https://www.ons.gov.uk/peoplepopulationandcommunity/crimeandjustice/bulletins/crimeinenglandandwales/yearendingseptember2017

Pierce, G.L., Spaar, S. and Briggs, L.R., 1988. *The character of police work: Strategic and tactical implications*. Center for Applied Social Research, Northeastern Unviersity.

Sherman, L. W., Neyroud, P. W., & Neyroud, E. C. (2016). The Cambridge crime harm Index: Measuring total harm from crime based on sentencing guidelines. Policing, 1e13.

Sherman, L.W., 2013. The rise of evidence-based policing: Targeting, testing, and tracking. *Crime and justice*, *42*(1), pp.377-451.

Sherman, L.W., Gartin, P.R. and Buerger, M.E., 1989. Hot spots of predatory crime: Routine activities and the criminology of place. Criminology, 27(1), pp.27-56.

Stylianou, S., 2003. Measuring crime seriousness perceptions: What have we learned and what else do we want to know. *Journal of criminal justice*, *31*(1), pp.37-56.

Walter, R.J., Tillyer, M.S. and Acolin, A., 2023. Spatiotemporal crime patterns across six US cities: Analyzing stability and change in clusters and outliers. *Journal of Quantitative Criminology*, *39*(4), pp.951-974.

Weinborn, C., Ariel, B., Sherman, L. W., & O'Dwyer, E. (2017). Hotspots vs. harmspots: Shifting focus from counts to harm in the criminology of place. *Applied Geography, 86*, 226–244.

Zhang, M. (2021). *socialFrontiers* [online]. Github. [Accessed 1 January 2023]. Available from: https://github.com/MengLeZhang/socialFrontiers

Chapter 2 Theoretical framework

2.1 Introduction

This chapter begins with a chronological overview of the theories that underpin the study of environmental criminology and will also examine the established literature on crime concentration and hot spots. The spatial techniques and methods used to understand the location of criminal activity will be interwoven through this as will the methodological concerns relating to spatial investigation.

The chapter will then move to cover crime harm and the formation and use of crime harm indices and introduce the emerging literature using a crime harm measure. The chapter will conclude by addressing the intersection of these elements as they relate to the overall aim of the thesis and the three individual empirical papers.

2.1.1 Environmental Criminology

Falling under the umbrella terms of ecological or environmental criminology these spatial criminological theories look at *where* crime is occurring rather than at *who* is committing it. A fuller definition from Bottoms et al (2002, p 326) states that "Environmental criminology is the study of crime, criminality, and victimization as they relate, *first*, to particular *places*, and *secondly*, to the way that individual and organizations shape their activities *spatially*, and in so doing are in turn influenced by *place-based* or *spatial* factors." Place, rather than the individual offender is centred within environmental criminology and motivation to offend is assumed and not examined.

Environmental criminology arose from the context of social disorganisation theory (Shaw and McKay, 1942) which explored the influence of neighbourhood composition on offenders (Andresen et al, 2010). Subsequent theories contributing to environmental criminology include routine activity theory (Cohen and Felson, 1979), rational choice theory (Cornish and Clarke, 2014), and the geometric theory of crime (Brantingham and Brantingham, 1981) with crime pattern theory (Brantingham and Brantingham, 1984) developing as a meta theory of the preceding three theories.

These theories have been developed using data concerning the amount and distribution of crime by volume. Within this thesis the framework provided by these theories in terms of identifying elements within the environment that contribute to crime volume will also be applied to crime harm. Crime harm is a growing area of analysis therefore will be an emerging area of environmental criminology.

The theories will be approached chronologically within this chapter. Firstly a brief discussion of Park et al's (1925) model of urban growth and Shaw and McKay's (1942) theory of Social Disorganisation which applies primarily to chapter 5 before the theories comprising crime pattern theory, and more applicable to chapters 3 and 4, are explored.

The thesis therefore adopts a pluralistic approach, rather than being constrained by a single theory, it draws from a variety of theoretical perspectives that fall under the broad umbrella of environmental criminology.

2.2 Concentric Zone and Social Disorganisation Theory

Concentric zone theory, based on the study of Chicago by human ecology researchers Park et al (1925) was conceived out of concern for the social composition and organisation of residential neighbourhoods in light of the rapid urbanisation, industrialisation and inward migration the city was experiencing in the early decades of the 20th century. Using ecological terms and concepts they likened the growth of the city to stages of succession where instead of flora and fauna competing for resources it is people competing for space for homes and businesses (Kubrin, 2009, Brown, 2011).

The downtown area of Chicago, named the central business district, was seen to expand outward in successive stages. As industrial growth expanded into successive residential areas those inhabitants with the means to do so would move out to quieter neighbourhoods on the periphery. The properties left behind, in neighbourhoods within this zone of transition, were either uncared for by new temporary residents looking for cheap housing and employment or left abandoned (Kubrin, 2009, Park et at, 1925). In time those residents would move on to be replaced with a new influx of people looking for the cheapest accommodation. Neighbourhood composition would be driven by this competition for space and the resulting impact of land rents, and lead to groupings of people sharing common social characteristics (Brown, 2011). "This differentiation into natural economic and cultural groupings gives form and character to the city." (Park et al, 1925, p56).

Park et al (1925) discuss urban growth as resulting from processes of organisation, disorganisation and reorganisation "In the expansion of the city a process of distribution takes place which sifts and sorts and relocates individuals and groups by residence and occupation." (Park et al, 1925, p 54). This movement of people is repetitious with areas seeing whole scale changes in the composition of communities (Kubrin and Weitzer, 2017). Areas with the highest levels of residential movement were noted by Park et al (1925) as "…regions in which are found juvenile delinquents, boys' gangs, crime, poverty, wife desertion, divorce, abandoned infants, vice." (ibid, 59). In response to the issue of poor behaviour and "…how utterly unfitted by nature man is for life in society" (p, 99) Park et al (1925) suggest that "it is the social environment to which the person […] responds…" (p.100) further suggesting that personality is shaped by responses to the environment.

It was this social environment that Shaw and McKay (1942) examined further with regard to rates of juvenile delinquency. Their work sought to determine if rates of delinquency tracked with levels of certain social and economic characteristics (Kubrin, 2009). In the case of juvenile delinquency Shaw and McKay (1942) found three structural factors of a neighbourhood that made increased amounts of juvenile delinquency more likely. A neighbourhood with high residential turnover, low levels of ethnic homogeneity and high levels of poverty would have low levels of social organisation. That in turn would influence the environment in which the children grew up. A socially organised neighbourhood with established neighbourly ties and strong community has high levels of informal social control (Bellair, 2017). This means residents are engaged with their surroundings, note the movement of outsiders and can monitor and correct any misbehaviour from children (Kubrin, 2009). This collective efficacy helps to lower crime and delinquency and can be seen in the lower levels of physical and social disorder evidenced in the neighbourhood (Sampson and Raudenbush, 1999).

By contrast, neighbourhoods without high levels of social control do not enjoy the same lowering of crime. Higher crime rates are seen in some disorganised neighbourhoods despite complete changes in the ethnic and racial make-up of residents leading to the conclusion that "neighborhood ecological conditions shape crime rates over and above the characteristics of individual residents." (Kubrin and Weitzer, 2017, p 374). This theory is particularly relevant to the analysis conducted in Chapter 5 concerning social frontiers as it relates to factors at the meso-spatial level of the neighbourhood.

Investigating the motivations behind an offender's actions or traits specific to the individual (such as race, age, gender) had long been the focus of criminology. This new examination by Park at al (1925) and Shaw and McKay (1942), of the characteristics of a place rather than the characteristics of individuals marks the divergence from traditional offender led criminology (Andresen et al, 2010). Environmental criminology by contrast is not interested in the reasons behind an individual's decision to offend, in theories such as routine activity and rational choice the motivation is taken as given. Instead, environmental criminology looks at characteristics of the environment and to what extent there are situational opportunities that make offending more likely.

2.3 Environmental Criminology post 1970s

2.3.1 Routine Activity Theory

Routine activity theory was developed by Cohen and Felson in 1979 and marks a response to the "sociological paradox" and "paradoxical trends" presented by both the 1969 summary report by the National Commision on the Cause and Prevention of Violence and the 1975 Federal Bureau of Investigation's (FBI) Uniform Crime Report (UCR) (Cohen and Felson, 1979, p. 588 -589).

The Violence Commission report noted an improvement in the sociodemographic factors traditionally thought to be contributors to criminal behaviour. Unemployment levels had dropped, incomes had risen and the number of people living in urban poverty had reduced by 3 million. Despite this both reports detailed a significant increase in violent and nonviolent crime. Cohen and Felson (1979) highlighted UCR data from 1960 - 1975 showing "reported rates of robbery, aggravated assault, forcible rape and homicide increased by 263%, 164%, 174%, and 188%, respectively" (p. 588), and noted the rate of nonviolent property crime such as burglary increased by 200%.

Routine activity theory (RAT) focuses on the temporal element of crime more so than other place based crime theories. It discusses how the temporal components of everyday life bring the three elements necessary for a crime to be committed into contact. At a minimum a crime requires an offender, a suitable target (object or person) and the absence of a guardian (Cohen and Felson, 1979). These elements were further qualified. An offender may not offend in every instance, in addition to inclination they need the skill to carry out their criminal motivations.

As a result of crime prevention measures not all targets are suitable targets and not all guardians (nearby people, CCTV or alarms) are capable of preventing criminal activity (Chainey, 2021).

The increasing crime trends noted in the two reports that formed the basis for their investigation were found to be due to the changing workforce that saw more women in employment and as a result a greater number of homes left unoccupied during the workday. This increase in criminal opportunity led to increased crime despite the usual crime predictors decreasing (Chainey, 2021). RAT applies to hot spot policing in terms of the increase in visible and capable guardians from targeted police patrols.

2.3.2 Rational Choice

Similar to RAT, rational choice theory assumes motivation to commit crime is a given (Hayward, 2017). It borrows heavily from choice behaviour theories from economics (without the complex mathematics) and claims that "…criminals and non-criminals differ only in the choices they make" (Walters, 2016, p 1). These choices are based on an assessment of risk and reward and if the balance tips in favour of reward, then the decision is made to commit the crime (Gül, 2009). The risk assessment conducted by the would-be offender could be done in a split second (and may not be fully rational if conducted under the influence of alcohol or drugs) but is done within a situation context which is taken into account (Cornish and Clarke, 2014, Chainey, 2021).

2.3.3 Geometry of Crime and Crime Pattern Theory

Our routine activities take place in our social and physical environments which provide the situational opportunities the rational actor bases their criminal decision making (Cornish and Clarke, 2014). The social environment described by Parks et al (1925) that shapes our responses and personality resembles what Brantingham and Brantingham (1981) described as our 'environmental backcloth'. It is the places (nodes) that we visit during our days and weeks and the routes we take to them (paths), as well as political and economic elements that combined allow us to conduct our roles and responsibilities and our legal (and criminal) activities. It is our 'awareness space'. The 'geometry of crime' is used to describe the movements we all make, be they as an offender, victim or member of law enforcement on our environmental backcloth (ibid).

Crime pattern theory, a meta-theory, combines elements of the preceding three. It is the combination of routine activities that move rational actors around their awareness space. The principle of 'least effort' is also a central idea within crime pattern theory (Zipf, 1965). It states that people usually choose the path of least resistance and exert the minimum effort required to complete their task, criminals included. It can help explain the spatial bounds of a criminal's offending, if two locations are available for criminal activity the one closer will more likely be chosen (Chainey and Ratcliffe, 2013, Townsley and Sidebottom, 2010). An offender's awareness space will be well known to them allowing them to appraise the area quickly and with minimal effort when deciding if offending has a net benefit (ibid).

As a result of these movements, areas of concentrated crime opportunity can emerge. Brantingham and Brantingham (1995) identified two distinct types of area within the urban landscape where potential offenders and potential victims could interact with crime as a possible result; crime generators and crime attractors.

Areas that attract large numbers of people for reasons unrelated to crime such as shopping centres or areas of offices are described as crime generators. These gatherings of people happen at predictable times and may present opportunities for criminal activity in people who did not go there solely to commit crime (Brantingham and Brantingham, 1995).

Crime attractors, by comparison, create criminal opportunities that attract highly motivated "intending offenders" (Brantingham and Brantingham, 1995, p, 8). These areas are well known to create criminal opportunities and some examples include pubs and clubs, retail areas, cashpoints (ibid). These establishments have also been dubbed risky facilities (Eck et al. 2007), places that see repeated criminal activity. Kennedy and Caplan (2012) created a risky places terrain map by identifying areas of repeated types of crime and scoring them and the surrounding areas on the risk posed.

2.3.4 GIS and Criminology

Later theories making up environmental criminology focus on the interplay of people, space and time needed for crime to take place. The scale of the investigation narrowing to finer spatial detail. All of which have been facilitated by the greater amounts of spatial data available for analysis and advances in computing.

This is seen in the terming of environmental criminology from the 1970s onwards as the GIS School (Chainey and Ratcliffe, 2013). The advancements in theory from RAT onwards "helped fortify the theoretical principles of environmental criminology" (Chainey, 2021, p, 7) but the expansion of affordable GIS, Global Positioning Systems (GPS) and computing power has allowed the study of crime to become ever more detailed, based on a wealth of newly available spatial data (Chainey 2021). That geospatial analysis of crime has advanced from its early basis in cartography to complex geospatial modelling techniques is due not only to advances in computing and GIS but also the growing availability and amount of spatially specific data.

Police forces, as the provider used in this thesis, are able to collect detailed geospatial data relating to calls for service, the location and movement of officers and their vehicles, in addition to location data relating to victims, offender and crime locations. This greater amount of spatial data coupled with technological advances in GIS and open source coding platforms has allowed analysis of spatial patterns within the data to be conducted with greater detail and precision leading to insights police forces may not have been aware of (Chainey and Ratcliffe, 2013).

The focus of this thesis is to use both the geospatial modelling techniques that have advanced over recent decades with the data available from police forces to produce novel insights regarding the concentration of crime. Geospatial techniques from early aggregated analysis of neighbourhoods to more recent micro scale analysis has traditionally focused on crime volume. In order to advance the examination of crime concentration this thesis applies geospatial techniques developed through analysis of volume to a weighted measure of crime severity. This will be conducted alongside an analysis of crime volume to provide comparison.

In terms of the theories outlined here and their application to the three empirical papers, the overarching framework of the theories making up the GIS School apply to Chapters 3 and 4 with the earlier work of the Chicago School with their meso-level explanation of crime being more applicable to Chapter 5. The remainder of this chapter focusses on reviewing the literature regarding the concentration of crime and the manner and impact of policing these areas. It then moves to introduce and critique crime harm and the measure used within the three empirical papers.

2.4 Spatial concentration of unweighted crime

At a similar time as environmental criminology was being termed the GIS School researchers began to examine crime concentration at a different scale than had been conducted previously. Work in the late 1980s found that a small number of micro-places; detailed spatial units, such as street segments, addresses or clusters of these (Weisburd et al, 2009), hosted a large proportion of police reported crimes. Pierce et al (1988) and Sherman et al (1989) were two of the first studies to confirm this using street segment data. Pierce et al, (1988) found that in Boston 50% of calls for service were generated by just 3.6% of street addresses, with the majority of gang related incidents occurring on only a few blockfaces and street intersections. In Minneapolis, Sherman et al (1989) noted 50% of calls for service originating from 3% of addresses and intersections (described as places within the paper), with calls reporting predatory crime such as robbery (2.2%) and rape (1.2%) more concentrated still.

These initial studies have been replicated and many other researchers have found strikingly similar results (for review see Lee et al, 2017). This led to Weisburd (2015), after assessing the findings from numerous studies across many cities and countries, to put forward a 'law of crime concentration'. This law 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" (p.138). Put simply, at the micro-place scale a cumulative amount of crime will be seen in a very small proportion of those micro-places. He went on to state the bandwidths after assessing concentrations found from analysis of both large and small urban areas. He states that "For 50 percent concentration, that bandwidth is about 4 percent (from 2.1 to 6 percent), and for 25 percent concentration, that bandwidth is less than 1.5 percent (from .4 to 1.6 percent)" (p. 143). The early findings of Pierce et al (1988) and Sherman et al (1989) fall within the stated range. That crime is concentrated in space is now considered an axiom within the field of environmental criminology.

Prior to Pierce et al (1988) and Sherman et al (1989), large aggregations of both people and space had been used in the ecological study of crime (Sherman et al, 1989). These larger groupings of population and space (cities, neighbourhoods) could hide causal factors and variation within the aggregation. The methodological concern being described is known as ecological fallacy. This states "that it may be illegitimate to make generalisations from data obtained between different settings, whether by aggregating data or by disaggregating it."

Spicker., 2001, p, 3). In the case of crime, the summed number of individual instances of crime occurring within an area is then used to describe the area as a whole, without consideration of the individual locations. This can lead, as Sherman et al (1989) note, to entire areas or neighbourhoods being described as high crime.

This methodological concern sits alongside the modifiable unit area problem (MUAP) within spatial analysis. MUAP relates to the construction of geographical areas, their size and the position of boundaries. Differing statistical results can be derived from different aggregations of the same data, due to changes in scale and / or the configuration of geographical units (Fotheringham and Wong., 1991). At its most simple the redrawing of neighbourhoods, changing their size or boundaries can influence the amount of summed crime contained within them and therefore their designation as high or low crime areas.

By using smaller units of analysis, such as street segments, micro-place independent variables related primarily to routine activity theory became available. This allowed within community variations in crime to be uncovered (Sherman et al, 1989). As a result, it was possible to see areas of high crime neighbourhoods that remained crime free (Weisburd et al, 2012).

When viewed at the micro-place scale the non-random distribution of crime is clear (Braga et al, 2019). These small areas that see high amount of crime are termed 'hot spots' and are more fully understood to be "an area that has a greater than average number of criminal or disorder events, or an area where people have a higher than average risk of victimization", Eck et al (2005, p, 2).

2.5 Understanding Crime Location

What is apparent from the hot spot meta-analysis conducted by Braga et al (2019) is the identification of hot spots can be left to the judgement of individual researchers. This means that there are no set criteria for creating hot spots other than they are areas of concentrated crime, and as such there are multiple ways to create these areas for analysis.

In generating hot spots there are two elements to consider, the size of the area the hot spot will cover, and the crime data used to generate it. The size of a hot spot can vary, Sherman et al (1989) document that an officer should be visible and be able to see the whole of a hot spot when they are stood at the centre of it. To be included within the meta-analysis of hot spot studies conducted by Braga et al (2019) a hot spot within a study should be described as "small units […] specific locations such as stores and apartment buildings as well as clusters of addresses, street blocks, street segments and street intersections" (p. 292). Exceptions were made for studies examining policing within larger areal units if the study specified that the focus was on specific locations within the larger area.

Within his survey of police agency personnel Koper (2014) notes that hot spots are areas of high crime, concentrated in areas of differing geographic size "specific addresses, intersections, street blocks, and clusters of street blocks" (p. 127) however, larger areas such as beats, or patrol areas were also defined as hot spots by nearly half of the US police agencies surveyed. This leads to considerable variation in the creation and understanding of the size of hot spots.

This was noted in the randomised trail conducted in Redlands, California which sought to reduce and prevent juvenile delinquency through problem solving and community-oriented policing at the census block level (Weisburd et al, 2008). The intervention had no measurable impact, and it was concluded that the unit of analysis, the census block, while smaller than a police precinct or neighbourhood, was too large for the type of place based focused policing attempted (ibid).

The second factor to consider when generating hot spots is the crime data forming the basis of the concentration. In terms of the crime types or crime data making up the hot spot using calls for service is a popular method and can be used in combination with other crime data. Calls for service can also be subset by the crime type the caller is reporting. Other methods include focusing on a particular crime type such as drug, gun or violent crimes and generating hot spots of that particular crime (Harinam et al, 2022). As chapters 4 and 5 partition the crime data by location it is interesting that crime location is not specified in many hot spot studies.

Very few focus explicitly on the type of location, the exceptions include bus stops that were targeted for hot spot policing and the effects examined by Ariel and Partridge (2017). Additionally, in the wake of the 1994 terrorist attack on the main Jewish centre in Argentina Di Tella and Schargrodsky (2004) assessed the impact of the 24 hour police presence given to all Jewish centres on the amount of car theft from nearby streets. There are cases where location is subset, usually in favour of overt crime in public places, by virtue of the manner of the targeted intervention. The use of CCTV for example (Piza et al, 2015, Marklund and Holmberg, 2015, Gerell, 2016) means the locations are accessible to the public.

Other studies chose crime types that can only occur in certain locations. Fielding and Jones (2012) assessed the effect of guardianship on repeat residential burglary. Hot spots are also created with crime types that contain the word 'street' or 'public'. Braga et al (2011) and Ratcliffe et al (2011) used violent street crimes to identify areas for foot patrols with Marklund and Merenius (2014) using public assault in their generation of hot spots. Williams (2015) used a combination of street crime and calls for service for anti-social behaviour (a non-crime taking place outside). What is missing from the work on hot spot generation is an appreciation that some crimes can occur in multiple locations (violent assault can occur anywhere) and examining those crimes by the location in which they occur can offer additional insight as to the influencing factors surrounding the committing of those crimes.

As noted in Chapter 1, geospatial police data from two police forces is used in the three empirical papers. Chapter 3 uses data from SYP while Chapters 4 and 5 analyse data provided by WMP. The crime types making up the analysis vary between the papers with Chapters 4 and 5 looking specifically at victim based crime after specifications made by Sherman et al (2020). Chapters 3 and 4 are also able to analyse crime by broad location and the data is partitioned to allow examination of crime taking place in a residential setting and those crimes occurring in an outside location.

These places, termed as hot spots, have served as focal points for police forces worldwide to target with place based approaches with the aim of reducing the crime in these micro areas and crime rates overall.

2.6 Hot Spots and policing

Hot spot policing is listed as having a very strong impact on crime when discussed as a strategy in the College of Policing's crime reduction toolkit (College of Policing, 2021). It is described as "the targeting of resources and activities to those places where crime is most concentrated" with additional explanation that it is the focus on small areas of concentrated high crime that define the strategy rather than any particular interventions or tactics (College of Policing, 2021).

Targeted police activity via randomly timed directed patrols where officers are highly visible and/or problem-oriented policing, can impact crime. Would-be criminals may be deterred from criminal activity if they believe policing numbers could increase at any time and with it the increased risk of arrest and punishment (Nagin et al, 2015, Sherman, 1990). Officers can also reduce crime opportunity by being a visible presence within the immediate surroundings.

The second strategy used, problem-oriented policing, tries to address the underlying cause of the hot spot. It uses the SARA method (scanning, analysis, response, assessment) to reduce crime by developing targeted interventions to specific problems in the hot spot (College of Policing, 2020, Weisburd et al, 2008). This strategy is a longer term method compared to the high visibility targeting where there are diminishing returns on the amount of crime prevented after approximately 15 minutes of patrol (Koper, 1995, Telep et al, 2014, Williams, 2015).

Critics of hot spot policing were concerned that focused attention on one area could "simply move crime around the corner" displacing it to adjacent non hot spot areas (Weisburd et al, 2004, p 2). The most recent update of the systematic review of hot spot literature assessed 40 displacement tests that show hot spot policing has "a small but statistically significant overall diffusion of crime control benefits effect" indicating that crime is not displaced, rather the crime reducing effects of the targeted policing spillover into nearby areas (Braga et al, 2019, p 300). From a crime pattern theory perspective, the specific place based conditions that make crime highly likely in one micro-place may not necessarily be present in nearby streets.

The meta-analysis within that systematic review also shows hot spot policing to be effective overall at reducing crime volume (Braga et al, 2019). It identified 73 main effects tests of targeted hot spot intervention in 65 studies which revealed "a small but statistically significant mean effect size favoring the effects of hot spots policing in reducing crime in treatment places relative to control places" (p.305). Problem-oriented interventions were found to result in "moderately larger overall effect sizes" than targeted patrols (p. 306). With Braga et al (2019) suggesting that the tailored approach to policing offered by problem-oriented policing can change the underlying conditions and characteristics of a hot spot and have larger crime-prevention benefits.

Within this thesis hot spots (and by extension harm spots) are only examined explicitly in Chapter 3. This chapter examines both crime volume and harm at the scale of street segments and makes use of Weinborn et al's (2017) typology to identify those street segments with crime volume and harm 2 standard deviations above the average. It classifies those street segments as 'hot' in terms of volume and harm and identifies those segments that are considered 'hot' for both measures.

Chapter 4 uses street segments as the micro unit and again examines the crime volume and harm occurring at this scale. As the analysis uses the count of crime volume or harm along each segment within a negative binominal regression there is no need to establish a cut off or threshold to identify 'hot' street segments of volume or harm as would be the case in a logistic regression (comparing 'hot' segments to non-hot segments, for example).

The micro unit used in chapter 5 is a 100m by 100m grid square. The area of study, Coventry, is overlaid with a grid and the summed crime volume and summed harm per grid square are used as the dependant variable within negative binominal regressions. Again, as negative binomial regressions are used there is no need to establish a cut off or threshold.

The targeting of areas for hot spot policing is done to make the areas safer through the reduction of crime. However, as crime can have differing impacts on victims the question more frequently asked is whether a reduction in crime volume is enough to make an area and its inhabitants safe. Hot spots created based on all police reported crime types may include areas with a high volume of less serious crime. Reducing the crime in those areas will of course be a benefit but would reducing more serious crime bring greater benefit?

2.7 Weighting crime

The need for a crime harm index is often summed up by researchers within the growing crime harm literature with the quote from Sherman (2013, p 46) that "all crimes are not created equal". Treating them as such, as with the traditional method of counting the number of crimes, is thought of as inadequate as it ignores that some crimes are more serious and result in greater amounts of harm. Continuing the quote from Sherman (2013) highlights this "Some crimes cause horrible injuries and deaths. Others cause scant meaningful harm to anyone…" (p. 46). As a result, it is not possible to tell from unweighted crime figures alone if public safety is affected by any drop in crime numbers. An increase in serious crimes could be masked by a substantial decrease in minor crimes.

There is also the issue of how raw counts of crime relate to crime prevention measures and resource allocation. Police budgets decreased in the United Kingdom during the coalition government of 2010 with staffing levels only recently returning to pre austerity levels (Home Office, 2023). However, irrespective of budgeting levels it can be argued that a triage approach to policing, where more serious offences are prioritised with staffing and time, is preferable to all crime being policed equally (Harinam et al, 2022).

This prioritisation would also tie into the concept of the 'power few' which refers to the idea that a small proportion of people, places and crimes are responsible for the majority of the harm caused by crime (Kärrholm et al, 2020, Sherman, 2007). If a harm measure was in place police forces could see a reduction in harm through the targeting of the 'power few' of harmful places, as they do at hot spots. The reduction of harm at these 'harm spots' with a recognised harm measure would allow more formal recognition of harm as a crime metric by which to assess crime prevention strategies rather than simply crime counts (van Ruitenburg and Ruiter, 2023).

2.7.1 Crime harm chronology: Operationalising a Harm Index.

Crime seriousness and crime harm are related terms with early research on perceptions of crime focused on crime seriousness. Using public surveys Sellin and Wolfgang's (1964) landmark study has been added to by a considerable body of work that finds consensus of opinion across different social groups and nationalities when respondents are asked to rank the crimes by their level of seriousness (Adriaenssen et al, 2020).

Despite this, there is concern that basing any crime seriousness weighting or sentencing on public perception and opinion can be influenced by "knowledge deficits, factual misjudgement, unprincipled attitudes and volatility of perceptions" (Adriaenssen et al, 2020, p,3). Warr (1989) was the first to conceptualise 'crime seriousness'. He identified two dimensions used to perceive the seriousness of a crime: its 'wrongfulness' and its 'harmfulness'. He explains that wrongfulness concerns the "moral gravity of committing the act, that is, the moral culpability or blameworthiness that would accrue to an individual committing the act" whereas the harmfulness of the criminal act concerns "the harm or damage that the action brings upon the victim […] a factual assessment of the consequences of the offense for the victim" (ibid, p 796).

Warr (1989) and Rosenmerkel (2001) were not able to conclude which of the dimensions controls perceptions of seriousness, it was dependant on the crime type under consideration, whereas O'Connell and Whelan (1996) and Alter et al (2007) found their respondents relied more heavily on the wrongfulness dimension when assessing an offenders behaviour. However, Stylianou (2003) in his review of the literature concerning crime perception notes consequence as another aspect of a crime driving perceptions of seriousness. “The most important characteristic associated with perceived seriousness of an act is the act’s perceived consequences…” with property offences being perceived as less serious than violent crimes (p.42). He adds that virtually all studies noted this conclusion.

Crime seriousness was the measure the police reported Crime Severity Index (CSI) aimed to capture when it was developed by Statistics Canada and released in 2009 (Wallace, 2009). There was an appreciation that crime volume expressed as a rate per 100,000 population allowed comparisons to be made over time as well as geographic areas, but crime rate changes can be driven by fluctuations in less serious, high volume offences. As noted previously, within crime rates all crimes have parity. In order to assess seriousness prior to the index’s development crime specific rates would be calculated (ibid).

The CSI was intended to complement crime rate data by allowing comparisons to be made regarding the relative seriousness of crime occurring year on year or across differing regions. The criteria for the measure aimed for it be “as empirical and objective as possible [..] based on existing data, easy to update over time, and easy to understand.” (p. 9) with sentencing data used to calculate the weights. The incarceration rate for each offence is multiplied by the average sentence received for that offence. That weight is then multiplied by the volume of that offence and then divided by population (100,000) (Wallace, 2009, van Ruitenberg and Ruiter, 2023). This measure was the first to utilised sentencing as a measure of seriousness or harm.

Although similar, the Cambridge Crime Harm Index (CCHI) developed by Sherman et al (2016) makes a number of changes to the methodology underpinning this harm measure. While still a relative weight of crimes the term harm is used rather than seriousness, but both use a measure of consequence, sentencing, in their calculations.

In the CCHI, initially operationalised for use in the UK, it is the starting sentence for an offence that is used (Sherman et al 2016, Huey, 2016). The rationale behind using the starting sentence is given that the harm score should reflect the offence rather than the offender. It is further explained that the harm experienced as the victim of a serial offender with a long criminal history is the same as that experienced from someone offending for the first time. The sentences each will receive, however, will be very different based on their previous offending (Sherman et al, 2016). Any starting prison sentence is converted to a number of days and any fines or community orders are converted to the number of days it would take to pay any money owed at adult minimum wage (ibid). Ignatans and Pease (2016) were early commentators on the

CCHI while it was still in development. While they acknowledged the stability of using starting sentences, they note that the body of experts who prepare the sentencing guidelines are far removed from the harm experienced in the immediacy of becoming a victim of a crime, nor do starting sentences account for impact of being a repeated victim of crime.

Sherman et al (2016) also put forward criteria that a harm index should meet. They suggest the "three-pronged test of suitability" (p.174) would make a crime harm index more likely to be adopted as an official crime metric. Any harm measure should reflect the democratic views of the populace, sentencing standards formalised by government for instance, rather than the opinions of academics. This would satisfy the democracy test. The index should also be reliable and give consistent scores irrespective of the researcher compiling it, this is not possible if the measure is drawn from average sentences which will change over time. It should also be cost effective and not require additional funding to undertake (ibid).

Two of these overlap with the four criteria Ashby (2018) put forward as requirements of a crime harm index that could be used for policing purposes. His criteria also stated a need for consistency (reliability) and cost effectiveness and additionally called for a measure of comparability and transparency. The measure of comparability is the crux of the index, the means by which crimes will be compared to each other with the need for transparency making sure the method for developing the harm value is understood (ibid).

The UK has an additional relative measure of crime effects that satisfies the four criteria set out by Ashby (2018); the Crime Severity Score (CSS) produced by the Office for National Statistics (ONS) (the ONS uses the term severity, but harm will be used here on out). This measure is similar to Canada's CSI as it uses previous sentencing to calculate the average sentence given for an offence handed down over the past five years (10 if the number of sentences given out is low) (Ashby, 2018, Bangs, 2016, Stripe, 2022). It also calculates the number of prison days for non-custodial sentences (Stripe, 2022).

Neither index/score has been adopted as an official measure of harm in the UK and when compared Ashby (2018) noted the result of any crime harm analysis or policing resource allocation would be substantially affected by the choice of measure.

The differing results would be due to the fundamental difference in the manor of compiling each measure, starting sentence versus average sentencing. As Ashby (2018) notes the two measures would be equivalent if all offenders were given the starting sentence as proposed by Sherman et al (2016). This is not the case as a number of aggravating or mitigating factors have a bearing on the sentence given and these factors are listed within the sentencing guidance which direct magistrates to the appropriate level of sanction.

This gives rise to harm values in the CSS that are generally higher than CCHI scores as the past history of the offender is taken into account during sentencing, something that Sherman et al (2016) argue should not occur. However, Ignatans and Pease (2016) argue that if aggravating factors are routinely seen, to the point of moving average sentencing far beyond the starting point, then the starting point sentence may not be a reasonable reflection of the harm caused by that offence.

In a comparison of the CCHI and the CSS, Ashby (2018) comments that: "If a measure of harm/severity were to be used to allocate scarce policing or crime-prevention resources, the choice of measure would substantially influence the results." (p. 446). While neither measure has been officially sanctioned the CCHI is being used with UK police data in academic work (Macbeth, 2015, Norton, 2016, Etheridge, 2015).

Other avenues for capturing the differing impacts of crime have been considered that do not use sentencing as the basis for the measure. The financial cost of crime has been examined but in a recent systematic review it was found that there are numerous different ways to calculate the overall financial implication for crime and there were large intangible costs relating to violent crimes (Wickramasekera et al, 2015). Using the Crime Survey for England and Wales Ignatans and Pease (2016) have used responses given by victims of crime to create a 'crime victim score' but infrequent crimes are not well covered. A truncated sentencing gravity score ranging from 1 – 14 was proposed by Ratcliffe (2015).

The most detailed examining of harm is presented by Greenfield and Paloi (2013). They developed an assessment of crime framework, which is a multistep analytical process that tries to capture the harm, not only to the immediate victim (if there is one) but to broader society. They first assess the bearer of the harm (both physical and social), creating four classes to include individuals, private sector entities, government and the environment and then outline the types of harm that could be inflicted such as "damages to functional integrity, material interests, reputation or privacy" (p, 868) but note "not all types of harm are relevant to all classes of bearers" (p. 868). Harms are also assessed and rated by severity on a 5 point scale from marginal to catastrophic and also by incidence, also a 5 point scale, rarely to always. They note that their framework "cannot give an overall ranking of criminal activities" (p. 881) but does allow qualitative comparisons to be made for each class of bearer. While this is a detailed framework that considers more than simply crime sentencing (starting point or average) it appears difficult to implement within a police force or research setting, different experts will have different opinions of the application of the scales making up the framework and in terms of the criteria put forward by Ashby (2018) the Greenfield and Paloi (2013) framework seems unusable in a policing setting.

In the case of this thesis the CCHI was chosen, in part for ease of use, the use of starting sentences allows individual criminal offences to researched and added to a growing list whereas the CSS collapses some rare offences into wider groups of crimes (Ashby, 2018). In addition the emerging work to use a crime harm index within the UK has used the CCHI which allows findings from this thesis to be compared.

2.7.2 Harm concentration and Harm Spots

The use of crime harm measures is growing but there is not yet consensus on the calculations used to derive the harm weights, with differing countries adapting their measures to suit their sentencing systems (see van Ruitenburg and Ruiter, 2023).

Of the crime harm scores in use initial findings indicate that high crime volume and high crime harm areas are not always in the same place, as Curtis-Ham (2022) states, if they were, there would be no need for a separate harm measure. From the limited work examining the spatial distribution of crime harm it is seen to have a different non-random distribution to crime volume (Etheridge, 2015; Fenimore, 2020). Fenimore (2020) notes the spatial concentration of harm in residential areas that is not matched by high crime volume. And although not supported by all studies (Fenimore, 2020), crime harm appears to be more concentrated geographically than crime volume (Etheridge, 2015; Macbeth, 2015; Weinborn et al, 2017). Crime volume and harm also concentrate at different points during the day (Norton et al, 2018). In the same way high concentrations of crime volume are identified as hot spots, so high crime harm areas can be identified as harm spots, but again, the specific threshold to determining a harm spot is left to the researcher as in the identification of hot spots.

Unlike hot spots that can only be formed when high crime volume is evident, harm spots can be created under two sets of conditions. Areas of concentrated harm can be created from a relatively low volume of high harm crimes, or conversely from a high volume of low harm crimes (Norton et al, 2018). Studies including harm as a variable within policing intervention have shown the use of having the additional metric. Walton et al (2020) found that while participants who took part in a community justice panel (a form of restorative justice) based on Māori principles and practice reoffended at the same rate as their matched control, the harm caused by their reoffending was 22.25% lower than their control. Without this additional measure the intervention would be seen as having no impact.

Making a similar point about the value of using both crime volume and harm Harinam et al (2022), using Canada's CSI compare the spatial distribution of both measures for Toronto. If crime volume was the only crime metric used resources would be directed larger areas of high volume rather than the "…multiple and discrete micro-locales where crime is most serious." (p. 13). They conclude by stating that "…discounting the count-based model altogether is inefficient…" (p. 14) making the case for the use of both measures in tandem.

2.7.3 Critiques of harm indices

In addition to the critiques made of the CCHI and CSS there are general criticisms that can be made of harm measures. The same critique made of crime counts, that they consider all crimes equally, can be made of crime harm scores that they consider crimes of the same type to affect people to the same extent. This is not the case, two victims can experience the same crime in very different ways (Ashby, 2018). There is the additional issue that both crime counts and crime harm scores can only reflect crimes reported to the police, unreported crimes, non-crime incidents, anti-social behaviour, all of which have a negative impact on individuals and communities, may not be prioritised when policing requirements are drawn up (Curtis-Ham and Walton, 2017, Innes, 2014).

The use of average sentences or sentencing guidelines can also be considered problematic because they are the result of past political policy decisions and priorities and so do not reflect the true impact of the offence (Paoli and Greenfield, 2018, Morrell and Rowe, 2019). Additionally, if the seriousness of a crime is judged by the consequence of committing that offence, survey results would also be reflective of those past policy decisions (Stylianou, 2003). Paoli and Greenfield (2018) when discussing the CCHI say of Sherman et al (2016) that "...in basing the index on sentencing guidelines, do not distinguish the harms of crime from the factors that came into play in developing those guidelines." (p. 67).

2.8 Conclusion

As stated initially environmental criminological theories are interested in where crime takes place rather than focusing on the motivation of the person committing the crime. As they have developed over time the geographic scale of the location under study has narrowed to the point that micro scale studies are deemed optimal (Hipp and Williams, 2020). The advances in GIS and associated analytic tools have allowed more detailed analysis to be undertaken. These theories, outlining the routine movement of people at predictable times around areas known to them and much of the micro scale spatial analysis to date has been based on unweighted crime counts or studies based on specific crime types. The understanding that crime concentrates in space is now considered an axiom with these areas of concentrated high crime labelled as hot spots. These areas of concentration have no single set of criteria by which they are created with 'hot spot policing' becoming a shorthand term for the targeted policing of areas of high crime areas (however measured) either by a visible police presence acting as deterrent or longer term problem solving looking to identify underlying criminogenic factors. The emergence of crime harm as an additional measure of crime aims to supplement the analysis of crime volume by acknowledging that crimes are not equal in their impact and effect. As yet no single measure or index has been formally approved for use within UK research but research using the CCHI has indicated that crime harm is more concentrated that crime volume and occurs in different places to concentrations of crime volume (Etheridge, 2015; Macbeth, 2015; Weinborn et al, 2017). The overall aim of this thesis is to examine the utility of including a crime harm measure when examining the spatial distribution of police reported victim based crime.

The theoretical framework that guides this thesis is drawn from environmental criminology, crime concentration and hot spot policing approaches. By combining these elements this thesis aims to explore the use of crime harm as an additional measure to better understand the non-random concentrations of crime volume and harm.

In the chapters that follow each empirical paper will expand on the theories applicable to the specific research question within each literature review. Each chapter will also fully explain the methodological decisions and pathways taken in order to deepen understanding within that analysis. The final chapter will summarise the findings of the thesis and its contribution to spatial criminology underpinned by environmental criminology theories.

References

Adriaenssen, A., Paoli, L., Karstedt, S., Visschers, J., Greenfield, V.A. and Pleysier, S., 2020. Public perceptions of the seriousness of crime: Weighing the harm and the wrong. *European Journal of Criminology*, *17*(2), pp.127-150.

Alter, A.L., Kernochan, J. and Darley, J.M., 2007. Transgression wrongfulness outweighs its harmfulness as a determinant of sentence severity. *Law and Human Behavior, 31*, pp.319-335.

Andresen, M.A., Brantingham, P.J. and Kinney, J.B. eds., 2010. Classics in environmental criminology. CRC Press.

Ariel, B. and Partridge, H., 2017. Predictable policing: Measuring the crime control benefits of hotspots policing at bus stops. *Journal of Quantitative Criminology, 33*, pp.809-833.

Ashby, M.P., 2018. Comparing methods for measuring crime harm/severity. *Policing: A Journal of Policy and Practice*, *12*(4), pp.439-454.

Bangs, M., 2016. Research outputs: developing a Crime Severity Score for England and Wales using data on crimes recorded by the police. *Newport: Office for National Statistics*.

Bellair, P., 2017. Social disorganization theory. In Oxford Research Encyclopedia of Criminology and Criminal Justice.

Bottoms, A.E., Wiles, P., Maguire, M., Morgan, R. and Reiner, R., 2002. Environmental criminology. Crime: Critical Concepts in Sociology, pp.326-72.

Braga, A. A., Hureau, D. M., & Papachristos, A. V. (2011). *An ex-post-facto evaluation framework for place-based police interventions. Final report submitted to the US Bureau of Justice Assistance*Cambridge, MA: Harvard University, Kennedy School of Government.

Braga, A.A., Turchan, B.S., Papachristos, A.V. and Hureau, D.M., 2019. Hot spots policing and crime reduction: An update of an ongoing systematic review and meta-analysis. *Journal of experimental criminology*, *15*, pp.289-311.

Brantingham, P. and Brantingham, P., 1995. Criminality of place: Crime generators and crime attractors. European journal on criminal policy and research, 3, pp.5-26.

Brantingham, P. J., Brantingham, P. L. (1981). Environmental Criminology. SAGE Publications.

Brantingham, P.J. and Brantingham, P.L., 1984. Patterns in crime. New York: Macmillan.

Brown, N., 2011. Robert Park and Ernest Burgess: Urban ecology studies, 1925. Center for Spatially Integrated Social Science.

Chainey, S. and Ratcliffe, J., 2013. GIS and crime mapping. John Wiley & Sons.

Chainey, S., 2021. Understanding crime: Analyzing the geography of crime. (No Title).

Cohen, L. and Felson, M., 1979. Social change and crime Rate Trends. A Routine Activity Approach American Sociological Review, 44.

College of Policing, 2020, Problem-oriented policing [Online].[Accessed 01 September 2023] Available at: https://www.college.police.uk/research/crime-reduction-toolkit/problem-oriented-policing

College of Policing, 2021, The effectiveness of visible police patrol [Online].[Accessed 01 September 2023] Available at: https://www.college.police.uk/research/what-works-policing-reduce-crime/visible-police-patrol

Cornish, D.B. and Clarke, R.V. eds., 2014. The reasoning criminal: Rational choice perspectives on offending

Curtis-Ham, S., & Walton, D. (2017). The New Zealand Crime Harm Index: Quantifying harm using sentencing data. *Policing: Journal of Policy Practice, 12*(4), 455–467.

Curtis-Ham, S., 2022. Measuring harm with crime harm indices. In *The Crime Analyst's Companion* (pp. 177-192). Cham: Springer International Publishing.

Di Tella, R. and Schargrodsky, E., 2004. Do police reduce crime? Estimates using the allocation of police forces after a terrorist attack. American Economic Review, 94(1), pp.115-133.

Eck, J. E., Clarke, R. V., & Guerette, R. T. (2007). Risky facilities: Crime concentration in homogenous sets of establishments and facilities. *Crime Prevention Studies, 21*, 225–264.

Eck, J., Chainey, S., Cameron, J. C., Leitner, M., & Wilson, R. E. (2005). *Mapping crime: Understanding hotspots.* Washington, DC: National Institute of Justice.

Etheridge, P., 2015. An exploratory study of the application of the Cambridge Harm Index (CHI) to crime data in South Yorkshire. *Police Executive Programme, Cambridge University (Unpublished)*.

Fenimore, D. M. (2020). Investigating the spatiotemporal distribution and environmental risk factors of harm-weighted crime. Texas State University.

Fielding, M. and Jones, V., 2012. 'Disrupting the optimal forager': predictive risk mapping and domestic burglary reduction in Trafford, Greater Manchester. International Journal of Police Science & Management, 14(1), pp.30-41.

Fotheringham, A.S. and Wong, D.W., 1991. The modifiable areal unit problem in multivariate statistical analysis. *Environment and planning A*, *23*(7), pp.1025-1044.

Gerell, M., 2016. Hot spot policing with actively monitored CCTV cameras: Does it reduce assaults in public places? International Criminal Justice Review, 26(2), pp.187-201.

Greenfield, V.A. and Paoli, L., 2013. A framework to assess the harms of crimes. *British journal of criminology*, *53*(5), pp.864-885.

Gul, S., 2009. An evaluation of rational choice theory in criminology. *Girne American University Journal of Sociology and Applied Science*, *4*(8), pp.36-44.

Harinam, V., Bavcevic, Z. and Ariel, B., 2022. Spatial distribution and developmental trajectories of crime versus crime severity: do not abandon the count-based model just yet. *Crime Science*, *11*(1), pp.1-15.

Hayward, K., 2017. Situational crime prevention and its discontents: Rational choice theory versus the 'culture of now'. In Crime Opportunity Theories (pp. 323-341). Routledge.

Hipp, J.R. and Williams, S.A., 2020. Advances in spatial criminology: The spatial scale of crime. *Annual Review of Criminology*, *3*, pp.75-95.

Home Office. 2023. Police workforce, England and Wales: 30 September 2022 [online]. [Accessed 01 September 2023]. Available from: https://www.gov.uk/government/statistics/police-workforce-england-and-wales-30-september-2022/police-workforce-england-and-wales-30-september-2022

Huey, L., 2016. Harm-focused policing. *Journal of Community Safety and Well-Being*, *1*(3), pp.83-85.

Ignatans, D. and Pease, K., 2016. Taking crime seriously: playing the weighting game. *Policing: a Journal of policy and practice*, *10*(3), pp.184-193.

Innes, M., 2014. Signal crimes. *Social Reactions to Crime, Disorder, and Control*.

Kärrholm, F., Neyroud, P. and Smaaland, J., 2020. Designing the Swedish Crime Harm Index: an evidence-based strategy. Cambridge Journal of Evidence-Based Policing, 4, pp.15-33.

Kennedy, L.W. and Caplan, J.M., 2012. A theory of risky places. Newark, NJ: Rutgers Center on Public Security. Accessed February, 12, p.2021.

Koper, C.S., 1995. Just enough police presence: Reducing crime and disorderly behavior by optimizing patrol time in crime hot spots. *Justice quarterly*, *12*(4), pp.649-672.

Koper, C.S., 2014. Assessing the practice of hot spots policing: survey results from a national convenience sample of local police agencies. *Journal of Contemporary Criminal Justice*, *30*(2), pp.123-146.

Kubrin, C.E., 2009. Social disorganization theory: Then, now, and in the future. *Handbook on crime and deviance*, pp.225-236.

Kubrin, C.E., and Weitzer, R., 2017. New directions in social disorganization theory. In Recent developments in criminological theory (pp. 265-294). Routledge.

Lee, Y., Eck, J.E., O, S. and Martinez, N.N., 2017. How concentrated is crime at places? A systematic review from 1970 to 2015. *Crime Science*, *6*, pp.1-16.

Macbeth, E. (2015). Evidence-based vs. experience-based targeting of crime and harm hotspots in Northern Ireland. Master thesis. University of Cambridge.

Marklund, F., & Holmberg, S. (2015). Camera monitoring in Stureplan and Civic Square: Full Report. Stockholm. Sweden: Brå.

Marklund, F., & Merenius, S. (2014). Policing crime "hot spots": Results and experiences from Two Projects against Personal Abuse and Abuse. Stockholm: Brå

Morrell, K. and Rowe, M., 2019. Democracy, accountability and evidence-based policing: Who calls the shots?. In *Critical reflections on evidence-based policing* (pp. 115-132). Routledge.

Nagin, D.S., Solow, R.M. and Lum, C., 2015. Deterrence, criminal opportunities, and police. *Criminology*, *53*(1), pp.74-100.

Norton, S. (2016). An exploratory analysis of high harmspots in Sussex. Master thesis. University of Cambridge.

Norton, S., Ariel, B., Weinborn, C. and O'Dwyer, E., 2018. Spatiotemporal patterns and distributions of harm within street segments: the story of the "harmspot". Policing: An International Journal, 41(3), pp.352-371.

O'Connell, M. and Whelan, A., 1996. Taking wrongs seriously: Public perceptions of crime seriousness. *The British Journal of Criminology*, *36*(2), pp.299-318.

Paoli, L. and Greenfield, V.A., 2018. Harm: a substitute for crime or central to it? *Zemiology: Reconnecting crime and social harm*, pp.57-84.

Park, R. E., Burgess, E. W., & McKenzie, R. D. (1925). The city. Chicago: University of Chicago Press.

Pierce, G.L., Spaar, S. and Briggs, L.R., 1988. *The character of police work: Strategic and tactical implications*. Center for Applied Social Research, Northeastern Unviersity.

Piza, E.L., Caplan, J.M., Kennedy, L.W. and Gilchrist, A.M., 2015. The effects of merging proactive CCTV monitoring with directed police patrol: A randomized controlled trial. Journal of Experimental Criminology, 11, pp.43-69.

Ratcliffe, J. H. (2015). 'Towards an Index for Harm-Focused Policing.' Policing 9(2): 164–183.

Ratcliffe, J.H. and Breen, C., 2011. Crime diffusion and displacement: Measuring the side effects of police operations. The Professional Geographer, 63(2), pp.230-243.

Rosenmerkel, S.P., 2001. Wrongfulness and harmfulness as components of seriousness of white-collar offenses. *Journal of Contemporary Criminal Justice*, *17*(4), pp.308-327.

Sampson, R.J. and Raudenbush, S.W., 1999. Systematic social observation of public spaces: A new look at disorder in urban neighborhoods. *American journal of sociology*, *105*(3), pp.603-651.

Sellin, T. and Wolfgang, M. (1964). The Measurement of Delinquency. Oxford: Wiley

Shaw, C. R., & McKay, H. D. (1942). Juvenile delinquency and urban areas. Chicago: University of Chicago Press.

Sherman, L. W., Neyroud, P. W., & Neyroud, E. C. (2016). The Cambridge crime harm Index: Measuring total harm from crime based on sentencing guidelines. Policing, 1e13.

Sherman, L.W. and Cambridge University associates, 2020. How to count crime: the Cambridge harm index consensus. *Cambridge Journal of Evidence-Based Policing*, *4*, pp.1-14.

Sherman, L.W., 1990. Police crackdowns: Initial and residual deterrence. *Crime and justice*, *12*, pp.1-48.

Sherman, L.W., 2007. The power few: Experimental criminology and the reduction of harm: The 2006 Joan McCord Prize Lecture. *Journal of experimental criminology*, *3*, pp.299-321.

Sherman, L.W., 2013. The rise of evidence-based policing: Targeting, testing, and tracking. *Crime and justice*, *42*(1), pp.377-451.

Sherman, L.W., Gartin, P.R. and Buerger, M.E., 1989. Hot spots of predatory crime: Routine activities and the criminology of place. Criminology, 27(1), pp.27-56.

Spicker, P., 2001. Poor areas and the'ecological fallacy'. *Radical statistics*, *76*(Winter).

Stripe, N., 2022. Crime Severity Score (Experimental Statistics) [Online].[Accessed 01 September 2023] Available at: https://www.ons.gov.uk/peoplepopulationandcommunity/crimeandjustice/datasets/crimeseverityscoreexperimentalstatistics

Stylianou, S., 2003. Measuring crime seriousness perceptions: What have we learned and what else do we want to know. *Journal of criminal justice*, *31*(1), pp.37-56.

Telep, C.W., Weisburd, D., Gill, C.E., Vitter, Z. and Teichman, D., 2014. Displacement of crime and diffusion of crime control benefits in large-scale geographic areas: A systematic review. *Journal of Experimental Criminology*, *10*, pp.515-548.

Townsley, M. and Sidebottom, A., 2010. All offenders are equal, but some are more equal than others: Variation in journeys to crime between offenders. Criminology, 48(3), pp.897-917.

van Ruitenburg, T. and Ruiter, S., 2023. The adoption of a crime harm index: A scoping literature review. *Police Practice and Research*, *24*(4), pp.423-445.

Wallace, M., 2009. Police-reported crime statistics in Canada, 2008. *Juristat: Canadian Centre for Justice Statistics*, *29*(3), p.1.

Walters, G.D., 2016. Decision to commit crime: rational or nonrational. Actual Probs. Econ. & L., p.252.

Walton, D., Martin, S. and Li, J., 2020. Iwi community justice panels reduce harm from re-offending. *Kōtuitui: New Zealand Journal of Social Sciences Online*, *15*(1), pp.75-92.

Warr, M., 1989. What is the perceived seriousness of crimes?. *Criminology*, *27*(4), pp.795-822.

Weinborn, C., Ariel, B., Sherman, L. W., & O'Dwyer, E. (2017). Hotspots vs. harmspots: Shifting focus from counts to harm in the criminology of place. *Applied Geography*, *86*, 226–244.

Weisburd, D. L., Bushway, S. D., Lum, C., & Yang, S.-M. (2004). Trajectories of crime at places: A longitudinal study of street segments in the city of Seattle. Criminology, 42(2), 283e321.

Weisburd, D., 2015. The law of crime concentration and the criminology of place. *Criminology*, *53*(2), pp.133-157.

Weisburd, D., Groff, E., & Yang, S. (2012). The criminology of place: Street segments and our understanding of the crime problem. Oxford: Oxford University Press.

Weisburd, D., Morris, N.A. and Groff, E.R., 2009. Hot spots of juvenile crime: A longitudinal study of arrest incidents at street segments in Seattle, Washington. *Journal of quantitative criminology*, *25*, pp.443-467.

Weisburd, D., Morris, N.A. and Ready, J., 2008. Risk-focused policing at places: an experimental evaluation. *Justice Quarterly*, *25*(1), pp.163-200.

Wickramasekera, N., Wright, J., Elsey, H., Murray, J. and Tubeuf, S., 2015. Cost of crime: A systematic review. *Journal of Criminal Justice*, *43*(3), pp.218-228.

Williams, G.F., 2015. Property crime: Investigating career patterns and earnings. *Journal of Economic Behavior & Organization*, *119*, pp.124-138.

Zipf, George K. 1965. Human Behavior and the Principle of Least Effort: An Introduction to Human Ecology. New York: Hafner.

Chapter 3. Hot and Harm spots: Utilising both police reported crime counts and crime harm in police route planning.

3.1 Introduction

The College of Policing (2013, p.2) notes that "Crime and disorder is not evenly spread across areas and policing should be concentrated in the areas of greatest demand". This is particularly pertinent advice coming as it did 3 years into the coalition government's policy of austerity that saw police funding fall by 25% between 2010/11 and 2014/15 (Mann et al, 2018). It continues to be relevant as increased police funding is unlikely to fully reverse the effects and may not bring police force personnel back to pre-austerity numbers (Dodd, 2019). However, concentrating policing in areas of greatest demand is not as straightforward as it first appears. In particular, there is a question of whether policing efforts should focus on areas with the highest concentration of all crime, or whether they should give higher priority to areas with greater concentrations of more severe crimes. This chapter seeks to inform this question by demonstrating an analytical approach for informing police patrols based on the spatial concentration of both crime volume and harm.

The contribution of this chapter is found in the application of the crime volume and crime harm classification put forward by Weinborn et al (2017). This classification is applied to street segments and allows the identification of segments that have high crime volume, high crime harm and those segments that are jointly high crime volume and high harm (priority segments). At the time of writing this is the first work to incorporate this classification in an analysis of non-emergency police vehicle routing. By including harm in this manner it extends the emerging work using crime harm beyond methodological decision making and the early descriptive work seen so far. What follows is a network analysis using the classification levels as an impediment within a routing analysis to highlight how non-emergency patrols maybe directed through high crime and high harm streets segments determined by the day and week and policing shift. This reveals the utility of using both volume and harm to identify areas for visible policing in addition to acknowledging the spatial-temporal change in crime location.

The chapter is structured as follows; first the literature regarding the spatial distribution of crime is reviewed with attention paid to the change from mapping raw counts of crime to weighted measures of harm with a discussion of the police patrol routing problem (PPRP). The data sets, preparation and methods are then described before a discussion of the results of the analysis. The final section discusses the findings with reference to theory and police practice.

3.2 Literature review

3.2.1 Crime Concentration

Greatest demand has traditionally been viewed as the area where the amount of crime is greater than the surrounding areas, known as a crime hot spot (Brantingham and Brantingham, 1999; Sherman et al, 1989; Chainey et al, 2008). These small geographical areas such as stores, or individual houses (as opposed to larger communities or neighbourhoods) are designated for "hot spotting" a form of policing that aims to identify these crime hot spots and allocate officers to that area to act as a deterrent (College of Policing, 2013). As police resources continue to be limited due to the impact of austerity the goal of hot spot targeting has been to allot these resources as effectively and efficiently as possible (Eck et al, 2005, 2007).

This has proved to be a sensible tactic. Many studies over the past few decades have found that in addition to the uneven distribution of crime as a whole, crime is also non-random in terms of its spatial distribution (Weinborn et al, 2017). A small number of places play host to the vast majority of crimes. This has led to a focusing of attention on smaller areas and a move from examining crime at the community or neighbourhood level (Hipp and Williams, 2020).

This reduction in scale, allowing the viewing of crime in ever finer resolution, began with Sherman et al (1989) who were one of the first to investigate offences at street level with their study into predatory crime in Minneapolis. They found that 3.3% of addresses accounted for approximately 50% of calls to the police that resulted in a police car being dispatched.

The study of crime concentrations has continued to be examined at this microspatial level and similar findings have emerged. Almost half of the drug arrests made in Jersey City came from 4.4% of the intersections and streets (Weisburd and Mazserolle, 2000) and in Seattle 50% of the offences reported in the city over a fourteen-year period came from 4% of street segments (Weisburd et al, 2004). This is also seen in specific land uses; 5% of train stations in England and Wales saw half of the reported crimes (Ariel, 2011).

This clustering of crime has led to the creation of terms such as the "power few" of places (Sherman, 2007) and the development of the "law of crime concentration" (Weisburd, 2015, Gill et al, 2017). The law Weisburd (2015) developed explains that when crime is viewed at the micro scale a small proportion of those micro places will be the location for a much larger cumulative proportion of crime (e.g. 50%). Bandwidths were generated based on multiple studies of crime concentration. For 50% of crime the bandwidths generated range from "2.1 to 6 percent" and at 25% the bandwidths reduce to ".4 to 1.6 percent" (Weisburd, 2015, p143).

In addition, using these locations to focus policing has had success (Sherman and Weisburd, 1995, Sherman and Rogan, 1995, Di Tella and Schargrodsky, 2004, Braga et al, 2011). Based on ongoing meta-analysis by Braga et al (2019), targeting those hot spots that contribute to 50% of the crime (or 5% of street segments) could see overt crime (crime taking place in a public setting) reduced by 13% (Felson and Eckert, 2017). However as covert crime (crime taking place in private settings) is unlikely to be affected by visible hot spot policing the overall percentage reduction will be smaller (Ariel, 2022).

These hot spot locations of high-volume crime have also been found to be spatially stable over time (Weisburd et al, 2004). Trends in crime showing areas as having rising or falling crime rates are not due to crime events rising or falling evenly across the area but a small number of places seeing dramatic change (ibid). Where changes to hot spots are recorded, the crime occurrences are not displaced to a neighbouring street segments or areas but rather there is a good likelihood of seeing a "diffusion of benefit" (Clarke and Weisburd, 1994. p. 168). The crime is reduced in adjacent street segments (Braga et al, 2019).

However, hot spots are measured using the raw count of crimes and have been described as one-dimensional. Ignatans and Pease (2015) liken it to health care policy based solely on hospital admissions without paying attention to the condition of the patient. The volume of crime recorded by police forces is a blunt instrument that counts a murder and a theft (for example) as equal single crime events. As Sherman et al (2016, p. 1) are often quoted as saying "All crimes are not created equal". When looking to answer questions regarding whether society is getting safer, how well the police are doing at tackling crime and what they should focus limited resources on, these counts offer limited information (Higgins, 2017; BBC, 2016).

As a result, research has moved into an exploration of the differing effects of offences. Certainly, a concentration of crime has implications for residents, increasing their fear of crime (Wyant, 2008), but greatest demand can mean more than simply the greatest frequency of crime. It can also be assessed as areas experiencing the greatest harm from crime. Since the work of Sellin and Wolfgang in 1964 a number of weighted crime measures have been developed both in the UK and elsewhere. An emerging body of literature uses recent sentencing decisions or sentencing guidelines as the basis on which to create harm-weighted crime measures.

3.2.2 Crime Harm

The most widely used and adapted measure is the Cambridge Crime Harm Index (CCHI) (Sherman et al, 2016). As chapter 2 introduced, it is based on sentencing guidelines for England and Wales and uses the sentence starting point. It does not consider the circumstances of the offence or any details of the offender. This means that mitigating or aggravating information is ignored and that "the 'harm' value of the crime is associated solely with the offence type *per se*" (Sherman et al, 2016, p,172). They argue that the concept of harm should be measured independently of culpability. They elaborate that the punishment an offender is seen to deserve is separate from the harm their crime has caused; a serial killer or a first-time murderer create the same harm to the victim's family and community.

These starting point sentences are converted into the number of days an offender would be imprisoned for the offence. Where an offence warrants a fine, the number of days required to pay the fine at minimum wage is used as a proxy for days in prison. This is also used to convert hours given in community orders into days in prison (ibid).

They also suggest that the CCHI, unlike other harm measures, passes tests in three key areas: by being based on sentencing guidelines created by the Sentencing Council, it is based on the work of members of the judiciary (and other experts), and it is therefore democratic in that it represents the population in a way that is impossible in a metric designed solely by academics. It is also deemed reliable as it is an unbiased measure that reports the same harm score for the same offence by ignoring the offence circumstance and associated demographics. It is seen as a low cost measure requiring little in the way of funding using resources already in the public domain (ibid).

By comparison the Crime Severity Score (CSS) developed by the Office of National Statistics, available since 2017, takes the average sentences given for offences in the preceding 5 years (10 years for offences with low numbers of offenders) (Bangs, 2016, Stripe, 2022). This is the main criticism made of the CSS. By using the average sentencing the focus of the score is based on the offender rather than the victim and as such the score does not pass 2 of the 3 key metrics suggested by Sherman et al (2016). The offenders past criminal history will influence the sentence they receive and will therefore influence the overall weighting meaning that weighting cannot be considered democratic or reliable (Sherman et al, 2020).

This is most clearly seen with sexual offences where the CSS has different scores based on both the age and sex of the victim. These reflect the body of sentences making up the averages and the offending history of the offender rather than the harm caused to the victim. In the CSS sexual offences against younger victims are weighted lower than adults and offences against male children under 13 weighted lower than those against female children under 13 (Sherman et al, 2020, Stripe, 2022). The sentencing guidelines on which the CCHI is based shows higher starting sentences for offences against younger victims and no difference in sentencing based on the sex of the victim (Sentencing Council, 2023).

The use of the CCHI in the study of crime, both in the UK and outside is in its infancy. As chapter 2 explains more fully, the use of a crime harm index based on sentencing is a pragmatic choice as they lack some of the complexity of the crime harm assessment framework proposed by Greenfield and Paoli (2013). The CCHI is used with that understanding. Where studies have taken place in areas without a comparative sentencing structure, researchers have had to make amendments to the index. House and Neyround (2018) found the lack of published sentencing guidelines prevented them from using the CCHI in Western Australia but utilised the idea of not allowing the criminal history of the offender to influence sentencing by using the sentences given to first time offenders. This is also true of Curtis-Ham and Walton (2017) who followed a similar approach using a first offender estimate based on court records to create a bespoke Crime Harm Index for New Zealand.

As the crime harm literature is in its early stages the majority of studies to date have focused on the need to include harm in future studies and the creation of harm indexes for specific locations. There are a smaller number of studies that apply the harm index to the study of crime. The CCHI is increasingly being used on data from locations within England and Wales. Norton et al (2018) examined the spatiotemporal make-up of harm spots using data provided by Sussex Police. They found that not only low-volume high-harm incidents created the harm spots they identified, but also high-volume low-harm events were included. They identified that amounts of harm change temporally, with their main finding being the peak in harm during the night. They were able to link the locations to areas with a nighttime economy.

3.2.3 Crime Volume / Harm Typology

As literature involving a crime harm measure has until recently been concerned with the formation of an index for a specific country or sentencing structure the work of Weinborn et al (2017) is one of the first to apply the CCHI using recorded spatially specific crime data. It focused on the spatial distribution of crime counts and harm scores for 15 councils. Their work found street segment formed harm spots to be three times more concentrated than crime hot spots. They also established a replicable manner to identify hot and harm spots. They calculated z-scores for street segments experiencing crime using the crime counts and summed harm scores per street segment. These z-scores form the basis of a 5-class typology that will be applied to the data provided for this study. The transformation of raw counts or summed harm now allow those street segments with crime or harm above the average to be identified and a threshold introduced to highlight those deemed high crime volume / harm / both.

They outline that street segments can be classified in the following ways:

Type I. These areas are designated as priority areas for policing. These street segments have met the criteria to be designated as both a hot spot and a harm spot indicating both high crime frequency and high harm. These will be a small number of streets that should be easily incorporated into patrols.

Type II. These are street segments that meet the threshold for being defined as a hot spot and may be familiar to forces as areas already earmarked for hot spot policing. These are segments with high crime volumes but low harm scores.

Type III. These are high harm streets (harm spots) with low crime volumes, possibly the locations of tragic but infrequent high harm incidents. However, these streets may benefit from further investigation from neighbourhood policing teams to prevent high harm incidents from increasing in frequency.

Type IV. These areas are low crime without the frequency or harm of Types I – III. These are areas that may be more difficult to target with specific interventions due to their large number and scattered locations.

Type V. These segments are crime free with no crimes reported to the local police force.

However, high harm crimes may not be the public's only concern. In his Philadelphia study, Ratcliffe (2015) noted that residents of areas perceived as violent often raised concerns about anti-social behaviour, graffiti, litter and speeding traffic. This has led to discussions about the role of the police as both enforcers of the law and also risk and harm minimisers.

Viewed through the lens of Cohen and Felson's (1979) routine activity theory, crime occurs when a likely offender and a suitable target converge in the absence of a capable guardian. The crime reductive power of the police as guardians either on foot patrol or in vehicles can add to the crime reductive power of the general population.

Given the success of concentrated attention to hot spots and the growing literature on the use of harm as a metric by which to view criminal activity in an area this paper will combine both volume and harm using the classification put forward by Weinborn et al (2017) and utilise it in a road network to prioritise movement along high crime and harm road segments.

3.2.4 Hot spot design and the Police patrol routing problem (PPRP)

Technical advances in both hardware and software coupled with greater affordability have allowed police forces to increase their use of Global Positioning Systems (GPS), computer aided dispatch (CAD) and Geographic Information Systems (GIS). The timing has been serendipitous as, as previously mentioned, police forces have experienced shrinking budgets and calls to optimise efficiency with less (Dewinter et al, 2020, Leigh et al, 2016). This has led to a number of differing strategies and algorithms being available to police forces to aid the deployment of their foot and vehicle patrols.

Generating police patrols, whether on foot or in a vehicle, is a complex process with officers needing to balance the overlapping responsibilities of patrolling. It is a means of preventing offences being committed through proactive patrol (which reduces future need) by reminding would-be offenders of the risks associated with criminal behaviour. It also boosts public confidence in the not criminally inclined (Wise and Cheng, 2016, College of Policing 2021). Patrols also need to be able to respond quickly to real-time incidents (Dewinter et al, 2020, Samanta et al, 2022). The former responsibility, that of preventative patrol, sets them apart from other emergency services whose movement to and from incidents do not have a preventative by product.

These differing requirements: preventative patrol and time sensitive incidence response necessitate two different approaches when optimising routes. The first is a static routing problem where all required information is known a priori, whereas the latter, where information becomes available in real-time, is described as dynamic. It is these static routing decisions that this paper will concentrate on.

It is now well understood that random police patrol is ineffective but despite this it is still the dominant strategy for a number of police forces, particularly in the US (Sherman and Eck, 2003; Weisburd and Eck, 2004, Wooditch, 2021). In critiquing the work of Kelling et al (1974) (the Kansas City Preventive Patrol Experiment) that varied the number of police vehicles assigned to patrol routes Sherman and Weisburd (1995) argued that rather than diluting police presence across the beat area it should be focused in areas of crime concentration, hot spot policing. There is a large literature base that notes the overall success of hot spot policing (see meta-analysis from Braga et al, 2019).

As chapter 2 makes clear there is no single definition of a hot or harm spot in use, researchers are able to define them as it suits their research interests (Eck, 2005). As a result the use of z-scores and threshold cut off proposed by Weinborn et al (2017) allows a replicable way to understand the distribution of crime volume and harm as they relate to street segments. This typology is used in this chapter to identify street segments that are combined hot/harm spots and hot and harm spots individually.

While street segments adhere to the micro geographic scale promoted as optimal for spatial research into crime concentration (Hipp and Williams, 2020) they present an area for targeted policing that is larger than the area often described by the term 'hot spot', for example, Sherman et al (1989) note that the entirety of a hot spot should be visible to an officer when they are stood at the centre of it. The review of hot spot effectiveness presented in the meta-analysis conducted by Braga et al (2019) describe hot spots as small units such as "stores and apartment buildings as well as clusters of addresses, street blocks, street segments and street intersections" (p. 292). Koper (2014) notes that hot spots are areas of high crime concentrated in areas of differing geographic size "specific addresses, intersections, street blocks, and clusters of street blocks" (p. 127).

The UK street segment, however, unlike a US block face is not a uniform length and can, in some cases, be a distance not easily covered on foot. In this regard it could be more appropriate to liken them to police beats or patrol areas, areas excluded from Braga et al's (2019) systematic review. Despite this, larger areas such as beats, or patrol areas *were* defined as hot spots by nearly half of the US police agencies surveyed by Koper (2014) when he conducted analysis into police practices regarding targeted policing.

Street segments therefore occupy an ambiguous middle ground particularly when examined as a connected route as offered in this analysis. While it is recognised that random patrol within a large area is ineffective (Sherman and Eck, 2003; Weisburd and Eck, 2004, Wooditch, 2021), increasing patrols within a larger area has been seen to offer crime reductive benefits (Weisburd et al (2024).

A review of the 1974 Kansas City Preventive Patrol Experiment using statistical tests appropriate for over dispersed count data (linear regressions were used in the initial study) broader categories of crime and focusing on a comparison of the proactive beats with the control beats found "modest crime prevention benefits for preventive patrol in large areas" (Weisburd et al, 2023, p. 545). Proactive beat areas received 2-3 times the level of police presence usually seen i.e. the control beats. While not definitive the re-examining of the original data does point to preventative patrol (increased patrol) having a crime preventive effect on violent crime, burglary and overall a 7% reductive effect on all crime. While this is an interesting finding it does not take away from the benefits of targeting high crime areas. As mentioned above in their critique of the initial study Sherman and Weisburd (1995) point to random police patrols spending time in areas that suffer with very little or more likely no crime, their study instead focussing on "very small clusters of high-crime addresses ("hot spots")" (p. 262).

Dau et al (2023) in their review of 49 studies assessing the effectiveness of all quantifiable forms of police presence found maximum efficacy when the police presence was aimed at "specific areas, times, and types of crime" (p. 191). The meta-analysis of preventative patrol conducted by Weisburd et al (2024) examined the crime reductive power of increasing patrols in larger areas such as "beats, precincts, or entire jurisdictions" and found a similar result (p. 1). While there is a crime reductive effect of police patrolling large areas, which increases with increasing police numbers, the greater impact is seen when patrol is targeted at specific places at specific times.

Operation Swordfish examined the impact of offering targeted police advice and target hardening measures to areas of recent burglaries, it also included police patrol. Areas that received the intervention reported slightly higher levels of satisfaction with the police and there was also a modest reduction in crime rates and re victimisation (more evident in low crime areas than high) (Johnson et al, 2017).

As targeted policing is seen to be effective there is a need to incorporate it to everyday police patrols via a routing system. There is a need for high crime areas to be patrolled in such a fashion that there is minimal lag time between patrols but also enough unpredictability to be useful. Patrol of hot spot areas that occur at regular times will allow offenders the opportunity to recalculate the risks involved and act accordingly (Ariel and Partridge, 2017). Chen et al (2015) developed a "Bayesian Ant Patrolling Strategy" (p. 108) which uses an ant colony algorithm to leave a visible marker behind after patrols. This allows officers to choose a hot spot area to patrol based on the level of the marker left from previous patrols.

The routing of routine movement around a patrol area would also reduce the over and under provision Davies and Bowers, (2019) found occurred on street segments in their study covering areas of London. They suggest a "behavioural bias" is evident (p. 813). They posit that underserved street segments may not have the necessary facilities needed for comfortable patrol in a vehicle. They could have undesirable features or a poor reputation making them less attractive to patrol, such a high number of risky facilities (Eck et al, 2007) or they may be known as streets not requiring patrol. The use of route planning will alleviate some of the issues of behavioural bias that may be seen.

This selection of studies recognises the requirement to identify and patrol hot spots as a basis for crime prevention which in turn reduces future demand. They offer a variety of differing techniques for identifying and then patrolling hot spots within police vehicles. Dewinter et al, 2020 and Samanta et al (2022) have both conducted reviews into the literature concerning both the PPRP and DVRP (Samanta et al, 2022, go further in their review of the allocation of policing resources).

Hot spots derived from single offence types such as Wooditch's (2021) study into street robbery would not benefit from the addition of a harm score but studies generating hot spots from multiple crime types should acknowledge the difference in the severity of the offences making up the hot spot.

3.3 Research Objectives

This chapter has three main objectives. First, to utilise a fully updated Cambridge Crime Harm Index developed by Sherman et al (2016) to examine the distribution of offences committed in Rotherham, South Yorkshire in 2018-19. It will then map crime hot spots and harm spot street segments using the typology suggested by Weinborn et al (2017) and finally, using network analysis in ArcGIS, assess the usefulness of the classification when route planning bringing into account day and policing shift. Route planning combining unweighted and weighted crime subset by time has not been examined before.

This is of particular interest when explored in the light of work conducted by Macbeth and Areil (2019) who found Waymarkers (police generated polygons of areas deemed to require additional police support) were nearly always incorrectly located when compared to statistically generated hot spots and harm spots.

This was also found to be the case when Sutherland and Mueller-Johnson (2019) surveyed police officers and asked them to identify the ten streets (the power few) that contributed the most crime in the areas they worked. They achieved an average mark of 23% with the range going from 0% to 60%. These studies indicate that despite hot spots staying relatively geographically stable over time (Weisburd et al, 2004), police officers may benefit from statistically derived routes that identify streets classified by their level of "hotness" (Weinborn et al, 2017, p. 234).

However, any use of hot spot and harm spot generated maps should be done in collaboration with neighbourhood policing teams and police officers in order for the implementation to be as successful as possible (Wain et al, 2017). Unintended impacts of hot spot policing were found concerning internal police legitimacy. The specificity regarding hot spot policing, namely the precise nature of when and where certain areas need patrols, strips officers of the ability to make those decisions. Wain et al (2017) also found that the more understanding police officers had of the methods employed in hot spot policing, the less likely they were to express positive opinions about it. They suggest that better communication around these practices and police officers having an input into the decision making could mitigate some of the negativity around policing in this manner.

3.4 Data and Methods

3.4.1 Rotherham study area

The Metropolitan Borough of Rotherham is one of four districts policed by South Yorkshire Police (SYP). Its largest urban area is the town of Rotherham, but it also contains several smaller towns and villages such as Maltby, Rawmarsh and Swinton. The area has an industrial history with several former mining areas. The 2021 census estimates the population to be around 265,800 (ONS, 2023).

The village of Thurcroft is then used to highlight the routing implications of the hot spot/harm classification. This area was chosen as an example of a small settlement with overall very low levels of crime and harm, predominantly Type IV and V, but that had street segments classified as Type I and II for the route planner to utilise (Etheridge, 2015).

3.4.2 Datasets

A number of datasets were used in this study with offence data provided by South Yorkshire Police. Individual crime data reported to SYP during 2018 and between January – November 2019 were collated on November 1st, 2019. This data represents a snapshot in time as offences can change or be cancelled as investigations progress.

The initial dataset contained 332,154 individual incident entries covering all four districts overseen by SYP. The data variables included the full title of the offence with its corresponding Home Office classification code as well as the groupings that make up the three tiers of Her Majesty's Inspectorate of Constabulary (HMIC) Crime Tree (Fig. 3.1). All offences had the date the offence occurred with the time if known. Where provided, the location the offence was committed was given with easting and northings.

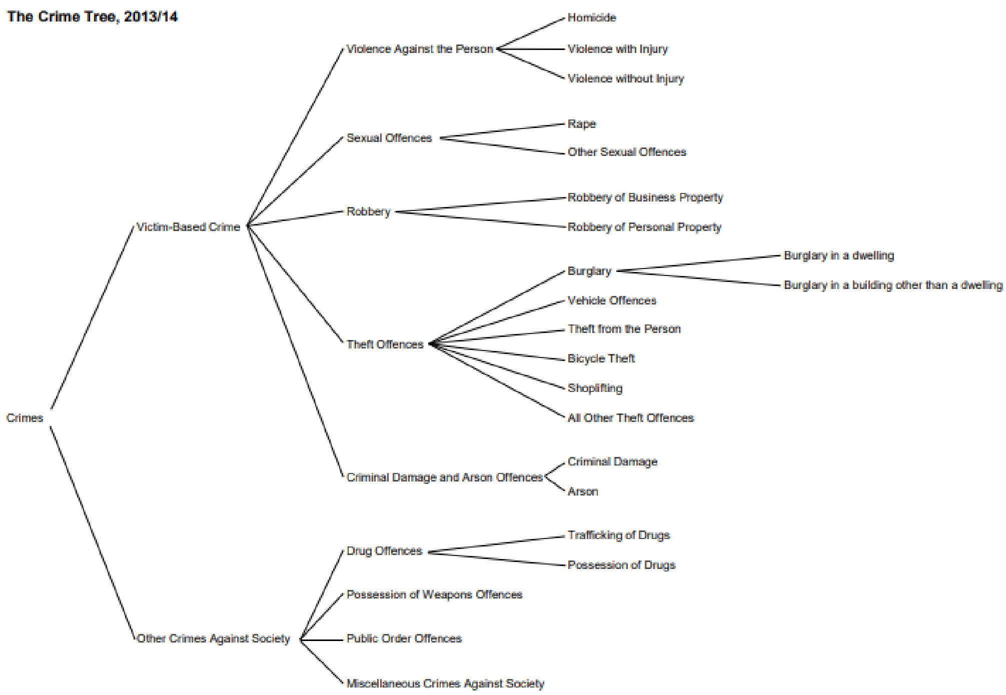


Figure 3.1: HMIC Crime Tree Levels 2013/2014 (HMICFRS, 2014)

Data cleaning removed offences classed as Non-Crime and Non-Notifiable crimes. Using the terms given in Crime Tree Level 1 those offences designated as Victim Based and Other Crimes Against Society remained. All crimes reported to SYP from January 2018 to November 2019 were contained in the dataset; however, historic crimes that took place before January 2018 were removed. A number of offences had no location information and were also removed. The date was used to obtain the day of the week and also expanded into three separate columns of day/month/year for further analysis. Using the time information, a shift variable was created to sort the offences into the appropriate police shifts of days (07:00 – 15:00), afternoons (15:00 – 23:00) and nights (23:00 – 07:00). A count variable was also added for later use within ArcGIS.

As SYP is divided and policed as four distinct districts, it was decided on advice from SYP to focus the analysis on one area, Rotherham. A boundary shape file was used to filter offences falling outside Rotherham Police District.

3.4.3 Cambridge Crime Harm Index

This chapter has benefited from the resources made available by the Criminology Department of Cambridge University, which has a July 2016 copy of the CCHI available to download. This resource provided an invaluable tool on which to begin updating and adding offences. In light of offence title changes, the Home Office classification codes were used to cross reference established harm scores and build upon them.

As discussed, the CCHI aims to establish an objective score for each offence without the context of the offender being a factor (Sherman et al, 2016). When deciding on an appropriate sentence, a magistrate will use sentencing guidelines to pick the suitable sentence. Where specific guidelines exist, the sentence relating to the lowest culpability and harm is allocated in the index e.g. Grievous Bodily Harm has a score of 1460, whereas Grievous Bodily Harm using acid results in a higher score 4380. The forethought and preparation required for an acid attack is taken into account within the guidance and the higher harm score reflects the longer sentence.

Sentencing guidelines do not exist for every offence and where there are no specific guidelines, magistrates refer to a new overreaching set of guidelines (personal correspondence). These act as a checklist of the factors they need to consider in relation to the offence such as the statutory maximum sentence, relevant case law and sentence guidelines for analogous offences. In addition, the culpability of the offender and the harm caused by their actions must be considered as should the purpose of the sentence i.e. punishment or protection. However, these elements should be ignored when establishing a harm score. Unfortunately, without the experience of a magistrate, this process is a time consuming and challenging exercise.

It is established practice, and written into guidelines, that offenders who plead guilty receive a lesser sentence (the maximum reduction is one third) (Sentencing Council, 2017). What is less clear is the reduction in sentence for those offenders caught mid offence who are charged with an 'attempted' crime. In the Rotherham dataset, 1,627 offences were attempted from 48 unique offence types. In personal correspondence with the Secret Barrister on Twitter, they explained that sentences will be reduced to reflect that the crime was attempted rather than completed and is therefore less serious, but it is not possible to apply a reduction across the board as numerous factors will need to be considered. For example, at what point and for what reason did the attempt fail? Other than attempted murder, the 2016 CCHI made available by the University of Cambridge Institute of Criminology does not include attempted crimes.

During the data cleaning process attempted crimes came under greater scrutiny, as the data set contained questionable entries such as ‘Attempted possession of a knife’. Attempted offences were collated and given to SYP’s Force Crime and Incident Registrar to assess. As a result, 150 offences were removed as they had been incorrectly allocated and two (‘Attempted theft *of* a motor vehicle’ and ‘Attempted theft *from* a motor vehicle’) were recoded as ‘Attempted interference with motor vehicle’.

In this analysis, attempted offences have had the CCHI score reduced by 20% to indicate the crime was not completed and therefore can be considered less harmful (20% reduction was chosen as an acknowledgment of lesser harm). As mentioned above, there is no set reduction for an attempted crime as there is for a guilty plea. 20% was chosen as an attempt indicate lesser harm but there is an appreciation that this is an area of ambiguity and that sensitivity analysis around attempted crimes is an area for further investigation. There is an argument that attempted offences should be given the full CCHI score as there is no way of knowing why or at what point the attempt failed.

3.4.4 Street Segments

Both crime counts and crime harm are analysed at the street segment level (Hipp and Williams, 2020). The Ordnance Survey provides a generalised digital representation of Britain’s roads with its Open Roads product. This resource is updated twice yearly and contains shapefiles of three feature types: RoadLink, RoadNode, and MotorwayJunction.

The alignment of the road carriageway is represented by the RoadLink polyline feature. The individual links (measured in metres) represent all or part of a road and end where there is a junction or a variation in attribute such as a change in road name (Ordnance Survey GB, 2023). This national dataset was downloaded, and the appropriate tiles joined and clipped to a boundary shapefile of Rotherham in ArcGIS 10.5.1. During the analysis it was found that 23 road segments were duplicated within the dataset; these were identified, and the duplicate data removed.

The crime instances were plotted using the easting and northing information and exported as a point shapefile. These points were then joined to the polyline road shapefile with a spatial join that summed the numeric data contained within each point (count and CCHI score) and joined it to the nearest road segment. These spatial joins produced a polyline shapefile containing road segments that each have the summed harm score and crime count of the nearest crime incidents.

However, an unforeseen issue in ArcGIS meant that if a point was equidistant from two or more polylines then the point's attributes were joined to all road segments. This resulted in data points being duplicated and over 5750 additional offences being created during the join (13% increase in offences). In order to overcome this, the join was reversed. The road data was joined to the individual offence point with each point gaining the unique identifier of the road segment nearest to it. This was then converted and exported as an Excel spreadsheet. The data was then pivoted, and crime count and crime harm scores were summarised for each road segment (by its unique identifier). At this stage, the dataset can be filtered by any of the variables to produce subgroups. After discussion with SYP, the offences were first divided and grouped into weekday (Monday – Thursday) and weekend (Friday – Sunday) with each group then divided and grouped by shift. 15.4% of offences did not have time information available and were removed from this section of the analysis. It is acknowledged that these shift patterns may not be standardised across all UK forces and may only be representative of SYP.

This file was then entered into ArcGIS and joined to the road polylines by the shared unique identifier column rather than as a join based on spatial location. This ensured the correct number of offences were analysed. Further data cleaning was undertaken once the crime data were joined to the street segments of Rotherham.

Initial analysis showed Main Street as the street segment with both the highest crime counts and harm score, 296 and 59,580 respectively. The harm score was considerably higher than the second highest score of 29,220 and gave an average harm score per offence of 201. On investigation it was found to be the street segment that houses Rotherham Police Station. As it was not possible to verify the police station as the location of these offences, they, and the street segment were removed from the dataset. This reduced the road segments to 13,356. Curtis-Ham et al (2024) highlight the issue of locational accuracy within police data and the use of default locations such as police stations.

There were also 8 homicides in the dataset. As previous studies have done, these were excluded as they are a rare event and have the highest CCHI score and could skew the results (Norton et al, 2018). In addition, 68 offences against police officers were removed as they are indicative of a police presence. This filtering and cleaning resulted in a dataset of 45,514 individual crime offences occurring within Rotherham between January 2018 – November 2019. Each of these offences has a Cambridge Crime Harm Index score.

3.4.5 Hot spots, Harm spots and Z Scores

As previously noted, there is no single established method for defining and mapping a crime hot spot; however, in order to compare with recent work on UK hot and harm spots, a common methodology was used (see Weinborn et al 2017, Norton et al 2018). As outlined in their work, street segments that had experienced crime had their crime volume and harm totals converted into z-scores using the standard method, equation 1. This essentially converts street segment crime counts into a relative score – i.e. the transformed variable now measures how large each street segment's crime count is relative to the average street segment crime count. The units of measurement are no longer raw crime counts but standard deviations. In other words, the crime counts are now expressed in terms of multiples/fractions of the average deviation of crime counts from the mean. For example, if a street segment has a z score value of 1.2, it means that the crime count in that location is 1.2 times the average deviation of street segment crime counts from the mean street segment crime count for the entire study area.

$$z = \frac{raw\ score - mean}{standard\ deviation} \qquad (1)$$

As Weinborn et al (2017) note, this transformation is conducted to change the metric of measure and allow the identification of street segments two or more standard deviations away from the mean (whilst Norton et al (2018), define hot and harm spots as those 3 standard deviations from the mean, there is currently no consensus on the cut off). This approach was also used for the identification of harm spots. This was conducted for the complete dataset and then for each of the 3 weekday and 3 weekend shifts. These z-scores, for both crime counts and harm scores per road segment, were then used to classify street segments as one of the five types outlined by Weinborn et al (2017) and for those to be used further within a network analysis.

3.4.6 Network analysis

Network spatial phenomena are various types of real world occurrences that take place on or very near to a network. They are not unusual, road traffic collisions for example, are reported in relation to the road network and occur directly on that network. Within urban areas however there are a larger number of what Okabe and Satoh (2009, p 443) describe as a "second class of network spatial phenomena", those facilities with entrances adjacent to the road network such as shops, pubs and other buildings found within built up areas. These second class network phenomena and the road network are in close proximity to each other.

The culmination of this analysis is a routing exercise using the date/time datasets with the street segments classified I to V. The street segments are the basis for the creation of a transportation network within ArcGIS. Once created this transportation network dataset contains the spatial information relating to the street segments, their attributes in addition to information concerning how these segments relate to each other and allows movement in both directions (if road stipulations allow) (ArcMap, unknown). The network analysis was also conducted in ArcGIS.

Routing is the most fundamental logistical operation. It is an activity undertaken by most people every day; it is the act of choosing a course of travel (Curtin, 2017). By routing police vehicles preferentially on street segments classified as Type I - III they will act as a visible and capable guardian to those neighbouring second class network phenomena. The assumption made about the movement of vehicles in this work is that they are not required to attend any specific destination in any specific time frame; they are free to 'patrol' and be a visible deterrent against potential criminal activity.

As the police vehicles are not bound by the requirement to attend an emergency in the quickest time possible or travel the shortest route (as would a delivery vehicle) the network cost is created to reflect the crime level typology of the street segment. As this work has not been undertaken before there are no guidelines to follow in setting the cost values. However, in order to emphasise the importance of the typology, an exponential weighting was used when creating the cost variable.

In this weighting system Type I segments (priority) were weighted with the lowest value, 1. Type II received a weight value of 2 through to Type V (no crime) with a value of 16. Using this weighting, road segments with a typology cost of 2 (Type II), for example, will be preferred to a road segment with a typology cost of 16 (Type V) in order that the accumulated route score is as low as possible. This will then lead to routes taking in areas of low values (priority street segments, hot and harm spots) and routing police patrols along road segments classified as Type I – III.

3.5 Results

3.5.1 Descriptive

Initial analysis generated descriptive statistics for 22 months of crime data (January 2019 – October 2019). The final cleaned dataset shows 45,514 geolocated crimes took place within Rotherham's boundary. Table 3.1 shows the breakdown of offences by the first HMIC Crime Tree Level. Non-notifiable and Non-crime entries were filtered out of the dataset. Victim Based crimes make up the majority of the offences both as counts (85.8%) and as harm (87.5%).

	Crime Count	Harm
Victim Based	39,039	2,403,653
Other Crimes Against Society	6,475	342,528
Grand Total	45,514	2,746,181

Table 3.1: HMCI Crime Tree Level 1

At the second level, Table 3.2, shows Theft Offences as the most prevalent crime type (37.4%); this was found to be the predominant offence category in Weinborn et al's (2017) study with a similar proportion of 36.9%. Rotherham's second most numerous offence category is Violence against the Person (32.4%) followed by Damage and Arson Offences (12.6%). The top five offences account for 94% of the crimes committed in Rotherham but this is not the case when examining the distribution of harm scores.

Violence against the Person accounts for 45.3% of the harm taking place and is the most harmful of the offence types. Sexual Offences resulted in 787,802 prison days and combined with Violence against the Person crimes make up nearly three quarters (74%) of the harm experienced in Rotherham.

	Crime Count	Crime Rank	Harm Rank	Harm
Theft Offences	16,999	1	5	138,365
Violence against the person	14,755	2	1	1,245,161
Damage and arson offences	5,716	3	7	74,207
Public order offences	4,246	4	9	28,409
Misc Crimes against Society	1,152	5	4	151,121
Sexual Offences	1,122	6	2	787,802
Drug offences	649	7	8	38,809
Robbery	447	8	3	158,118
Possess Weapon Offences	428	9	6	124,189
Total				

Table 3.2: HMIC Tree Level 2

3.5.2 Temporal analysis

When viewed over the entire duration of the dataset, from Fig. 3.2. it is possible to see a peak of crime and harm in May 2018 and a peak of harm in October 2018 without the corresponding percentage increase in crime. This indicates that high-harm low-volume crimes were committed. This may be an anomaly. Conversely, the summer of July 2018 saw lower harm crimes being committed.

When viewed over the course of a week, Fig 3.3, harm and crime counts fluctuate similarly, with both increasing from Thursday into Friday and Saturday. Interestingly, Monday sees similar crime amounts to both Friday and Saturday, which is unusual. It may be possible that crimes are being reported on the Monday that took place over the weekend but being assigned Monday’s date.

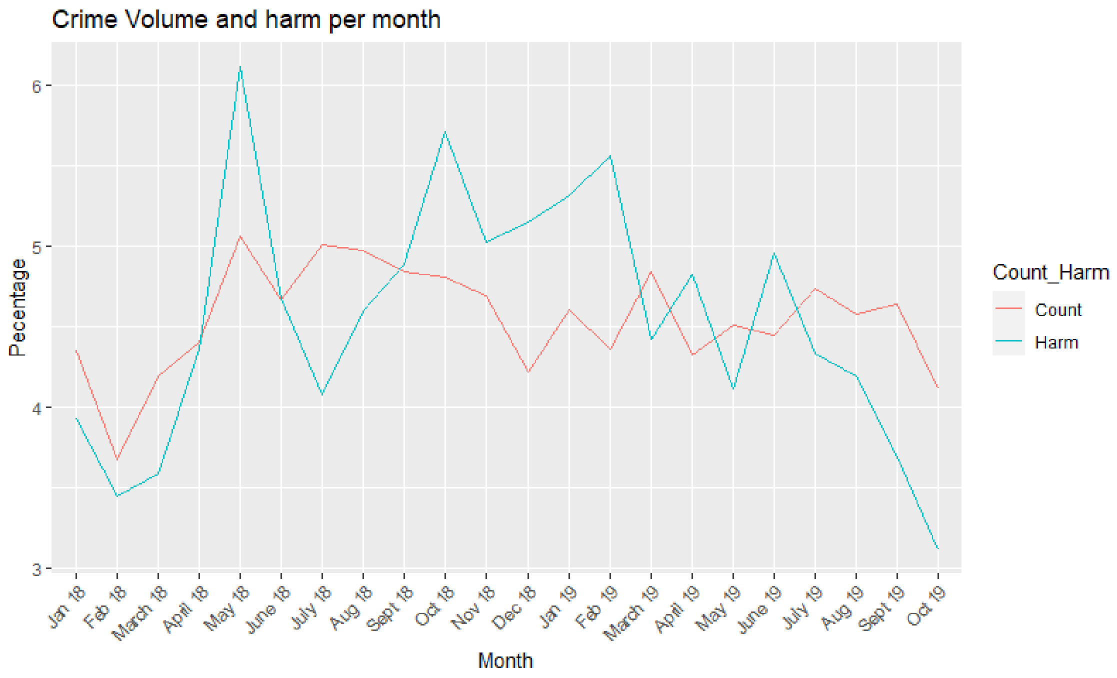


Figure 3.2: Percentage of crime volume and harm across data timeframe

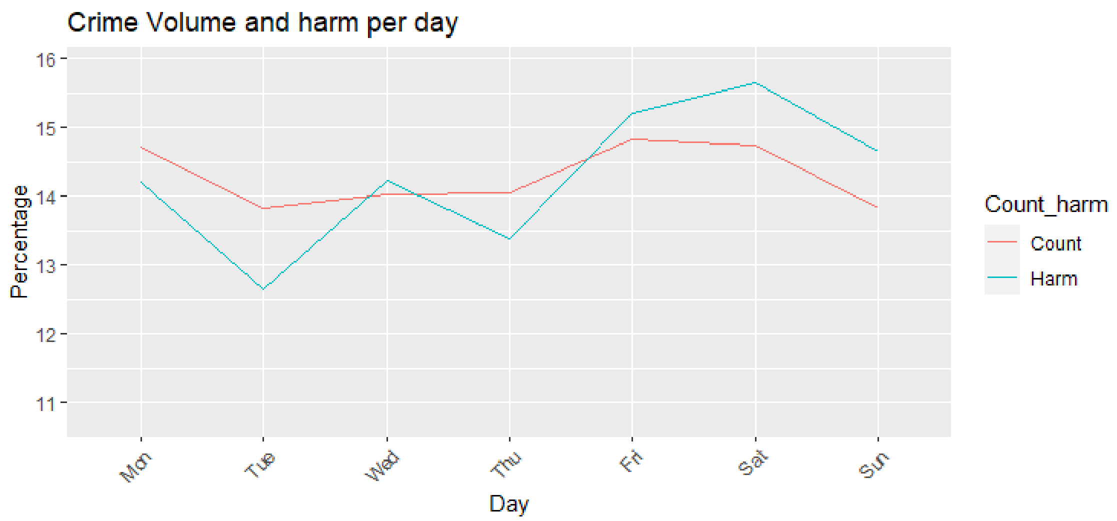


Figure 3.3: Percentage of crime volume and harm across week.

Just over 15% of crime data did not have a time associated with the offence. This relates to 21% of the harm. For the offences that did have a time recorded, Fig. 3.4. shows the afternoon/evening shift (15:00 – 23:00) having the greatest proportion of both crime and harm, with the morning and night shifts mirroring each other. The morning shift sees lower harm crimes, while the night shift sees crimes with higher CCHI scores taking place. This may have an impact on the way in which the police choose to enact crime prevention measures. This is similar to Norton et al's (2017) findings that showed that crime volume and crime harm peaked at different points of the day.

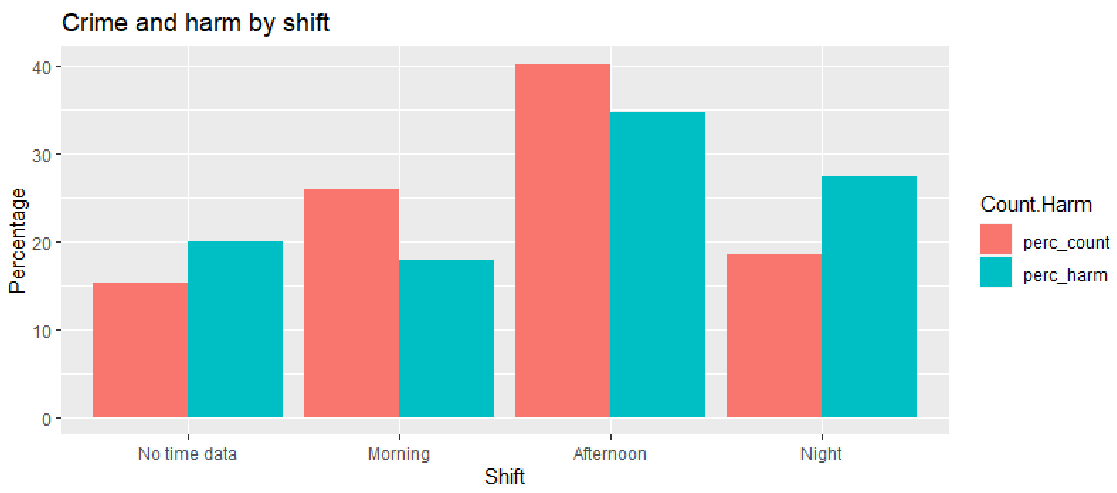


Figure 3.4: Percentage of crime volume and harm by policing shift

3.5.3 By Street Segment

Rotherham is made up of 13,357 street segments (as designated by RoadLink with duplicates removed). ArcGIS 10.4.1 and 10.5.1 were used to complete the spatial analysis of the data.

The final dataset consists of 45,514 offences with a combined harm score of 2,746,797.85 and a road network containing 13,356 road segments. Within Rotherham, 44.9% of street segments (6002) reported no offences taking place between 01 January 2018 – 31 October 2019 and were, as far as South Yorkshire Police are aware, crime free.

Crime is less concentrated than previous studies have found with 50% of crime incidents in the Rotherham district taking place in 6.3% of street segments (842). In line with Weinborn et al (2017) crime harm was more concentrated than crime counts with 50% of harm located in 2.6% of segments (347), but not as concentrated as was found in their study.

By adopting a similar methodology, it is possible to utilise the typology of "hotness" set out in Weinborn et al (2017, p.234). Unlike Weinborn et al (2017) who reduced their hot/harm spot cut-off to 1 standard deviation away from the z-score mean (in order to better showcase their typology), given the ongoing budgetary concerns, this analysis has maintained the 2 standard deviation thresholds. Fig. 3.5. shows the distribution of hot spot and harm spot street segments using the classification previously described:

Type I. Priority Areas (both hot spot & harm spot): In the Rotherham police district 95 street segments (0.7%) meet the criteria of being both 2 standard deviations away from the mean of z-scores for both crime counts and 2 standard deviations away from the z-scores of the harm score. These would be the street segments that should be prioritised as areas with both high crime volume and high crime harm.

Type II. Hot spots (High crime, Low harm): 132 hot spots were identified. These are areas with high crime volumes but consist of crimes with lower harm scores. These lower harm crimes may be more easily prevented with targeted hot spot policing giving rise to a visible police presence.

Type III. Harm spots (High harm): Harm spots are identified for more targeted intervention. 190 street segments were the locations for high-harm low-volume crimes. As table 2 states, crimes against the person as opposed to property make up the majority of higher harm crimes.

Type IV. Low Crime, Low Harm Areas: Low crime areas number 6,937 street segments or 52% of the road segments in Rotherham. These dispersed streets will make it difficult to target low levels of crime.

Type V. Crime Free: There are 6,002 segments (45%) without any reported crime.

Fig 3.5 shows the majority of the segments as light or dark green as expected as Type IV and V account for 96% of the road network. Type I, II and III areas are found predominantly in Rotherham town centre. Fig 3.6 shows this more clearly with a reduced scale and Type IV and V segments left blank.

There are, however, a number of individual priority (Type I), hot and harm spots found in smaller towns in the district. Fig. 3.7, shows Thurcroft, a former mining village located to East of the M1 motorway (junction 32), and the distribution of crime and harm found in that area.

Within the highlighted area, 3 street segments can be seen to be Type 1 priority segments showing areas of both high crime volume and high harm. These would be areas Rotherham's neighbourhood policing teams should pay the highest attention to. One cul-de-sac is the only hot spot segment indicating high crime counts but low harm. 6 segments are classified as harm spots (Type III) and these locations would benefit from a more detailed examination of the offences that have taken place. More difficult to target are those segments that have had at least one offence take place but are considered low crime areas. However, it may be that the classification of these segments' changes over the course of a week or day.

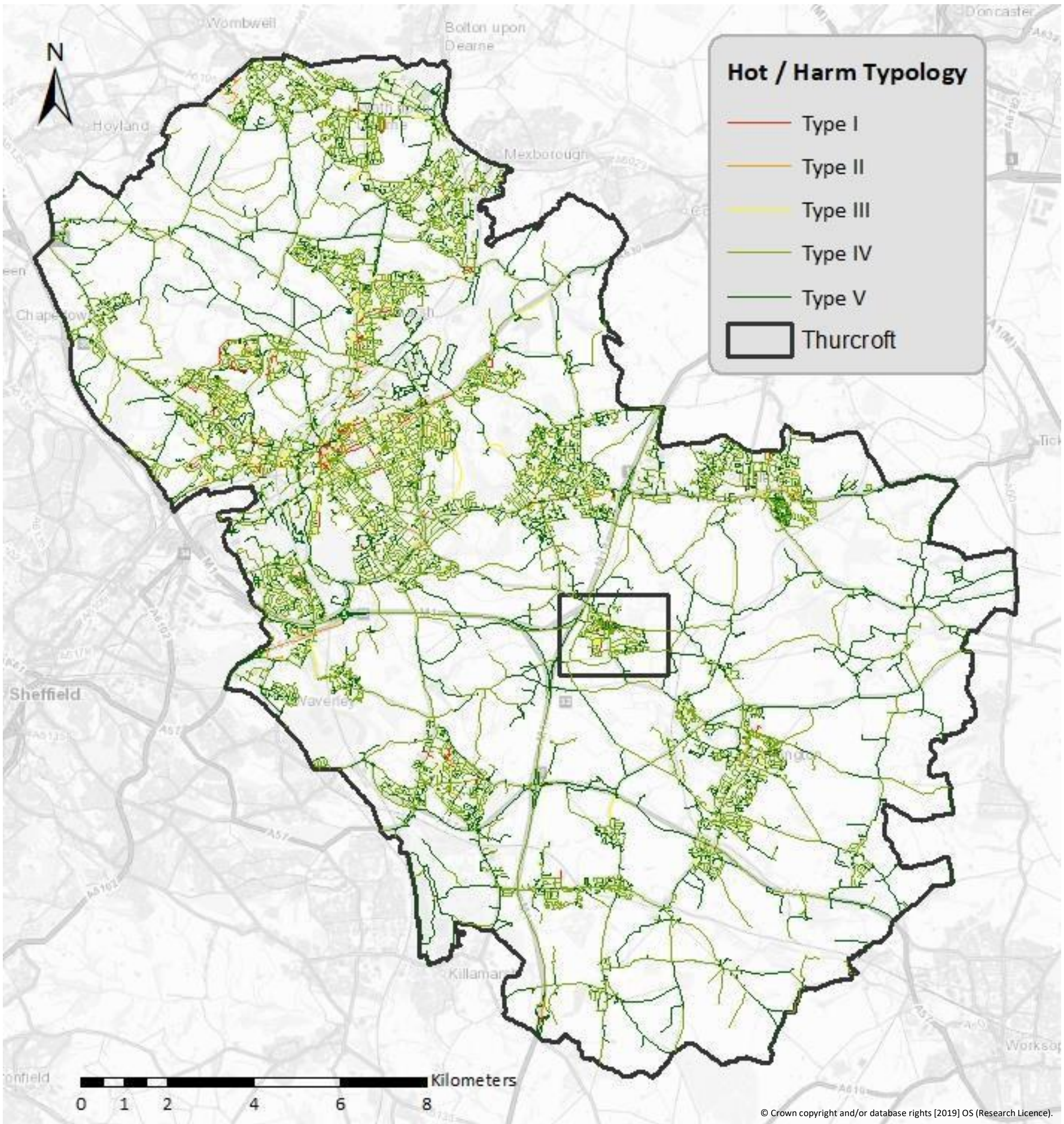


Figure 3.5: Hot spot / Harm spot typology map of Rotherham

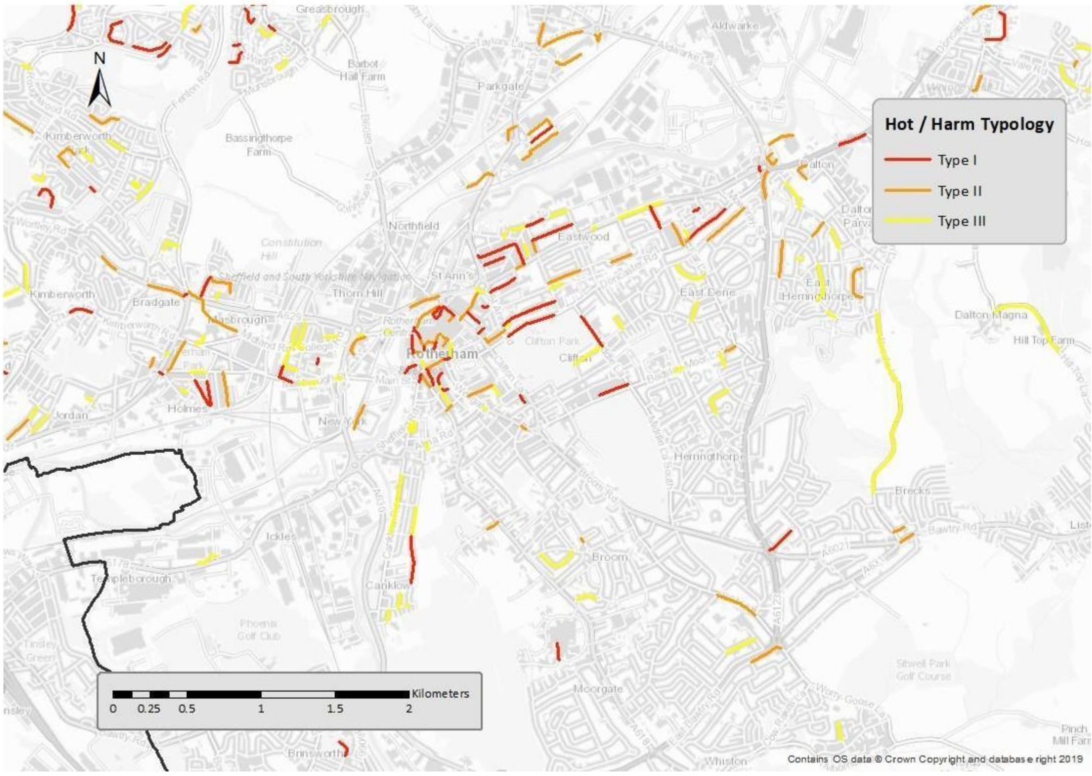


Figure 3.6: Reduced scale view of Rotherham town centre

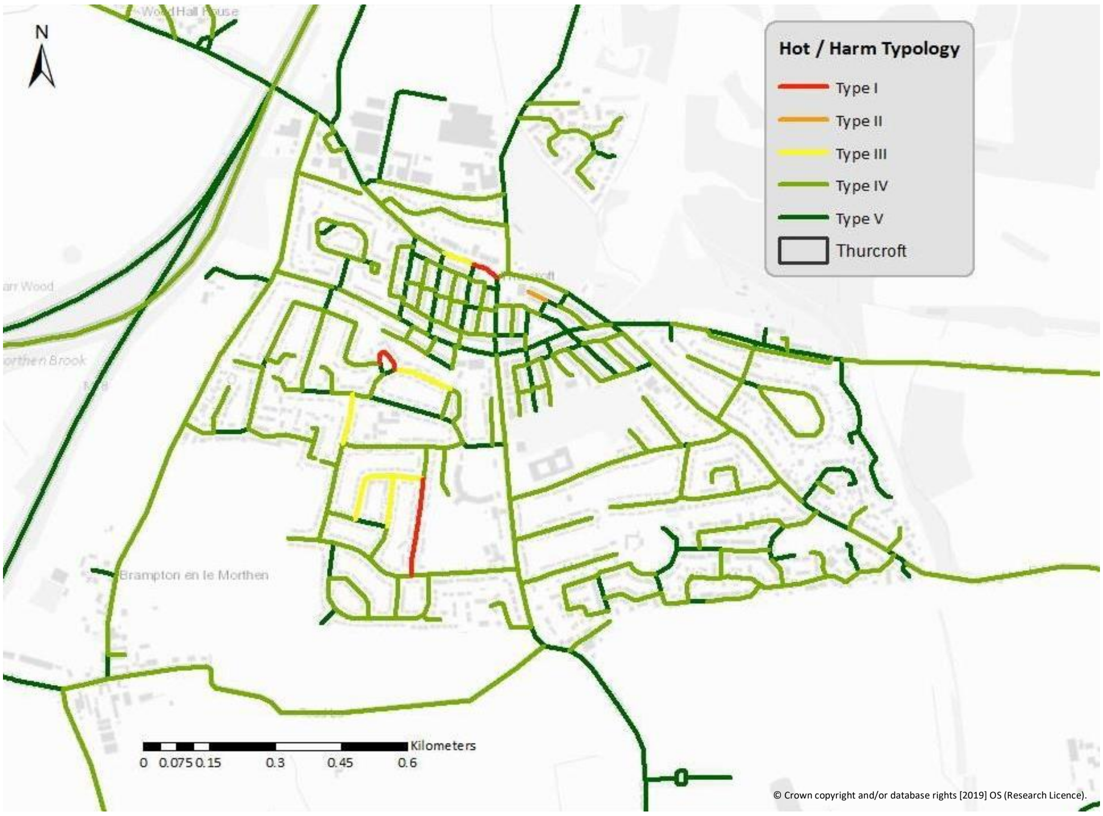


Figure 3.7: Thurcroft showing streets classified by "hotness" (extracted from complete dataset)

Figure 3.8 shows a side by side comparison of afternoon shifts and how they differ weekday to weekend. While they are on the whole fairly similar, there are differences that could require slightly different approaches from policing teams. The data suggests that higher harm crimes occur during the weekdays (streets in the southwest section of the village) with no high-volume low-harm (hot spot) areas showing. During the weekend, however, there are street segments classified as hot spots.

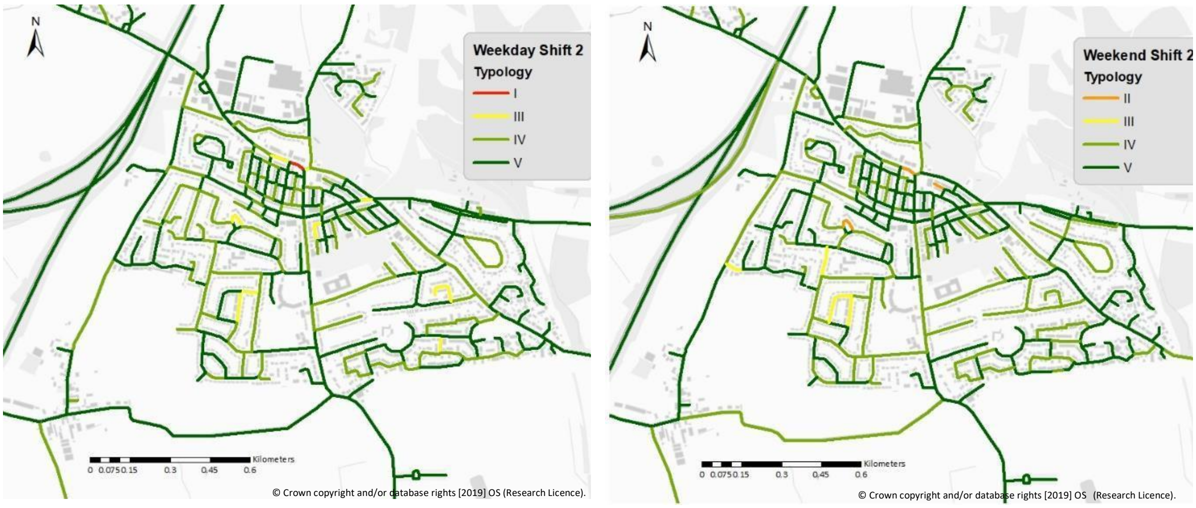


Figure 3.8: Street segment typology showing weekday and weekend afternoon shift comparison

Figures 3.9 and 3.10 indicate how route planning can be used to take into consideration these differences in typology. Figure 3.9 shows a traditional route plan, where the aim is to reduce the distance taken moving from A to B (this short distance is just for illustrative purposes and the distance saved would be minimal if a slightly different route were chosen). In Fig. 3.10, the route chosen takes in road segments with a lower typology cost. This means it routes either cars or foot patrols along street segments designated as having higher crime or harm amounts.

Given the dislike of hot spot policing found by Wain et al's (2017) study, it may be more successful to allow officers to plan their routes based on the contents of the map rather than dictate using specific route planning. Route planning may be best utilised for routine movement around the district by officers travelling from station to station for example.

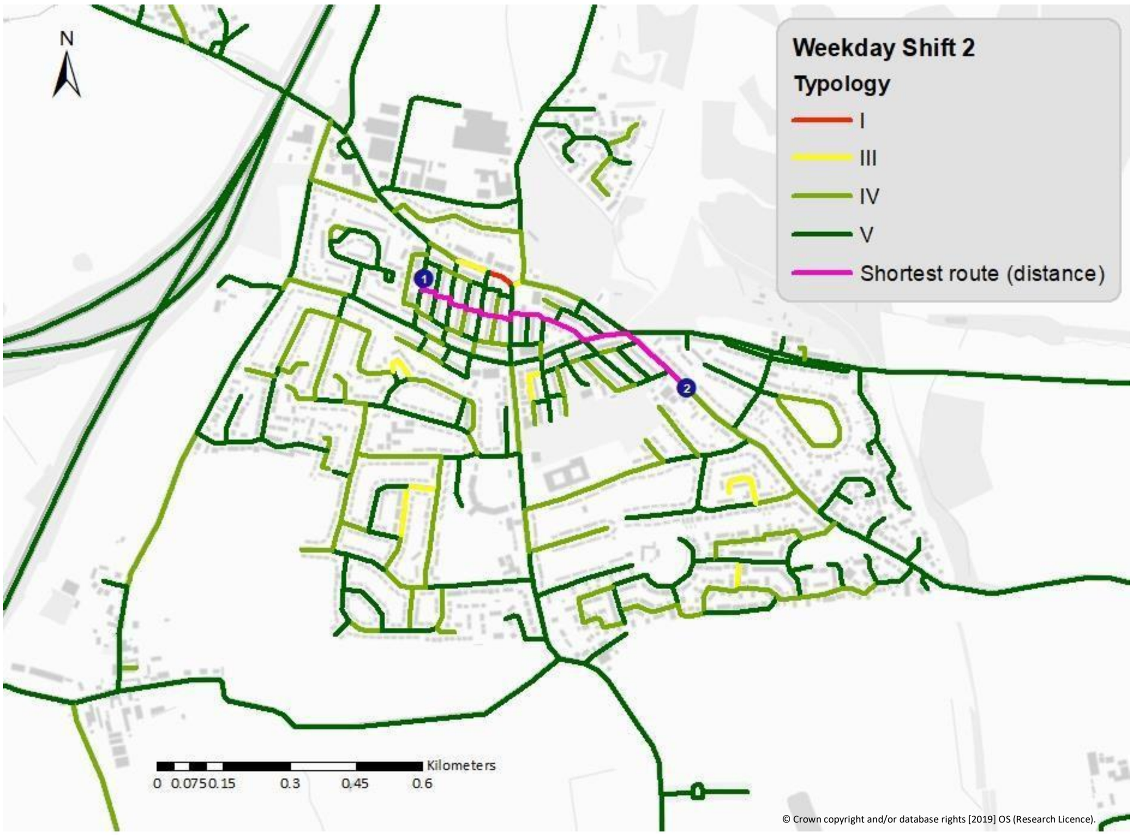


Figure 3.9: Shortest route between A and B during weekday afternoon shift

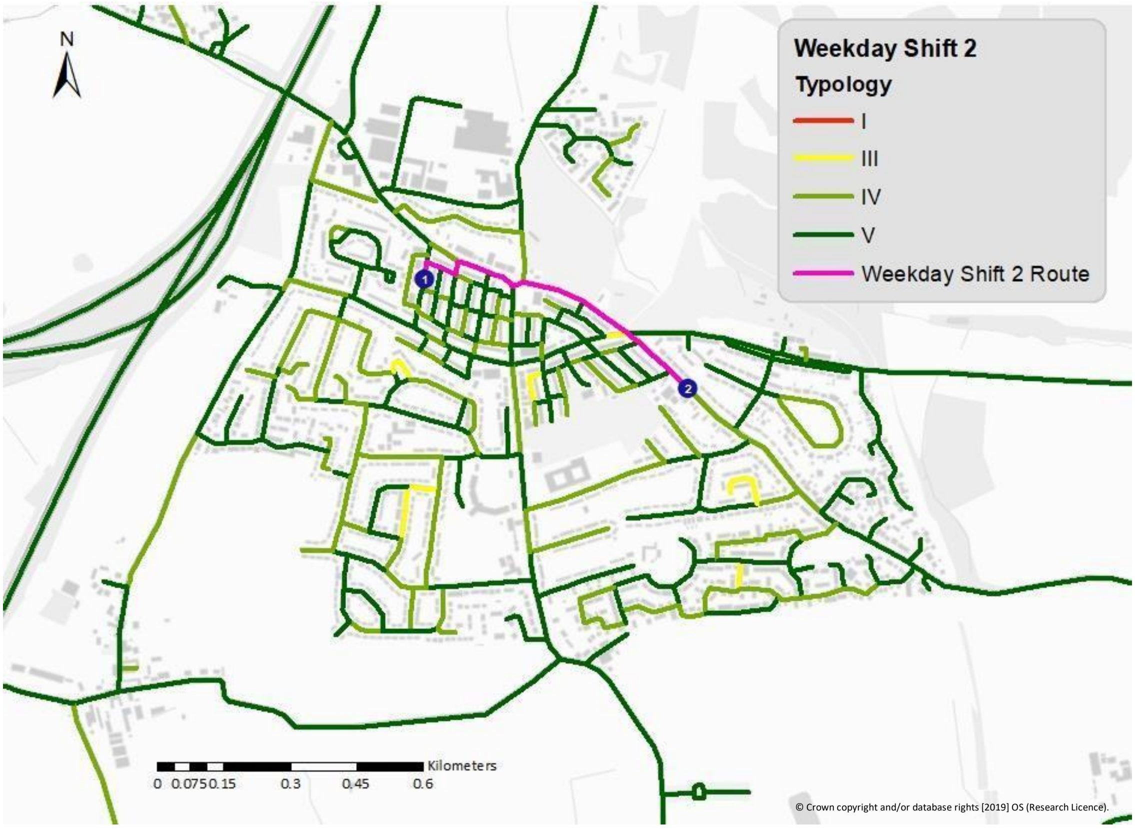


Figure 3.10: Targeted route between A and B during weekday afternoon shift

3.6 Discussion

The data from Rotherham is in line with previous findings on the distribution of crime, with a small number of street segments hosting approximately half the crime. It is also similar to the limited work (Weinborn et al, 2017) that show harm as having a more concentrated distribution when compared to counts of crime.

The areas where high harm and high-volume coincide highlight areas requiring specific attention, but more interesting are the areas where hot spots and harm spots occur separately. The areas designated as hot spots will continue to benefit from targeted hot spot policing, as they are made up of high-volume low-harm offences. These, as Table 3.2 shows, are predominantly theft and damage offences that can occur in more public locations and will be reduced with additional visible guardians (Cohen and Felson, 1979).

Policing harm spot areas will require different intervention as high harm offences are more personal; violence against the person and sexual offences, these will not be reduced in a similar manner with additional police patrols. These crimes can often occur in private, in the home, out of sight (Felson and Eckert, 2017). It is important that interventions are undertaken, as a reduction in high harm offences can be argued as more beneficial to our society than simply a reduction of crime counts in general (Weinborn et al, 2017). However, care should be taken to identify ephemeral harm spots created by tragic infrequent incidents of high harm. These can be identified by using a rolling dataset.

This chapter has used 22 months of data and provided a snapshot of the distribution of crime volumes and harm in Rotherham over that time. In order to be more useful to police forces, this dataset should be updated regularly. A suggestion is to use a rolling year dataset that adds data from each passing month while dropping the month from the previous year. Additional analyses can be undertaken tracking the differences in distribution and number of street segments achieving the 2 standard deviation threshold for hot/harm spot designation. Planned routes can then change accordingly.

3.7 Limitations and next steps

There are a number of limitations to be aware of with this study. The harm index on which it is based requires regular updates in order to reflect any changes to sentencing guidelines. In relation to this, the scores given for those offences without guidelines is a best guess based on similar offences with guidelines but without the expertise of a trained magistrate. The choice to award attempted crimes a 20% reduction may not be made by every researcher who uses the index and as such there enters a small amount of subjectivity into what is designed to be an objective measure of harm.

The dataset does not contain historic offences which means crimes reported during the analysis time frame but committed outside of those months are in effect erased. This may have a particular impact on the harm spots generated, as sexual offences are often crimes that victims may take time reporting. These crimes are particularly high harm offences which could change the map significantly.

This ties in with the accuracy of the data recorded by police forces. The hot spots and harm spots generated are dependent on the data they are derived from; this means that they are as accurate as the data used to create them. The issue surrounding Main Street and the unexpected rise in both crime and harm on Mondays suggests there may be room to increase the accuracy of the records being entered into the police database. It should also be noted that the geographical boundary set for analysis will affect the results achieved, understood as the modifiable areal unit problem (Openshaw, 1984).

Examining the route planning aspect of the analysis leads to issues with the use of street segments as a unit of analysis. Street segment length varies, but in this analysis the crime cost was given irrespective of that. These impedances were summed and formed a total journey cost and the route returned was the lowest cost way to travel from A to B. If that route is made up of numerous short street segments with a low cost it may still be more efficient for the algorithm to utilise a longer higher cost segment in the returned route. Future analysis will need to take account of this by incorporating the length of the street segment to generate a 'cost per metre' value.

It may simply be enough for police officers to be aware of Type I – III street segments for their day and shift and to endeavour to include them on any non-emergency travel they make through the area.

3.8 Conclusions

This study has contributed to the growing crime harm literature and shown that in keeping with emerging findings that crime harm is more concentrated than crime volume and is also non-random. Areas of high harm occur in different areas than areas of high crime volume and are therefore different. As such there needs to be closer examination of the differences in the locations of these concentrations of high crime volume and high harm.

The typology developed by Weinborn et al (2017) provides a useful classification for hot spots and harm spots and allows for the identification of priority areas that are high for both measures. This chapter has utilised this typology for the city of Rotherham and developed a route analysis with the classification at its core. Using the typology to route non-emergency police vehicles shows how forces could increase their visibility in areas that most require it though routine movement through an area and limit any behavioural bias that might lead to certain street segments being over or underutilised (Davies and Bowers, 2019). By showing the differences in route generated for different day/shift this chapter also evidenced the requirement to factor day of week and policing shift within the analysis to acknowledge the temporal influence on offending.

However, until public sector funding returns to pre-austerity levels, it may be prudent to calculate street segment types using a cut off of 2 standard deviations from the mean so the top 5% of hot and harm spots are identified for targeted intervention. The typology makes distinguishing different segments easy to do and the weekday/end and shift split offers the police more specific areas to examine. By incorporating this into route planning it allows travel around the district to be more efficient and effective.

References

Research tools: Cambridge University https://www.crim.cam.ac.uk/Research/research-tools

ArcMap. Unknown. *What is the ArcGIS Network Analyst extension?* [Online].[Accessed 01 September 2023] Available at: https://desktop.arcgis.com/en/arcmap/10.5/extensions/network-analyst/what-is-network-analyst-.htm

Ariel, B. (2011). Hot dots and hot Lines: Analysis of crime in london underground. In Presented at the annual american society of criminology (Washington DC, November 06, 2011).

Ariel, B. and Partridge, H., 2017. Predictable policing: Measuring the crime control benefits of hotspots policing at bus stops. *Journal of Quantitative Criminology*, *33*, pp.809-833.

Ariel, B., 2022. Implementation issues with hot spots policing. *OSF Center for Open Source. https://osf. io/t4xg9*

Bangs, M., 2016. Research outputs: developing a Crime Severity Score for England and Wales using data on crimes recorded by the police. *Newport: Office for National Statistics*.

BBC, 2016, Crime Severity Score measures 'relative harm' of crimes. [Online].[Accessed 29/11/2019] available from: http://www.bbc.co.uk/news/uk-38157840

Braga, A. A., Hureau, D. M., & Papachristos, A. V. (2011). *An ex-post-facto evaluation framework for place-based police interventions. Final report submitted to the US Bureau of Justice Assistance*Cambridge, MA: Harvard University, Kennedy School of Government.

Braga, A.A., Turchan, B.S., Papachristos, A.V. and Hureau, D.M., 2019. Hot spots policing and crime reduction: An update of an ongoing systematic review and meta-analysis. *Journal of experimental criminology*, *15*, pp.289-311.

Brantingham, P. L., & Brantingham, P. J. (1999). A theoretical model of crime hot spot generation. Studies on Crime and Crime Prevention, 8(1), 7e26.

Chainey, S., Tompson, L. and Uhlig, S., 2008. The utility of hotspot mapping for predicting spatial patterns of crime. Security journal, 21(1-2), pp.4-28.

Chen, H., Cheng, T. and Wise, S., 2015. Designing daily patrol routes for policing based on ant colony algorithm. *ISPRS Annals of Photogrammetry, Remote Sensing & Spatial Information Sciences*, *2*.

Clarke, R.V. and Weisburd, D., 1994. Diffusion of crime control benefits: Observations on the reverse of displacement. Crime prevention studies, 2, pp.165-184.

Cohen, L. E., & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review, 44*(4), 588–608.

College of Policing, 2021, The effectiveness of visible police patrol [Online].[Accessed 01 September 2023] Available at: https://www.college.police.uk/research/what-works-policing-reduce-crime/visible-police-patrol

College of Policing. 2013 The effects of Hot-Spot Policing on Crime: What Works Briefing [Online].[Accessed 01/10/2019] http://library.college.police.uk/docs/what-works/What-works-briefing-hotspot-policing-2013.pdf

Curtin, K.M., 2007. Network analysis in geographic information science: Review, assessment, and projections. *Cartography and geographic information science, 34*(2), pp.103-111.

Curtis-Ham, S., & Walton, D. (2017). The New Zealand Crime Harm Index: Quantifying harm using sentencing data. *Policing: Journal of Policy Practice, 12*(4), 455–467.

Curtis-Ham, S., Tompson, L. and Czarnomski, S., 2024. Forewarned is forearmed: the hidden curriculum of working with police crime data. *The Crime Data Handbook*, p.9.

Dau, P.M., Vandeviver, C., Dewinter, M., Witlox, F. and Vander Beken, T., 2023. Policing directions: A systematic review on the effectiveness of police presence. European journal on criminal policy and research, 29(2), pp.191-225.

Davies, T. and Bowers, K., 2019. Patterns in the supply and demand of urban policing at the street segment level. *Policing and society*.

Dewinter, M., Vandeviver, C., Vander Beken, T. and Witlox, F., 2020. Analysing the police patrol routing problem: A review. *ISPRS International Journal of Geo-Information*, *9*(3), p.157.

Di Tella, R. and Schargrodsky, E., 2004. Do police reduce crime? Estimates using the allocation of police forces after a terrorist attack. American Economic Review, 94(1), pp.115-133.

Dodd, V, 2019. Police chief: cuts must be reversed to fix 'social fabric' and stop gangs. *The Guardian* [Online] 30 July 2019 [Accessed 01/12/2019] Available at:https://www.theguardian.com/uk-news/2019/jul/30/police-chief-reverse-cuts-repair- social-fabric-stop-gangs-england

Eck, J. E., Clarke, R. V., & Guerette, R. T. (2007). Risky facilities: Crime concentration in homogenous sets of establishments and facilities. *Crime Prevention Studies, 21*, 225–264.

Eck, J., Chainey, S., Cameron, J. C., Leitner, M., & Wilson, R. E. (2005). *Mapping crime: Understanding hotspots.* Washington, DC: National Institute of Justice.

Etheridge, P. J. (2015). An exploratory study of the application of the cambridge harm index (CHI) to crime data in South yorkshire. Master thesis. University of Cambridge.

Felson, M. and Eckert, M.A., 2017. *Introductory criminology: The study of risky situations*. Routledge.

Gill, C., Wooditch, A. and Weisburd, D., 2017. Testing the "law of crime concentration at place" in a suburban setting: Implications for research and practice. Journal of quantitative criminology, 33(3), pp.519-545.

Greenfield, V.A. and Paoli, L., 2013. A framework to assess the harms of crimes. *British journal of criminology, 53*(5), pp.864-885.

Her Majesty's Inspectorate of Constabulary and Fire and Rescue Services (HMICFRS). (2014). The Crime Tree [online]. London: HMICFRS. [Viewed 18th September 2023]. Available from: https://www.justiceinspectorates.gov.uk/hmicfrs/media/crime-tree.pdf

Higgins, A. 2017 Perspectives on policing, Mixed signals for police improvement: The value of your Crime Severity Score may go up as well as down. *The Police Foundation* [Online]http://www.police-foundation.org.uk/2017/wp-content/uploads/2017/08/perspectives_on_policing_paper_1.pdf

Hipp, J.R. and Williams, S.A., 2020. Advances in spatial criminology: The spatial scale of crime. *Annual Review of Criminology, 3*, pp.75-95.

House, P. D., & Neyroud, P. W. (2018). Developing a crime harm index for Western Australia: The WACHI. *Cambridge Journal of Evidence Based Policing, 2*, 70–94.

Ignatans, D. and Pease, K., 2015. Taking crime seriously: playing the weighting game. *Policing: A Journal of Policy and Practice*, *10*(3), pp.184-193.

Johnson, S.D., Davies, T., Murray, A., Ditta, P., Belur, J. and Bowers, K., 2017. Evaluation of operation swordfish: a near-repeat target-hardening strategy. *Journal of experimental criminology*, *13*, pp.505-525.

Kelling, G.L., Pate, T., Dieckman, D. and Brown, C., 1974. *The Kansas City Preventive Patrol Experiment: A Tecnical Report*. Washington, DC: Police Foundation.

Koper, C.S., 2014. Assessing the practice of hot spots policing: survey results from a national convenience sample of local police agencies. *Journal of Contemporary Criminal Justice*, *30*(2), pp.123-146.

Leigh, J., Jackson, L. and Dunnett, S., 2016, February. Police officer dynamic positioning for incident response and community presence. In *Proceedings of the 5th International Conference on Operations Research and Enterprise Systems (ICORES 2016)* (pp. 261-270).

Macbeth, E., & Ariel, B. (2019). Place-based statistical versus clinical predictions of crime hot spots and harm locations in Northern Ireland. Justice Quarterly, 36(1), 93–126. https://doi.org/10.1080/07418825.2017.1360379

Mann, N., Devendran, P. and Lundrigan, S., 2018. Policing in a Time of Austerity: Understanding the Public Protection Paradox through Qualitative Interviews with Police Monitoring Officers. Policing: A Journal of Policy and Practice.

Norton, S., Ariel, B., Weinborn, C. and O'Dwyer, E., 2018. Spatiotemporal patterns and distributions of harm within street segments: the story of the "harmspot". Policing: An International Journal, 41(3), pp.352-371.

Office for National Statistics, 2023. *How life has changed in Rotherham: Census 2021* [Online].[Accessed 01 September 2023] Available at: https://www.ons.gov.uk/visualisations/censusareachanges/E08000018/

Okabe, A. and Satoh, T., 2009. Spatial analysis on a network. *The SAGE handbook on spatial analysis*, pp.443-464.

Openshaw, S., 1984. The modifiable areal unit problem. *Concepts and techniques in modern geography*.

Ordnance Survey GB. 2023. *OS Open Roads – Overview*. [Online].[Accessed 01 September 2023] Available at: https://www.ordnancesurvey.co.uk/documents/product-support/user-guide/os-open-roads-overview.pdf

Ratcliffe, J. H. (2015). 'Towards an Index for Harm-Focused Policing.' Policing 9(2): 164–183.

Samanta, S., Sen, G. and Ghosh, S.K., 2022. A literature review on police patrolling problems. *Annals of Operations Research*, *316*(2), pp.1063-1106.

Sellin, T. and Wolfgang, M. (1964). The Measurement of Delinquency. Oxford: Wiley

Sentencing Council, 2017. *Reduction in Sentence for a Guilty plea Definitive Guideline* [Online].[Accessed 15/12/2019] available from:https://www.sentencingcouncil.org.uk/wp-content/uploads/Reduction-in-Sentence-for-Guilty-Plea-definitive-guideline-SC-Web.pdf

Sentencing Council. 2023. *Rape of a child under 13* [Online].[Accessed 01 September 2023] Available at: https://www.sentencingcouncil.org.uk/offences/crown-court/item/rape-of-a-child-under-13/

Sherman, L. W., Gartin, P. R., & Buerger, M. E. (1989). Hot spots of predatory Crime: Routine activities and the criminology of place. Criminology, 27(1), 27e56.

Sherman, L. W., Neyroud, P. W., & Neyroud, E. C. (2016). The Cambridge crime harm Index: Measuring total harm from crime based on sentencing guidelines. Policing, 1e13.

Sherman, L., & Rogan, D. (1995). Effects of gun seizures on gun violence: "Hot spots" patrol in Kansas city. *Justice Quarterly*, *12*, 673–694.

Sherman, L., & Weisburd, D. (1995). General deterrent effects of police patrol in crime hot spots: A randomized controlled trial. *Justice Quarterly*, *12*, 625–648.

Sherman, L.W. and Cambridge University associates, 2020. How to count crime: the Cambridge harm index consensus. *Cambridge Journal of Evidence-Based Policing*, *4*, pp.1-14.

Sherman, L.W. and Eck, J.E., 2003. Policing for crime prevention. In *Evidence-based crime prevention* (pp. 295-329). Routledge.

Sherman, L.W. and Weisburd, D., 1995. General deterrent effects of police patrol in crime “hot spots”: A randomized, controlled trial. *Justice quarterly*, *12*(4), pp.625-648.

Sherman, L.W., 2007. The power few: Experimental criminology and the reduction of harm: The 2006 Joan McCord Prize Lecture. *Journal of experimental criminology*, *3*, pp.299-321.

Sherman, L.W., Gartin, P.R. and Buerger, M.E., 1989. Hot spots of predatory crime: Routine activities and the criminology of place. *Criminology*, *27*(1), pp.27-56.

Stripe, N., 2022. *Crime Severity Score (Experimental Statistics)* [Online].[Accessed 01 September 2023] Available at: https://www.ons.gov.uk/peoplepopulationandcommunity/crimeandjustice/datasets/crimeseverityscoreexperimentalstatistics

Sutherland, J. and Mueller-Johnson, K., 2019. Evidence vs. Professional Judgment in Ranking “Power Few” Crime Targets: A Comparative Analysis. Cambridge Journal of Evidence-Based Policing, 3(1-2), pp.54-72.

Wain, N., Ariel, B. and Tankebe, J., 2017. The collateral consequences of GPS-LED supervision in hot spots policing. Police Practice and Research, 18(4), pp.376-390.

Weinborn, C., Ariel, B., Sherman, L. W., & O'Dwyer, E. (2017). Hotspots vs. harmspots: Shifting focus from counts to harm in the criminology of place. *Applied Geography, 86*, 226–244.

Weisburd, D. (2015). The law of crime concentration and the criminology of place. *Criminology*, *53*(2), 133–157.

Weisburd, D. and Eck, J.E., 2004. What can police do to reduce crime, disorder, and fear? *The annals of the American academy of political and social science*, *593*(1), pp.42-65.

Weisburd, D. L., & Mazserolle, L. (2000). Crime and disorder in drug hot Spots: Implications for theory and practice in policing. Police Quarterly, 3(3), 331e349.

Weisburd, D. L., Bushway, S. D., Lum, C., & Yang, S.-M. (2004). Trajectories of crime at places: A longitudinal study of street segments in the city of Seattle. Criminology, 42(2), 283e321.

Weisburd, D., Petersen, K., Telep, C.W. and Fay, S.A., 2024. Can increasing preventive patrol in large geographic areas reduce crime?: A systematic review and meta-analysis. Criminology & Public Policy.

Weisburd, D., Wilson, D.B., Petersen, K. and Telep, C.W., 2023. Does police patrol in large areas prevent crime? Revisiting the Kansas City Preventive Patrol Experiment. Criminology & Public Policy, 22(3), pp.543-560.

Wise, S.C. and Cheng, T., 2016. How officers create guardianship: An agent-based model of policing. *Transactions in GIS*, *20*(5), pp.790-806.

Wooditch, A., 2021. The benefits of patrol officers using unallocated time for everyday crime prevention. *Journal of quantitative criminology*, pp.1-25.

Wyant, B.R., 2008. Multilevel impacts of perceived incivilities and perceptions of crime risk on fear of crime: Isolating endogenous impacts. *Journal of research in crime and delinquency*, *45*(1), pp.39-64.

Chapter 4. Home is where the harm is.

A comparative study of crime harm and volume occurring in outside locations and residential properties at street segment level.

4.1 Introduction

As discussed in Chapter 1, it is now considered an axiom that crime is spatially concentrated (see Lee et al, 2017). However, this understanding is based on studies of calls to service or counts of police reported crimes. Within the field of spatial criminology there has been a recent move away from solely examining crime volume and to acknowledge that “all crimes are not created equal” by incorporating a harm or severity measure to spatial analysis (Sherman et al, 2016, p.1).

The contribution of this chapter is to use operationalised elements of crime pattern theory to expand on the both the crime harm and spatial criminology literature. It will do this by not only comparing the influence of environmental elements on victim based crime volume and harm but by additionally sub-setting or partitioning these datasets by broad location. To date it is understood this is the first work to do so. This will allow the investigation of both overt crime (crime taking place in a public setting) and covert crime not easily witnessed taking place in private[1] (Felson and Eckert, 2017). This provides additional insights to the analysis beyond simply the addition of crime harm. These insights will be actionable by police forces, providing greater understanding of outside areas that require visible targeted police presence and those residential street segments that would benefit from neighbourhood problem oriented policing input.

Using data provided by West Midlands Police (WMP) for the city of Coventry and employing descriptive location information this work is able to analyse crimes subset by their broad location. This work will be theoretically underpinned by situational and environmental crime theories. Interest in the role of situational crime theory on both crime volume and crime harm coupled with the ability to partition crime data by broad location has led to the following research question:

[1] For the purposes of this chapter and chapter 5, overt crime refers to crime taking place outside, and covert crime refers to crime taking place in a residential setting.

Q2: To what extent are operationalised elements of pattern crime theory associated with crime volume and crime harm at street segment level?

Q2a: Does that association change when crime volume and harm are subset by broad location?

Negative binomial regressions are used to address these questions to test the influence of operationalised elements of crime opportunity theory on both crime volume and harm overall and subdivided by outside (overt) and residential (covert) location.

This chapter is set out as follows. First the current literature on crime concentration and the formation and use of crime harm indices will be overviewed. The literature relating to crime pattern theory will then be examined followed by an overview of negative binominal regression. The methods and variable creation will then be discussed. The chapter concludes with an overview of the results and discussion for future work, as well as the wider implications for policy and policing.

4.2 Literature review

This section will outline literature relating to crime concentration and the policing of these 'hot spot' areas. It will then discuss the methods used to add a severity weight to criminal offences and also the emerging literature on 'harm spots'.

4.2.1 Crime volume concentration

There is considerable evidence from criminological research that shows that crime is spatially concentrated (Sherman et al, 1989, Weisburd, 2015). It is also stable over time (Groff et al, 2010, Weisburd et al, 2004). The law of crime concentration was set out by Weisburd (2015) who stated that when examined at a micro spatial scale cumulative proportions of crime will occur in a small percentage of locations.

When considering the results from studies from both large and small cities, Weisburd (2015) noted similar levels of concentration and calculated the following ranges, or as he labelled them, bandwidths, that the level of concentration would fall between. "For 50 percent concentration, that bandwidth is about 4 percent (from 2.1 to 6 percent), and for 25 percent concentration, that bandwidth is less than 1.5 percent (from .4 to 1.6 percent)" (p. 143). Micro geographic units such as intersections, street blocks and segments and groups of addresses are noted to be the preferred spatial scale used in this concentration analysis (Hipp and Williams, 2020).

The term ‘criminology of place’ was coined to describe examination of crime at this micro scale by Sherman et al, (1989). In their work Sherman et al (1989) found that 3.3% of places (addresses) in Minneapolis accounted for just over half of all calls for service with predatory crimes being more concentrated still (calls regarding rape came from just 1.2% of locations). This was one of the first analyses that identified crime concentration (falling within the 50% bandwidth) which has been seen in numerous studies since (see Lee et al, 2017). The use of micro-locations allows for intra-neighbourhood variations in the occurrence of crime to be visible which could otherwise be lost when viewed at the neighbourhood level (Groff et al, 2010). To paraphrase Sherman et al (1989, p 43), dangerous neighbourhoods are mainly safe.

These areas of concentrated crime have been dubbed hot spots with a single hot spot understood to be “an area that has a greater than average number of criminal or disorder events, or an area where people have a higher than average risk of victimization” (Eck et al, 2005, p.2). Understanding that crime has a non-random and non-uniform distribution has allowed police to focus their attention and limited resources on these high volume areas (Harinan et al, 2022).

4.2.2 Crime volume concentration - hot spots

These areas where crime concentrates are often referred to as hot spots, which is a widely used term without a single agreed upon definition. It is understood to refer to a relative difference between an area of high crime where people have a higher-than-average risk of victimisation, compared to those neighbouring it (Eck et al, 2005, p.2). The lack of a set of clear requirements gives researchers considerable scope to define and create hot spots. It allows them to be created based on varying criteria. Researchers and police forces can set benchmarks for specific research or crime targeting. Hot spots can be varied by size (place, street, neighbourhood) and can also be generated to contain specified crime types (Eck et al, 2005, Chainey 2021).

The micro-scale concentration and stability of crime over time have implications for policing as these hot spot areas can become the focus of targeted policing. This is nothing new; police officers get to know their beat areas well and will be familiar with the high crime locations within them and before the routine availability of GPS, crime mapping software and GIS it was a well-established practice to place officers in those high crime spaces in order to deter criminal activity (Braga et al, 2019). As crime analysis methods became more commonplace Chainey (2021) notes that practitioner judgement has been paired with spatial analysis to generate the areas to be targeted with hot spot policing.

The notion behind hot spot policing is that a targeted police presence will result in a reduction in crime (Braga et al, 2019). Numerous studies with differing methodologies have shown this to be the case (see meta-analysis - Braga et al, 2019) and the UK's College of Policing include hot spot policing, "A strategy that targets police and partner resources and activities to those places where crime is most concentrated" it in their crime reduction toolkit and consider it to have a very strong impact on crime (College of Policing, 2021).

The identification of crime concentration was initially based on calls for service and or crime volume data, where each call, crime or incidence is logged, and the resulting crime-dense areas identified. The current update of the ongoing meta-analysis into the effectiveness of hot spot policing lists the studies included in the review (Braga et al, 2019). It also identifies the parameters of each work. Areas identified for targeted policing could be based on calls for service where the complete dataset is used to identify areas of concentration, or they can be generated for a subset of specific crimes. This can also be applied to police data.

What is apparent is that the location of the crime is often secondary to crime type in the creation of the hot spot. Only a small number expressly noted a location separate to offence type. In the wake of the 1994 terrorist attack on the main Jewish centre in Argentina all Jewish centres were given 24 hour police attendance. Di Tella and Schargrodsky (2004) assessed the impact of this on the amount of on street car theft. Ariel and Partridge (2017) examined the targeting of bus stops for hot spot policing. Some hot spots could only be generated in a broad location by virtue of the manner of the targeted intervention. The use of CCTV for example (Piza et al, 2015; Marklund and Holmberg, 2015; Gerell, 2016) means the locations will be publicly accessible.

Other studies chose crime types that can only occur in certain locations. Braga et al (2011) and Ratcliffe and Breen (2011) used violent street crimes to identify areas for foot patrols with Marklund and Merenius (2014) using public assault in their generation of hot spots. Williams (2015) used a combination of street crime and calls for service for anti-social behaviour. Fielding and Jones (2012) assessed the effect of guardianship on repeat residential burglary. What is missing from the work on hot spot generation is an appreciation that some crimes can only occur in specific locations (residential burglary for example) while some can occur in multiple locations (violent assault can occur anywhere). The targeting of outside spaces for increased policing should be based on all the crimes that have occurred outside. Similarly, being aware of areas of high amount of crime within and around residential properties could benefit neighbourhood policing teams.

However, even if crime was subset by broad location the resulting concentrations would be based on the volume of crimes in these areas. More recently there has been a move to include the severity of the crime, its impact or harm, within concentration studies.

4.2.3 Crime harm concentration – harm spots

Several researchers have created differing methods to weight crimes by their relative harm or cost. Early proponents Sellin and Wolfgang (1964) surveyed public opinion on crime seriousness, while Greenfield and Paoli (2013) created a harm assessment framework based on scales of crime severity and incidence.

More recently using sentencing guidelines and / or actual sentences has emerged as the frontrunner in techniques to create harm based indices. The Cambridge Crime Harm Index (CCHI) was created using UK sentencing guidelines with a number of researchers adapting it for use with their own country's sentencing framework (see Curtis-Ham and Walton, 2017, House, 2017, Andersen and Mueller-Johnson, 2018, Mitchell, 2019, Fenimore, 2019, 2020, Kärrholm et al, 2020).

Much of the literature to date has detailed the methodological choices behind the creation of harm indexes in countries with differing sentencing frameworks. A very small amount of research has utilised those measures in detailing the spatial distribution and concentration of harm (Chapter 3, Norton et al, 2018, Fenimore, 2020, Weinborn, 2017). Early indications suggest that harm is more concentrated than crime volume (Weinborn, 2017, Macbeth, 2015) and harm offers an additional "defined measure of crime" by which to assess the distribution and concentration of crime and the identification of areas for focused policing (Weisburd, 2015, p 133). This study will add to the limited research focusing on both crime volume and harm at street segment level by analysing police data for the city of Coventry in the UK.

When crime figures are produced that use the volume of crime; the count of individual crimes, it suggests that the reader should consider those crimes to have parity. However, as the often quoted Sherman et al (2016) state "All crimes are not created equal" (p1). As Curtis-Ham

(2022) elaborates, crime figures that contain counts ignore any relative differences between crime types. Including different crime types (such as murder and mugging) within the same total crime figures hides the different levels of harm that differing crimes can cause. An increasingly used solution has been the development of crime severity indices which look to assign a value of harm to different crimes in order to weight them in further analysis (ibid).

Harm is a fundamental element of criminal law theory, “the harm 'caused' by a criminal activity is considered crucial to justify the very criminalization of such activity” (Paoli and Greenfield, 2018, p, 865) and to the creation of penalties that are then handed down (ibid). A weighted index is therefore a more useful approach, and the task then becomes one of operationalising the concept of harm and developing a score.

Using sentencing guidelines (or creating them) or using past sentences handed down in previous years has become a more commonly used way to develop harm weights to apply to specific crimes. The Danish crime harm index compiled by Andersen and Mueller-Johnson, 2018 required consultation with prosecutors to develop their harm index as sentencing guidelines were not available. Guidelines also needed to be created by Kärrholm et al (2020) in their development of the Swedish crime index. Curtis-Ham and Walton (2017) use the average time served by offenders for specific crimes in the NZ crime harm index. This is also the approach used by the ONS in their crime severity score. By contrast the California crime harm index uses maximum sentencing recommendations (Mitchel, 2019).

The Cambridge Crime Harm Index is a relative measure, comparing crimes based on their minimum sentence. In the UK, the Sentencing Council sets out a starting point tariff for a number of offences. These also includes conditions that would move the sentence from the baseline tariff to the next rung of severity. This can be seen in the guidelines given for a sexual offence where the baseline sentence is given for an adult victim and the starting point sentencing increases as the age band of the victim decreases. If the baseline tariff is custodial the sentence length is converted from the years and months given by the council to the number of days. Should the tariff be a community order the number of days is recorded and where a financial penalty is listed the number of days it requires to pay the fine working at minimum wage is used as a proxy (Sherman et al, 2016). The CCHI score is therefore the baseline sentence given in number of days (either the custodial days or the necessary workdays) for each offence.

Sherman et al (2016) stipulate that for a harm index to be useful it should succeed when measured against three key indicators. Firstly, it should be based on crime and punishment measures agreed upon by a democratic government which reflect the views of the populace. This will allow it to be seen as democratic and be more likely to be accepted by law enforcement and the wider population. Secondly, it also needs to be cost-effective in an age of limited budgets. Lastly, it needs to give the same levels of harm reliably and consistently over differing times, places and people. This is a critique of crime indices that base their harm score on previous sentencing as they will differ in the future.

This is the main criticism of the Crime Severity Score devised by the ONS (Stripe, 2023). They use average sentencing for the preceding five years (10 for crimes with small numbers of offenders). By doing so the CSS score is based in part on the criminal history of the offenders who were sentenced. Offenders with a previous criminal record receive harsher sentences which in turn influences the sentence they receive. The CSS is therefore not solely reflective of the harm caused by an offence.

The CCHI can be applied to all crimes where a sentence can be passed down. In later work, Sherman et al (2020) refined the methodology for use of the CCHI and suggested that the crime harm index be used for victim based crimes. Crimes that are detected by the police or staff employed to reduce shoplifting can be assessed using a Proactive Policing Index and a Company-Detected Crime Harm Index respectively. The suggestion was that the offences included in these indicators are not crimes that give a measure of public safety but rather an indication of policing focus and company resources.

Once a harm index is in use it is possible to compare concentrations of harm with those derived from counts of crime volume. Weinborn et al (2017) has developed a 5-point classification that utilises both volume and harm to identify the areas most in need of focused intervention. These can then be considered when patrol routes and targeted interventions are developed (Chapter 3). Weinborn et al (2017) also found harm to be more concentrated than volume with 50% of crime harm occurring on 1% of street segments compared to the same proportion of volume occurring on 3% of segments in their study of Birmingham, UK.

Norton et al (2018) did not state the concentration of the harm in their study using police data from Sussex, UK but did note that harm is more concentrated in the evening and on the weekends and is closely tied to the nighttime economy, more so than counts of unweighted crime. They note the policy implications of this in terms of hot spot policing that may not take into account time of day or day of week when allocating an area for patrol (ibid).

In work based in the United States Fenimore (2020) examined over her thesis if analysis conducted into crime harm thus far was generalisable. Her initial analysis, using a crime harm index based on the CCHI but using sentencing guidelines for the US found similarly to Norton et al (2018) that unweighted crime volume and harm have differing distributions. She identified harm spots located away from the city centre in more residential areas and hypothesised that residential areas could contain the requisite criminal opportunities for serious high harm crimes.

Her final analysis examined the environmental context of high harm street segments and used facilities noted within crime pattern theory to be crime attractors and generators (Fenimore, 2020). Despite noting the diffusion of harm into residential areas Fenimore did not include any crime data that indicated family or domestic violence. As she notes this is an area in the emerging crime harm literature that needs to be explored. This chapter will explore the association of operationalised elements of crime pattern theory on both unweighted volume and harm at outside locations as well as within and around the home.

4.2.4 Opportunity Crime Theories

Opportunity crime theories, and what has become known as environmental criminology (Brantingham and Brantingham, 1981) focus on the role of the environment or place in producing opportunities for criminal activity and inciting criminal behaviour, rather than the characteristics of the offender (Johnson, 2010).

Cohen and Felson’s (1979) Routine Activity Theory (RAT) proposed that in order for a crime to be committed there needed to be a convergence in time and place of a suitable target (be it person, object or property), a person willing to commit crime and a lack of a ‘capable guardian’. Within RAT motivation on the part of the offender is assumed and not examined, nor will it be examined in this work.

Their theory is clear and simple to understand. The routine activities of everyday life allow the convergence of these three elements at predictable points: houses left empty during the working day, people mixing and relaxing after work and on weekends, for example. What is less clear and presents a challenge is the operationalising of the elements within the equation (Hipp and

Williams, 2020). A person could become a suitable target in one situation but prevent a crime by being a capable guardian in another. These elements were not specified or qualified which makes testing the theory difficult (ibid).

Guardians, for example, do not have to be members of law enforcement; they could be members of the public or things in the environment that dissuade criminal activity (e.g., street lighting, CCTV) (Johnson, 2010). The definition of guardian has developed since the publication of the initial theory with different subsets of guardians being put forward by researchers. However, Felson and Boba (2010) stated that the definition of guardian is "someone whose mere presence serves as a gentle reminder that someone is looking" (p, 28) and they need not be aware that they are preventing criminal activity.

RAT is often combined with rational choice theory, which, originating from economics assumes that people are rational decision makers who chose to commit crime based on a cost benefit analysis of the situation (Gul, 2009). Crime could take place if the situational opportunity has a net benefit.

These situational opportunities take place in our physical and social environments, in which we all complete our routine activities. The rational actor takes stock of this and bases their criminal decision making on it (Clarke and Cornish, 1985). These physical and social environments, the places that we visit during our days and weeks (nodes) and the routes we take to them (paths), are described by Brantingham and Brantingham (1981) as our 'environmental backcloth'. It is on this backcloth (which also comprises political and economic elements) that we play out our roles and activities (both legal and criminal). Our movements, be they as an offender, victim or member of law enforcement, that take place on our environmental backcloth, are described as the 'geometry of crime' (ibid).

It is this combination of rational actors undertaking their routine activities on an environmental backcloth that comprises crime pattern theory (a meta-theory combining the preceding three) within environmental criminology (Brantingham and Brantingham, 1984, 1995). As a result of these movements Brantingham and Brantingham (1995) identified crime generators and crime attractors as two distinct types of areas within the urban landscape. These places would allow potential offenders and potential victims to interact with crime a possible result.

Crime generators are said to be areas that attract large numbers of people for reasons unrelated to crime such as shopping centres or areas of offices. As these gatherings of people happen at predictable times they offer opportunities for criminal activity in people who did not go there with the express intention to commit crime (Brantingham and Brantingham, 1995).

In comparison, crime attractors, create criminal opportunities and as a result attract highly motivated "intending offenders" (Brantingham and Brantingham, 1995, p, 8). These areas include but are not limited to areas of pubs and clubs, retail areas, cashpoints – areas that are well known to create criminal opportunities (ibid). Eck et al (2007) have dubbed these places that see repeated criminal activity as risky facilities. Risky places terrain mapping can be achieved by identifying areas of repeated types of crime and scoring them and the surrounding areas on the risk posed (Kennedy and Caplan, 2012).

These theories all indicate place as an important component in offending. While undertaking their noncriminal routine activities travelling through their backcloth the rational offender will be aware of places with potential targets and without sufficient guardians. It is these places that will experience increased rates of offending (Eck and Weisburd, 2015).

As mentioned, the analysis of crime at the micro-scale of the street segment is the preferred scale by which to examine crime concentration and criminology of place (Hipp and Williams, 2020; Sherman et al, 1989). Weisburd et al, (2012) have sought to integrate elements of social disorganisation theory, more usually linked to the meso-scale areal unit of neighbourhood, to work at the micro level. They note that opportunity theories often ignore that micro-places have an underlying social context that may have a bearing on crime as their focus is on the environment in which the crime is occurring. While the focus of this analysis is on investigating operationalised elements of crime pattern theory underlying social context will also be acknowledged.

4.3 Current Study

4.3.1 Analytic strategy

This paper is concerned with both the volume of crime and the summed harm arising from those crimes, per path or street segment, and whether elements in the environment have a differing association with these two measures of police reported crime. In addition to descriptive statistics and measures of crime and harm concentration this chapter employs negative binomial regression to test the influence of elements of crime pattern theory on both crime count and crime harm and subsets of both. As the links between crime volume, crime harm potential explanatory contextual variables are currently unexplored both theoretically and empirically it is difficult to anticipate the strength and direction of relationships that will be uncovered when the data is analysed. However, given that previous research indicates that harm is more concentrated than unweighted crime volume it is expected that some differences will be noted. It is possible that crime generators and attractors will have a greater influence on outside crime and harm than on crime occurring in and round the home.

Operationalising elements of crime pattern theory is informed by past research, however, to date, only two studies have incorporated harm in their analysis and just one examined the environmental context of harm at street segment level. Fenimore (2020) used a US generated harm index and assessed the impact of a number of crime attractors and generators such as financial institutions, alcohol establishments and retail facilities at street segment level. However, her work excluded family or domestic violence from the offences contained in her analysis. She found that all facilities bar law enforcement agencies were significant risk factors for the presence of a high harm spot on a street segment. In their supplementary analysis Norton et al (2018) found harm spots located near areas with facilities related to the night-time economy such as pubs, nightclubs; areas where people congregate in the evening.

Past research examining crime attractors and generators have used unweighted crime volume. The analyses have either examined specific risky facilities and/or focused on specific crime types. The relationship between robbery and various facilities (retail, elements of the nighttime economy, bus stops) has been examined extensively (Barnum et al, 2017, Bernasco and Block, 2011, Ejiogu, 2020, Hart and Miethe, 2014, Summers and Caballero, 2017, Wüllenweber and Burrell, 2023).

In addition to robbery, considerable research has focused on the impact of the alcohol retail environment on violent crime in particular. Mair et al (2022) reviewed a large body of work in this area and found studies indicating that alcohol availability is linked to the rate of interpersonal violence. A more expansive examination was conducted by Groff and Lockwood (2014). They investigated bars, drug treatment centres, subway stops, halfway houses and non-elementary schools and examined the impact of those on violent offenses, property offenses (excluding arson) and disorder offenses at different distances.

Besides crime attractors and generators, this analysis will also examine the impact of guardian features. Streetlights have long been found to be associated with a reduction of crime (see Welsh et al, 2022; cf. Tompson et al, 2022). Non-crime domestic incidents (NCDI) taking place in a residential setting will also be examined. NCDI refers to incidents where the police are called to a disturbance involving members of a family or household. If no criminal charges are brought the incident is reported as a non-crime and domestic. This variable is used as a proxy for motivated offenders within RAT as Dowling et al (2021) outline that most domestic offenders appear to be "criminally versatile" (p, 3).

This research utilises many different datasets and the preparation of each is described in the following section. Data sources used include open-source products from Office for National Statistic (ONS), open and licenced products from the Ordnance Survey (OS), data requested directly from Coventry City Council, and restricted access crime data from WMP.

4.3.2 Study setting

WMP granted access to the data used in this study and required a data-sharing and ethical agreement. Coventry was chosen from the ten policing areas that make up WMP. This was primarily due to Coventry being almost entirely enclosed by the West Midlands Green Belt which reduces the impact of edge effects (Rengert and Lockwood, 2009, Salafranca Barreda et al, 2022). Braga et al (2019) found the majority of hot spot studies (41.5%) are conducted in medium sized cities with populations ranging from 200,000 to 500,000 people. Coventry falls into this category with a population of around 345,300 in 2021 allowing findings to be comparable with other studies (ONS, 2023)

Coventry is a growing and relatively young city (median age 35, UK 40) (Coventry City Council, 2021). The proportion of Coventry neighbourhoods in the 10% most deprived in England reduced by 4.1% between 2015 -19 and in 2019 the city ranked 64th most deprived local authority. Coventry has two universities within its border and the 2021 census reports 40% of adults have a higher level qualification suggestive of graduate retention (ibid).

In terms of crime and policing Coventry is policed as 7 neighbourhood areas and has a lower crime rate than the average recorded for the West Midlands force area, 113.77 per 1000 compared to 127.77 per 1000 residents for the year ending September 2022 (all crime types) (WMP, unknown, Police.uk, 2023).

4.3.3 Crime data

The annual redacted datasets used in this study contain entries for offences committed from 1st January 2015 – 30th September 2019. Each offence is held under a unique crime number. Where multiple entries existed with the same crime number (separate entries for victim/offender) these were collapsed into a single row entry. The time and date of each offence were given as separate first and last entries. For crimes where the exact date and time of the offence were known these were the same entry, for others it allowed for a window of time to be recorded within which the offence was thought to have occurred. The date the crime was reported to, and recorded by West Midlands Police was also given. A single date variable was generated from the last date given and a day of the week variable created from that. Entries were removed if the date fell outside the timeframe of interest (historic crimes should be analysed within the year they were committed, Sherman et al, 2020). Entries were also removed where the recorded location of the crime was missing, incomplete or fell outside the West Midlands force boundary for Coventry.

Also in keeping with the methodology put forward from Sherman et al (2020) any offences categorised as solely Crimes Against the State were removed. These are crimes that typically require active policing to detect, such as drug offences. The Notifiable Offence list 2020 was used to identify those offences categorised as Victim Based or dually as Victim based and Crimes Against the State. A key word search was also completed to filter out victim based offences that involved police officers, proactive prevention and any non-crime incidents (resist, constable, police, non-crime, shop). These crimes would make up the Proactive Policing Index and Company-Detected Crime Harm Index (ibid). A data cleaning workflow outlines the data cleaning process (Appendix 3).

4.3.4 Location descriptor

Crime scene location information is collected by officers at the reporting of incidents and descriptors are chosen from a prepopulated alphabetical drop-down list of 143 options. The primary location information was used to create two binary location variables detailing whether the crime occurred inside or outside or in a residential or non-residential setting (Appendix 2). The location information was categorised based on the most likely understanding of the descriptor. For example, ‘Office’ was classified as inside and non-residential while ‘Road’ was classified as outside and non-residential. There are also non-location options; ‘NA’, ‘Other’, ‘Void’ and ‘Spare’ and crimes with these location descriptors were removed from the dataset.

In correspondence with WMP about this variable, human input error was discussed as a possible reason for errors within this data. ‘Abattoir’ is the first location in the alphabetised list, and it appears 26 as the primary location despite these facilities being relatively few in number across the Coventry area. These are very broad classifications and there is an appreciation that some may not fully capture the specific location of the crime.

4.3.5 CCHI – formation

Within the CCHI each crime is given a harm value, however, not every crime that is counted by police forces for the purposes of monthly Home Office reporting can result in a conviction of the same name. It will therefore not have a sentencing guideline tariff. When this occurs, it is possible to adapt crime harm scores of similar offences[2]. Offenders can also be caught during the commission of an offence leading to an attempted charge. In Chapter 3 attempted offences were given a reduced CCHI score however within a Q&A with the Cambridge Centre for Evidence-Based Policing (unknown) it was advised to leave the harm score complete.

4.3.6 Data joins and buffers

Two approaches were used when analysing the two crime files subset from the main dataset. As this analysis is interested in examining crime volume and harm at the micro-scale, street segments were used as the unit of investigation. Two products, OS Master Map Roads and Paths were used and cropped to the boundary of the Coventry neighbourhood policing area. This process generates an additional variable that gives the new length of each segment; this is useful for those segments truncated when cropped.

[2] The following example highlights this. The crime of ‘rape by multiple offenders’ describes a situation where a victim has reported being raped by more than one offender but is unable to distinguish between them. This incident is entered into the policing system under the Home Office code 19/23 (adult women) or 19/25 (adult man) for the purposes of reporting monthly crime volume (additional codes exist for other age groups). If or when the victim is able, or, if evidence distinguishes between the perpetrators, separate crime references will be generated for the individual offenders and the offences they have committed. The initial offence code will be replaced with separate entries detailing the crimes of the individual offenders which will have their own CCHI score. For the purposes of this work, the crime of rape by multiple offenders is given the CCHI score of 2x rape score as recognition that more than a single rape by one offender occurred.

The small section of motorway was removed as this road type is subject to different rules on its use (no stopping) it also contains no housing, offices, shops, or transport points along its length. For analysis of the complete crime dataset and crimes occurring outside the combined roads and paths information was used, for the residential crime subset only the roads product was used.

As in chapter 3, to avoid the possibility of duplicate crimes being generated the street (and path), segments were spatially joined to each crime point (line to point). This transferred information pertaining to each segment to each point. This process of linking road attributes (lines) to point data before rejoining was used for all point data. This process also creates an additional variable that gives the distance in meters of each point to the segment.

4.3.7 Independent variables

To assess the association of elements of situational crime theory on both crime volume and harm, additional georeferenced data is required. Variables relating to guardianship, motivated offenders, crime attractors, crime generators and risky facilities were created based on the research cited in 4.2.4 and 4.3.1.

Guardianship variables comprise of streetlights and Police and Fire station locations. Street light data was provided directly from Coventry City council. The roads and paths segment dataset was used for the initial join as councils illuminate both roads and paths. The paths and their lighting features were cropped from the residential analysis. Motorways and their lighting features were cropped from both analysis subsets. Police and Fire station points were taken from the OS Points of Interest product (POI). The motivated offender proxy variable was contained within the data provided by WMP. NCDI points were joined to the road segment dataset and those joined to non-residential street segments were removed.

Crime generators, attractors and other risky facilities were compiled from both the OS POI and AddressBase products. Transport points collated from the POI product (bus stops, bus and train stations) were joined to the road segment dataset. Crime generators from the POI include commons and playgrounds, hospitals, accident and emergency hospitals, broad age range and secondary state schools, further education establishments, libraries, halls and community centres. Broader retail and office address points were sourced from OS AddresBase. Crime attractors (POI) include fast food and takeaway outlets, fish and chip shops, pubs, bars and inns, nightclubs, alcoholic drinks including off-licences and wholesalers, cash machines, pawnbrokers, bookmakers and casinos.

Within Arcpro buffers of 200m and 400m were created for each street/path segment. A sum of the crime generator and attractor points intersecting each buffer was recorded. These buffer distances were based the quarter mile area around street segments used in Weisburd et al (2012). As in Weisburd et al (2012) this allows the impact of a facility to be felt further than solely on the street segment on which it is located. As the buffers extend beyond the Coventry boundary facilities located outside the policing area were included.

Domains of deprivation were included to control for the underlying social context of the study area. These were taken from the 2019 release of the ONS Index of Deprivation (1 indicating the most deprived, 10 the least). The LSOA decile value of each deprivation domain was then attached to the road or path segments that ran through it using spatial join in ArcPro. The join function 'most' was used to account for segments that run across LSOA boundaries of differing values. Where this occurred, the segment was given the value of the LSOA the majority of the segment intersected with. After analysing the domain measures for correlation, the four included are described below.

The proportion of the population experiencing deprivation due to low income, either through being out-of-work or through jobs with low wages is given in the Income Deprivation domain (Gov.UK, 2019). The health deprivation and disability domain measures premature mortality, disability and morbidity but not any predictive aspects of future health deprivation such as physical environment or behaviour. It is also a measure of the loss of quality of life due to poor mental and physical health as well as the risk of premature death (ibid).

The physical proximity to local services and access to housing is measured by the Barriers to Housing and Services decile which covers both geographical and wider barriers to these elements. The living environment deprivation domain is a measure of both indoor and outdoor local environment quality. Indoor relates to housing quality with outdoor being a measure of road traffic safety and air quality (Gov.UK, 2019).

The difficulty posed to the analysis of crime volume and harm concentrations is the scale at which these datasets have been constructed. Secondary data are more readily found at the LSOA level in the UK. Any street by street or within neighbourhood differences are lost. An additional issue to be aware of with neighbourhood level analysis is the modifiable areal unit problem (MAUP) where a change of boundaries can alter the patterns and relationships observed (Openshaw, 1984). It can also be argued that the LSOA boundaries do not correspond with the boundaries people living in the area would draw to represent their neighbourhoods (Weir, 2019).

4.3.8 Final data cleaning

The completed datasets at street segment level were reviewed before analysis. Residential crime points that were joined to streets without residential properties were cut from the dataset (279 by volume, 76,635 harm). It is impossible to know whether these were incorrectly classified as residential crimes or correctly classified residential crimes that were incorrectly linked to a non-residential street segment. Therefore, for the purposes of this analysis they have been removed from the dataset.

The St John’s Road street segment running between Coventry Central Police Station and Coventry Magistrates’ court was removed (with associated data) due to the number of crimes and harm (244 / 59,372) given the police station’s easting and northing location (irrespective of differing primary location description). Again, it is not possible to know if these crimes were incorrectly given the location details of the police station or if this was an intentional decision. Descriptive statistics used in the analysis are shown in Table 4.1.

	All roads and paths		Residential roads	
	Mean	**SD**	**Mean**	**SD**
Crime				
All Crime Volume per street segment	2.72	9.91		
All Harm per street segment	211.15	1055.95		
Outside Crime Volume per street segment	1.26	5.50		
Outside Harm per street segment	85.58	615.89		
Residential Crime Volume per residential street segment			2.46	5.52
Residential Crime Harm per residential street segment			241.48	917.21
Unit length				
Street and path length	50.98m	60.74		
Residential street length			66.25m	63.50
Variables				
Guardians				
Streetlights per street segment	0.87	1.59	1.36	1.73
Police and fire stations within 200m	0.02	0.15	0.02	0.13
Police and fire stations within 400m	0.07	0.27	0.06	0.25
Motivated Offenders				
NCDI per street segment	0.40	1.83	0.96	2.75
Crime Generators				
Retail / office properties per street segment	0.23	4.10	0.39	5.86
Retail / office properties within 200m	25.28	92.89	13.81	50.11
Crime generating facilities within 200m	2.37	5.11	1.97	3.94
Crime generating facilities within 400m	8.64	14.01	6.83	8.96
Crime Attractors				
Bus stops per street segment	0.04	0.26	0.08	0.35
Bus stops within 200m	3.36	2.99	3.34	2.43
Bus stops within 400m	11.62	6.70	11.32	5.35
Crime attractors within 200m	0.43	0.77	0.40	0.74
Crime attractors within 400m	1.58	1.59	1.46	1.50
Social Context				
Number of residences per street segment	6.01	30.95	14.57	46.90
Income Decile				
Health Decile				
Barriers to Housing Decile				
Living Decile				

Table 4.1: Descriptive statistics

4.3.9 Negative binominal regression

Crime volume and crime harm are both examples of count data, as while the value of crime and harm per segment can be an integer equal or greater than zero, it cannot be a negative or fractional or non-integer value (Hilbe, 2014). Count data is not usually normally distributed and as such linear regression, including ordinary least square models, are not appropriate. When these models are used incorrectly with count data it can lead to biased estimates where the size of the effect of the predictor variable is over or underestimated (Hu et al, 2011).

When the mean and variance are equal the count data is said to be 'equidispersed' and have a Poisson distribution. However, count data departs from a Poisson distribution when the variance is greater than the mean (over-dispersion) which can be due to an increased frequency of extreme values (Hu et al, 2011). It has already been established that crime is concentrated, with a small number of micro areas experiencing extremely high volumes of crime and crime harm. When data is overdispersed, *negative-binomial regression* is an alternative and more appropriate modelling option.

The origin and meaning of the zero values within the dataset vary and the literature labels them as either true or false zeros (Blasco-Moreno et al, 2019). False zeros occur due to reporting errors, a crime location can be incorrectly classified, or the spatial location incorrectly snapped to a nearer street, limitations that have been discussed above. Crime can also occur but not be reported, so the segment appears crime-free. False zeros should be minimised with accurate crime reporting and error checking (ibid).

True zero values can be differentiated as either structural or random zeros and result from the underlying nature of criminal activity and the environment. Structural zeros relate to restrictions found within the area under study. Within the residential crime data subset one example of structural zeros has been removed. Street segments without residential properties have been cut from the dataset as residential crime cannot occur on a street segment without residential properties. The remaining true zeros are random zeros; the residential street segment where a crime *could* potentially occur within a residential property, but has not (Blasco-Moreno et al, 2019). No such restrictions apply to the complete crime dataset or the outside crime subset.

It is also possible to add a denominator (referred to as an offset within r programming language) within models to adjust for counts of behaviour over differing time, distance or volumes. This allows that the dependent variable events be examined as being in an area or period of time independently of other events (Hilbe, 2014). The residential datasets have the number of residential properties on the street segment as the offset while the outside crime subset uses street path segment length (m).

In each residential model the number of residential properties per street segment was added to the model as an offset to account for the differing number of properties that can be found per street segment, such as high rise buildings containing many individual dwellings (e.g. student accommodation). The following interpretation will assume an understanding that the explanation holds the other values at a constant.

Collinearity was tested for after each regression. Despite the large data set (22,811 street segments) as facilities have been summed per buffer there is the potential for correlation between independent variables. To test for multicollinearity between explanatory variables the variance inflation factors (VIF) were calculated. If VIF scores are high, it is an indication of multicollinearity. In each model the retail and office buffer at 400m returned the highest score (over 5) and was removed from the model.

4.4 Results

4.4.1 Descriptive Results

There were 98,328 victim based crimes and a total CCHI score of 7,631,172 in Coventry within the study timeframe. Table 4.2 shows the breakdown by primary location of the final subset datasets. Within this analysis crimes taking place in an indoor, non-residential setting (such as pubs, offices etc) are not examined beyond being included within the analysis of the complete dataset.

Before details of concentration are reported it is interesting to examine the breakdown of crime volume and harm by broad location. Table 4.2 indicates that offences taking place in a residential setting experience a greater amount of harm than those with an outside location. Additionally, this higher harm is generated from 8,753 fewer crime incidents than occur outdoors. Home is where the harm is.

Location	Volume	Harm
All crime locations (post-cleaning)	98,328	7,631,172
Outside	45,436	3,093,075
Residential (cleaned)	36,683	3,598,056
Inside (non-residential)	16,209	940,041
Unknown location (cut from residential)	279	76635

Table 4.2: Crime volume and harm by location

4.4.2 Crime and harm concentration

Coventry is made up of 22,811 street segments (less motorway segments and St John's Road) with an additional 13,330 paths. Given that the street segments and paths are generated by changes in attribute rather than counting complete individual roads and pathways, a more useful way to discuss the road network is in metres and kilometres. The road network within the Coventry policing boundary is 1,349.89 km with 492.68 km of paths. Within the residential crime subset, of the 1,349.89 km of road segments 987.11 km are segments (n = 14,900) with at least one residential property.

Traditionally crime concentration is reported as the number or percentage of places / street segments where 50% of crime incidents or harm occur. This is a useful way to report these figures when they originate in the US or in countries with city blocks or more grid based layouts as they give rise to street segments of more uniform length. In this study, using OS road links of varying length, that output would not be as useful a metric. In addition to reporting the concentration this way the concentrations of volume and harm will also be given as a percentage of the complete road (and path) network. Table 4.3 reports the concentration at 25% and 50% of cumulative volume and harm by location.

As mentioned previously the bandwidths set out by Weisburd (2015) are as follows, "For 50 percent concentration, that bandwidth is about 4 percent (from 2.1 to 6 percent), and for 25 percent concentration, that bandwidth is less than 1.5 percent (from .4 to 1.6 percent)" (p. 143). Victim crime data for Coventry fall into to these bandwidths when examining the complete dataset and outside crimes using street segment percentages with crime harm being more concentrated than unweighted volume. Just under one percent of street segments host 25% of all unweighted victim based crimes, with 50% of cumulative crime volume found on just 3.74%. Crime harm is more concentrated with 25% of cumulative harm on 175 street segments (0.48%) and 50% on 1.71% which is lower than Weisburd's (2015) bandwidth starting point.

This pattern is repeated with outside crime with harm more concentrated than unweighted crime and falling outside of the bandwidths generated from studies of crime volume. Just 82 street and path segments (0.23%) or 7.67km of the total road and path network have 25% of the outside crime harm. Residential crime does not appear as concentrated as the road network is much reduced. The cumulative percentages have been assessed against the number of street segments with residential properties, in addition no pathways are included. However, the same pattern of crime harm being more concentrated than crime volume is seen here.

	Location					
	All Volume	**All Harm**	**Outside Volume**	**Outside Harm**	**Residential Volume**	**Residential Harm**
Crime measure	98,328	7,631,172	45,436	3,093,075	36,683	3,598,056
Number of street and path segments	36,141	36,141	36,141	36,141	14,900	14,900
Distance in KM of roads and paths within Coventry boundary	1,842.57	1,842.57	1,842.57	1,842.57	987.11	987.11
% of street segments and paths accounting for 25% of crime (n streets)	0.88% (n = 319)	0.48% (n = 175)	0.59% (n = 213)	0.23.% (n = 82)	2.07% (n = 309)	0.85% (n = 126)
% of street segments and paths accounting for 50% of crime (n streets)	3.74% (n =1351)	1.71% (n = 618)	2.91% (n =1051)	0.84% (n = 304)	7.38% (1099)	2.75% (410)
Distance of road and path network accounting of 25% of crime	44.24 km (2.4%)	21.66 km (1.18%)	27.38 km (1.49%)	7.67 km (0.42%)	46.43 km (4.7%)	18.88 km (1.91%)
Distance of road and path network accounting of 50% of crime	173.62 km (9.42%)	73.38 km (3.98%)	133.81 km (7.26%)	32.21km (1.75%)	137.33 km (13.9%)	49.53 km (5.02%)

Table 4.3 Crime concentration by location

	Complete dataset		Outside subset		Residential subset	
	Volume	**Harm**	**Volume**	**Harm**	**Volume**	**Harm**
Guardians						
Streetlights	0.017**	0.024.	0.031***	0.04**	-0.009	-0.023
Police and fire stations within 200m	-0.268**	-0.568***	-0.354***	-0.639***	-0.117	-1.177***
Police and fire stations within 400m	0.044	0.188*	0.034	0.146	-0.031	0.329**
Motivated Offenders						
NCDI	0.204***	0.303***	0.075***	0.097***	0.099***	0.156***
Crime Generators						
Retail/Office	0.048***	0.065***	0.037***	0.048***	-0.003	-0.003
Retail/Office within 200m	-0.0005**	-0.001**	-0.0005*	-0.001.	-0.001***	-0.002**
Crime generators within 200m	0.041*	0.046	0.038*	0.058	0.003	-0.026
Crime generators within 400m	0.015.	0.088***	0.034***	0.15***	0.0001	-0.014
Crime Attractors						
Transport on street segment	0.195***	0.305***	0.141***	0.359***	0.171***	0.309***
Transport within 200m	0.042***	0.034***	0.042***	0.026*	0.034***	0.029*
Transport within 400m	-0.012***	-0.003	-0.012***	0.0004	-0.028***	-0.022***
Crime attractors within 200m	0.038***	0.056***	0.033***	0.055***	0.004	0.021*
Crime attractors within 400m	0.012***	0.010***	0.013***	0.01**	0.002	0.001
Social context						
Number of residences	0.007***	0.011***	0.002***	0.001		
Income Decile	-0.061***	-0.081***	-0.072***	-0.104***	-0.133***	-0.061***
Health Decile	0.006	0.013	0.008	-0.017	0.006	-0.106***
Barriers to Housing Decile	-0.006	-0.052***	0.004	-0.058***	-0.0001	0.015
Living Decile	-0.008	-0.025*	-0.016*	-0.057***	0.008	-0.026*
Intercept	-3.306***	0.869***	-3.846***	0.47***	-1.058***	3.566***
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1,						

Table 4.4: Models of operationalised crime pattern theory and crime volume and harm at 3 locations

4.4.3 Negative binominal regression modelling

Negative binominal models were estimated for victim based crime and harm in all locations and also subset by outside and residential locations. The 36,141 street and path segments in the full and outside datasets and the 14,900 residential street segments are the units of analysis for the respective models and the independent variables are operationalised elements of crime pattern theory. Table 4.4 presents the results of the each of the models. Complete regression results are given in the appendix.

Not all guardianship measures have a crime reductive influence. Streetlights are not significant for residential crime and harm but an additional streetlight on a street segment is expected to see increased risk of both crime volume and harm in all locations and outside with a risk of 4% more outside harm. This finding requires further investigation. Streetlight and crime data used in the analysis is location only and has not acknowledged the timing of offending, nor does it include any energy saving measures that may see streetlights turned off in certain areas and times. This is also an area where examining the relationship of crime types occurring outside with streetlighting may also be beneficial. Residential car theft or urban centre violent crime may be influenced by energy saving measures or streetlight density (Tompson et al, 2022, Xu et al, 2018).

The presence of police and fire stations within 200m of a street segment, as expected, has a crime reducing impact, the largest of which is seen in outside harm. This could be due to the number of emergency staff and vehicles entering and leaving the premises or the speed at which staff can respond to crime. Davies and Bowers (2019) noted the roads around police stations as being over utilised in their study of police vehicle movement to calls to services in areas of London. Unlike the behavioural bias they note could be in place for other route choices the finite number of routes around key police buildings means they will see large number of vehicles on these segments. Unfortunately, it is unlikely that more police and fire stations will be built so the crime reductive effect is fixed in place. This reductive power, though, is lost beyond 200m, possibly due the additional route choices available to vehicles.

The proxy variable for motivated offenders showing the number of NCDI recorded on a street segment is associated with an increase in both volume and harm for all locations. This impact is not uniform; outside harm and volume is not affected to the same degree as both all locations and residential. In the complete dataset this variable has a greater impact on crime harm (an additional NDCI on a street segment increases the risk of victim based harm by 35%). Within the residential subset, it has greater effect on harm with an 17% increased risk.

Crime generators and attractors have different impacts. Retail and office establishments are considered crime generators, bringing people to their premises at regular expected times. However, their impact at street segment level is not significant for residential crime and harm. For the complete dataset, an additional shop or office opening on a street segment increases the risk of crime harm slightly more that crime volume. The risk of additional crime volume is raised by just under 5% and harm by just under 7% in the complete dataset. Outside crime volume risk in increased by just under 4% and harm by approximately 5%. Crime generators such as schools, hospitals and playgrounds within a 200m buffer are again not significant for residential crime and harm and only return a significant result for all crime volume (4%) and outside crime volume (just under 4%). Unexpectedly they have the largest impact on outside harm at 400m increasing the risk of by 16%.

The addition of a transport variable (bus stop) on a street segment increases the risk of outside harm by just under 43% and residential harm by 36% with a similar result for all crime harm. This may in part be due to increased accessibility of street segments with bus stops but also the type of road a bus stop is added to which are usually main roads. Transport also has a significant impact on volume but not to the same extent (under 22%). The addition of a bus stop within 200m of a street segment would be expected to increase crime and harm in all locations but to a lesser extent. Much like the impact of streetlights this analysis highlights a need for further investigation of the differing impact of bus stops on crime volume and harm when examined by location. This may include an exploration of the crime types occurring within the two settings. Stucky and Smith (2017) found property crime and violent crime lower in areas without bus stops. Their study also incorporated land use within the modelling and found the strength of relationship between bus stops and crime increased in areas of commercial and industrial land use but the effect of bus stops on crime was dampened by high density residential land use. While this is an interesting finding they did not distinguish where the crime had occurred, whether outside or in or around the residential properties.

An additional crime attractor within 200m (pub, club, cash point) returns a significant result for increased residential harm (2%) but not crime volume. An additional facility can increase the risk of additional crime and harm outside by 3.3% and 5.6% respectively. More modest increased risk is found at the 400m buffer for all but the residential subset. These lower impacts are unexpected as crime attractors are places theorised to pull motivated offenders to them for the purpose of criminal activity.

The underlying social context of the street segments also returned significant negative results indicating that an increase in decile (moving to least deprived) has a crime and harm decreasing effect. The income decile which relates to the impact of low wages or unemployment shows significant negative impact on both crime volume and crime harm across all models. An increase in decile can reduce the expected amount of outside crime harm by just under 10%. The effect on residential harm is greater at 12%. As the health of an area improves it has an effect on residential harm reducing the expected risk by 10% for every additional decile. This is an interesting finding as this domain examines not only physical health but also the mental health of residents.

Improved access to housing and services sees a harm reductive effect in the complete and outside crime harm and improved indoor and outdoor environmental quality also has a crime reductive effect. It should be noted that these relationships are not necessarily causal, there may be confounders and selection effects taking place. The results are presented as a description of the naive associations as observed within the data. An avenue for future work will be to uncover the causal processes at work.

4.5 Conclusions and Discussion

This chapter has followed the methodology set out by Sherman et al (2020) in the formation of datasets to contain victim based crimes and a measure of associated harm. Using a unique variable within the data provided by WMP the dataset was subset by broad location allowing for differences in location to be examined. Based on past research, variables relating to crime pattern theory were created. Publicly available and special-access datasets were used to create a data environment to represent crime attractors and generators, guardians and motivated offenders. In addition to the environmental risk context the social context of the micro-scale street segments was also acknowledged.

Two research questions were posed, the first asking to what extent are operationalised elements of pattern crime theory associated with crime volume and crime harm at street segment level? And whether that association changes when crime volume and harm are subset by broad location.

It has shown that residential subset crime is lower in volume, but higher in harm, than crime occurring outside. Additionally, crime volume and harm are both concentrated in space and adds to the literature that finds harm more concentrated than unweighted crime volume (Chapter 3, Weinborn et al. 2017). The findings for all crime and outside locations fall within the bandwidths outlined by Weisburd, 2015. The restricted residential street segment base meant that residential crime volume and harm were not concentrated to that extent. An additional measure of concentration, using the proportion of the street segment network, was proposed. The differing proportions of victim based crimes making up the subsets were not explored at this time beyond that in the appendix.

Negative binomial regression was used to account for over dispersion found in each dataset given that it allows a wider range of variability than the Poisson model (Hilbe, 2014). Each model was assessed for multicollinearity and variables removed based on the VIF score. Despite the independent variables being created based on previous research the same limitation noted by Fenimore (2020) in her work on environmental risk factors and high harm street segments applies here. The facilities used in the analysis were derived from previous work on unweighted crime volume and crime pattern theory that sought to explain the relationship between crime types and crime attractors and generators. It is possible that other aspects of the environment need to be explored when examining crime harm.

This work found street lighting to increase the risk of crime volume and harm outside but not for the residential subset. The environmental factor having the largest impact on crime and harm are bus stops on street segments. However, another limitation of this work could be overlooking the use of unused elements of the data provided by WMP. Bernasco and Block (2011) identified crime attractors using locations of criminal activity such as drug, prostitution and gambling-related incidents. There is therefore precedent for utilising the unanalysed non-victim based crimes cut during data cleaning.

There is also the issue discussed by Clarke and Eck (2007) who note that not all the facilities classified as crime attractors experience high rates of crime. They identify the 80/20 rule whereby 20% of risky facilities will account for 80% of the issues. In addition, when examining crime concentration and the impact of attractors and generators it should be noted that a number of facilities are permeant fixtures in the environment. Council run public facilities for example may have occupied the same location for decades. Future research could identify those longstanding elements and assess their influence as a separate grouping.

That said this chapter has identified that victim based overt and covert crime subsets are affected to different extents by elements in the environment. This is also true when those unweighted crimes are given a severity weighting. There are also issues regarding the use of crime harm measure. As mentioned, but not discussed, there is the question of how intent translates to the harm score. For this work where CCHI scores were missing from the resource provided by the Institute of Criminology at the University of Cambridge they were generated based on sentencing guidelines, where those exist, and similar offences when not. There is therefore an element of subjectivity within the CCHI created for this work.

To conclude, this work has added to the literature regarding the concentration of crime harm and added additional novelty by examining concentration of overt and covert crime by way of location sub setting, the first work to do so. It has identified elements of crime pattern theory having differing strength of influence on crime volume and harm in these subsets and shown the addition of variable capturing social context return significant results.

References

Andersen, H.A. and Mueller-Johnson, K., 2018. The Danish Crime Harm Index: how it works and why it matters. *Cambridge Journal of Evidence-Based Policing*, *2*, pp.52-69.

Ariel, B. and Partridge, H., 2017. Predictable policing: Measuring the crime control benefits of hotspots policing at bus stops. Journal of Quantitative Criminology, 33, pp.809-833.

Barnum, J.D., Caplan, J.M., Kennedy, L.W. and Piza, E.L., 2017. The crime kaleidoscope: A cross-jurisdictional analysis of place features and crime in three urban environments. *Applied Geography*, *79*, pp.203-211.

Bernasco, W., & Block, R. (2011). Robberies in Chicago: A block-level analysis of the influence of crime generators, crime attractors, and offender anchor points. Journal of Research in Crime and Delinquency, 48(1), 33-57.

Blasco-Moreno, A., Pérez-Casany, M., Puig, P., Morante, M. and Castells, E., 2019. What does a zero mean? Understanding false, random and structural zeros in ecology. *Methods in Ecology and Evolution*, *10*(7), pp.949-959.

Braga, A.A., Hureau, D.M. and Papachristos, A.V., 2011. An ex post facto evaluation framework for place-based police interventions. *Evaluation review*, *35*(6), pp.592-626.

Braga, A.A., Turchan, B.S., Papachristos, A.V. and Hureau, D.M., 2019. Hot spots policing and crime reduction: An update of an ongoing systematic review and meta-analysis. *Journal of experimental criminology*, *15*, pp.289-311.

Brantingham, P. and Brantingham, P., 1995. Criminality of place: Crime generators and crime attractors. *European journal on criminal policy and research*, *3*, pp.5-26.

Brantingham, P. J. and Brantingham, P. L. (1981). Environmental Criminology. Beverley Hills: Sage Publications.

Brantingham, P.J. and Brantingham, P.L., 1984. *Patterns in crime*. New York: Macmillan.

Cambridge Centre for Evidence Based Policing, Unknown, *CCEBP Conferences and Webinars* [Online].[Accessed 10 January 2023] Available at: https://www.cambridge-ebp.co.uk/conferences-webinars Crime Harm Index Q&A webinar, 14:25 onward

Chainey, S., 2021. Understanding crime: Analyzing the geography of crime. *(No Title)*.

Cohen, L. and Felson, M., 1979. Social change and crime Rate Trends. *A Routine Activity Approach American Sociological Review, 44*.

Clarke, R.V. and Cornish, D.B., 1985. Modeling Offenders' Decisions-A Framework for Research and Policy (From Crime and Justice-An Annual Review of Research, Volume 6, P 147-185, 1985, Micheal Tonry and Norval Morris, ed.-See NCJ-98380).

Clarke, R.V.G. and Eck, J.E., 2007. *Understanding risky facilities* (No. 6). Washington, DC: US Department of Justice, Office of Community Oriented Policing Services.

College of policing, 2021, *Hot spots policing* [Online]. [Accessed 20 September 2023] Available from: https://www.college.police.uk/research/crime-reduction-toolkit/hot-spots-policing

Coventry City Council, 2021. *Population and demographics* [Online]. [Accessed 20 September 2023] Available from: https://www.coventry.gov.uk/facts-coventry/population-demographics/2

Curtis-Ham, S. and Walton, D., 2017. Mapping crime harm and priority locations in New Zealand: A comparison of spatial analysis methods. *Applied geography*, *86*, pp.245-254.

Curtis-Ham, S., 2022. Measuring harm with crime harm indices. In *The Crime Analyst's Companion* (pp. 177-192). Cham: Springer International Publishing.

Davies, T. and Bowers, K., 2019. Patterns in the supply and demand of urban policing at the street segment level. *Policing and society*.

Di Tella, R. and Schargrodsky, E., 2004. Do police reduce crime? Estimates using the allocation of police forces after a terrorist attack. American Economic Review, 94(1), pp.115-133.

Dowling, C., Boxall, H. and Morgan, A., 2021. The criminal career trajectories of domestic violence offenders. *Trends and Issues in Crime and Criminal Justice*, (624), pp.1-17.

Eck, J. and Weisburd, D.L., 2015. Crime places in crime theory. *Crime and place: Crime prevention studies*, *4*.

Eck, J., Chainey, S., Cameron, J. and Wilson, R., 2005. Mapping crime: Understanding hotspots.

Eck, J.E., Clarke, R.V. and Guerette, R.T., 2007. Risky facilities: Crime concentration in homogeneous sets of establishments and facilities. *Crime prevention studies*, *21*, p.225.

Ejiogu, K.U., 2020. Block-Level analysis of the attractors of robbery in a downtown area. *Sage Open*, *10*(4), p.2158244020963671.

Felson, M. and Boba, R.L. eds., 2010. *Crime and everyday life*. Sage.

Felson, M. and Eckert, M.A., 2017. *Introductory criminology: The study of risky situations*. Routledge.

Fenimore, D. M. (2019). Mapping harmspots: an exploration of the spatial distribution of crime harm. Applied Geography, 109, 102034. https://doi.org/10.1016/j.apgeog.2019.06.002

Fenimore, D. M. (2020). Investigating the spatiotemporal distribution and environmental risk factors of harm-weighted crime. Texas State University.

Fielding, M. and Jones, V., 2012. 'Disrupting the optimal forager': predictive risk mapping and domestic burglary reduction in Trafford, Greater Manchester. International Journal of Police Science & Management, 14(1), pp.30-41.

Gerell, M., 2016. Hot spot policing with actively monitored CCTV cameras: Does it reduce assaults in public places? International Criminal Justice Review, 26(2), pp.187-201.

Gov.UK, 2019. *The English Indices of Deprivation 2019 (IoD2019)* [Online]. [Accessed 20 September 2023] Available from: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/835115/IoD2019_Statistical_Release.pdf

Greenfield, V.A. and Paoli, L., 2013. A framework to assess the harms of crimes. *British journal of criminology*, *53*(5), pp.864-885.

Groff, E.R. and Lockwood, B., 2014. Criminogenic facilities and crime across street segments in Philadelphia: Uncovering evidence about the spatial extent of facility influence. *Journal of research in crime and delinquency*, *51*(3), pp.277-314.

Groff, E.R., Weisburd, D. and Yang, S.M., 2010. Is it important to examine crime trends at a local “micro” level?: A longitudinal analysis of street to street variability in crime trajectories. *Journal of Quantitative Criminology*, *26*, pp.7-32.

Gul, S., 2009. An evaluation of rational choice theory in criminology. *Girne American University Journal of Sociology and Applied Science*, *4*(8), pp.36-44.

Harinam, V., Bavcevic, Z. and Ariel, B., 2022. Spatial distribution and developmental trajectories of crime versus crime severity: do not abandon the count-based model just yet. *Crime Science*, *11*(1), pp.1-15.

Hart, T.C. and Miethe, T.D., 2014. Street robbery and public bus stops: A case study of activity nodes and situational risk. *Security Journal*, *27*, pp.180-193.

Hilbe, J.M., 2014. *Modeling count data*. Cambridge University Press.

Hipp, J.R. and Williams, S.A., 2020. Advances in spatial criminology: The spatial scale of crime. *Annual Review of Criminology*, *3*, pp.75-95.

House, P. D. (2017). Developing a Crime Harm Index for Western Australia. Master thesis. University of Cambridge.

Hu, M.C., Pavlicova, M. and Nunes, E.V., 2011. Zero-inflated and hurdle models of count data with extra zeros: examples from an HIV-risk reduction intervention trial. *The American journal of drug and alcohol abuse*, *37*(5), pp.367-375.

Johnson, S.D., 2010. A brief history of the analysis of crime concentration. *European Journal of Applied Mathematics*, *21*(4-5), pp.349-370.

Kärrholm, F., Neyroud, P. and Smaaland, J., 2020. Designing the Swedish Crime Harm Index: an evidence-based strategy. Cambridge Journal of Evidence-Based Policing, 4, pp.15-33.

Kennedy, L.W. and Caplan, J.M., 2012. A theory of risky places. *Newark, NJ: Rutgers Center on Public Security. Accessed February*, *12*, p.2021.

Lee, Y., Eck, J.E., O, S. and Martinez, N.N., 2017. How concentrated is crime at places? A systematic review from 1970 to 2015. *Crime Science*, *6*, pp.1-16.

Macbeth, E. (2015). Evidence-based vs. experience-based targeting of crime and harm hotspots in Northern Ireland. Master thesis. University of Cambridge.

Mair, C., Sumetsky, N., Dougherty, M. and Thakar, M., 2022. Do changes to the alcohol retail environment reduce interpersonal violence? *Current epidemiology reports*, *9*(4), pp.282-289.

Marklund, F., & Holmberg, S. (2015). Camera monitoring in Stureplan and Civic Square: Full Report. Stockholm. Sweden: Brå.

Marklund, F., & Merenius, S. (2014). Policing crime "hot spots": Results and experiences from Two Projects against Personal Abuse and Abuse. Stockholm: Brå

Mitchell, R. J. (2019). The usefulness of a crime harm index: Analyzing the sacramento hot spot experiment using the california crime harm index (CA-CHI). Journal of Experimental Criminology, 15(1), 103–113. https://doi.org/10.1007/ s11292-017-9318-y

Norton, S., Ariel, B., Weinborn, C. and O'Dwyer, E., 2018. Spatiotemporal patterns and distributions of harm within street segments: the story of the "harmspot". Policing: An International Journal, 41(3), pp.352-371.

Office for National Statistics, 2023. *How life has changed in Coventry: Census 2021* [Online]. [Accessed 20 September 2023] Available from: https://www.ons.gov.uk/visualisations/censusareachanges/E08000026/

Openshaw, S., 1984. The modifiable areal unit problem. *Concepts and techniques in modern geography*.

Paoli, L. and Greenfield, V.A., 2018. Harm: a substitute for crime or central to it? *Zemiology: Reconnecting crime and social harm*, pp.57-84.

Piza, E.L., Caplan, J.M., Kennedy, L.W. and Gilchrist, A.M., 2015. The effects of merging proactive CCTV monitoring with directed police patrol: A randomized controlled trial. Journal of Experimental Criminology, 11, pp.43-69.

Police.uk. 2023. *Compare your area* [Online]. [Accessed 20 September 2023] Available from: https://www.police.uk/pu/your-area/west-midlands-police/performance/compare-your-area/?tc=BW001

Ratcliffe, J.H. and Breen, C., 2011. Crime diffusion and displacement: Measuring the side effects of police operations. The Professional Geographer, 63(2), pp.230-243.

Rengert, G.F. and Lockwood, B., 2009. Geographical units of analysis and the analysis of crime. *Putting crime in its place: Units of analysis in geographic criminology*, pp.109-122.

Salafranca Barreda, D., Maldonado-Guzman, D.J. and Saldaña-Taboada, P., 2022. Crime beyond the edge: development of a tool to correct the edge effect on crime count. *Annals of GIS*, *28*(3), pp.279-292.

Sellin, T., & Wolfgang, M. E. (1964). The measurement of delinquency. Wiley.

Sherman, L.W, Neyroud, P.W. and Neyroud, E., 2016. The Cambridge crime harm index: Measuring total harm from crime based on sentencing guidelines. *Policing: a journal of policy and practice*, *10*(3), pp.171-183.

Sherman, L.W. and Cambridge University associates, 2020. How to count crime: the Cambridge harm index consensus. *Cambridge Journal of Evidence-Based Policing*, *4,* pp.1-14.

Sherman, L.W., Gartin, P.R. and Buerger, M.E., 1989. Hot spots of predatory crime: Routine activities and the criminology of place. *Criminology*, *27*(1), pp.27-56.

Sherman, L.W., Gartin, P.R. and Buerger, M.E., 1989. Hot spots of predatory crime: Routine activities and the criminology of place. Criminology, 27(1), pp.27-56.

Stripe, N., 2022. *Crime Severity Score (Experimental Statistics)* [Online].[Accessed 01 September 2023] Available at: https://www.ons.gov.uk/peoplepopulationandcommunity/crimeandjustice/datasets/crimeseverityscoreexperimentalstatistics

Stucky, T.D. and Smith, S.L., 2017. Exploring the conditional effects of bus stops on crime. *Security Journal*, *30,* pp.290-309.

Summers, L. and Caballero, M., 2017. Spatial conjunctive analysis of (crime) case configurations: Using Monte Carlo methods for significance testing. *Applied Geography*, *84,* pp.55-63.

Tompson, L., Steinbach, R., Johnson, S.D., Teh, C.S., Perkins, C., Edwards, P. and Armstrong, B., 2022. Absence of street lighting may prevent vehicle crime, but spatial and temporal displacement remains a concern. *Journal of Quantitative Criminology*, pp.1-21.

Weinborn, C., Ariel, B., Sherman, L.W. and O'Dwyer, E., 2017. Hotspots vs. harmspots: Shifting the focus from counts to harm in the criminology of place. *Applied geography*, *86*, pp.226-244.

Weir, R., 2019. Using geographically weighted regression to explore neighborhood-level predictors of domestic abuse in the UK. *Transactions in GIS*, *23*(6), pp.1232-1250.

Weisburd, D., 2015. The law of crime concentration and the criminology of place. *Criminology*, *53*(2), pp.133-157.

Weisburd, D., Bushway, S., Lum, C. and Yang, S.M., 2004. Trajectories of crime at places: A longitudinal study of street segments in the city of Seattle. *Criminology*, *42*(2), pp.283-322.

Weisburd, D., Groff, E., & Yang, S. (2012). The criminology of place: Street segments and our understanding of the crime problem. Oxford: Oxford University Press.

Welsh, B.C., Farrington, D.P. and Douglas, S., 2022. The impact and policy relevance of street lighting for crime prevention: A systematic review based on a half-century of evaluation research. *Criminology & Public Policy*, *21*(3), pp.739-765.

West Midlands Police, unknown, *Your Local Police* [Online]. [Accessed 20 September 2023] Available from: https://www.west-midlands.police.uk/your-local-police

Williams, S.A., 2015. Do visits or time spent in hot spots patrol matter most? A randomised control trial in the west midlands police. Unpublished masters dissertation]. University of Cambridge.

Wüllenweber, S. and Burrell, A., 2023. The crime and the place: Robbery in the night-time economy. *Journal of Investigative Psychology and Offender Profiling*.

Xu, Y., Fu, C., Kennedy, E., Jiang, S. and Owusu-Agyemang, S., 2018. The impact of street lights on spatial-temporal patterns of crime in Detroit, Michigan. *Cities*, *79*, pp.45-52.

Chapter 5. C/overt victim-based crime volume and harm at social frontiers

Are social frontiers areas of increased residential and outside victim-based crime harm and volume?

5.1 Introduction

In the previous two chapters the analysis has been at the micro scale of street segments for both Rotherham and Coventry. In this chapter the spatial analysis is conducted at both LSOA and 100m by 100m grid level. This analysis examines crime volume and harm in relation to social frontiers. The term social frontier has been coined to describe "places of sharp difference in social/ethnic characteristics between neighbouring communities" Dean et al (2019, p,271). Growing literature is examining the impact of these areas between adjacent areas on elements of social life such as household mobility (Olner et al, 2023) and property prices (Myatt et al, 2023), as well as the location of crime (Legewie and Schaeffer, 2016, Dean et al, 2019, Smith, 2021, Křížková et al, 2021). The limited number of studies thus far have explored the relationship between social frontiers and crime using the volume of anti-social behaviour (Legewie and Schaeffer,2016), criminal offences (Legewie, 2018, Dean et al, 2019, Smith, 2021, Křížková et al, 2021) and residential concentration of offenders (Smith, 2021), but have not yet considered the relative severity of the crimes within their data. They have also not been able to incorporate the broad location the crime took place, namely whether it occurred in an outside location or within a residential setting.

The contribution of this chapter therefore lies in advancing understanding of the influence of social frontiers not only for all crime volume but by location. It initially partitions the data so crimes occurring within residential setting can be examined separately as can crimes occurring outside. That it does this using crime harm is further contribution. The creation of an intersectional frontier, a frontier between neighbourhoods identified for multiple variables, also pushes the work on frontiers forward. The analysis conducted in this chapter revealed challenges relating to methodological choices so additionally contributes to the discussion of the impact of decisions made throughout the analysis process.

In 2012 Weisburd et al suggested that the criminology of place was a growing area of interest within the study of spatial criminology and that small geographic units, areas within neighbourhoods such as city blocks and street segments, should receive more attention. As stated in previous chapters, numerous studies have identified the concentration of crime (Sherman et al, 1989, see also Johnson, 2010) so much so that a law of crime concentration was put forward by Weisbund et al (2012). Since then, the conclusion has been that the smallest unit of spatial measurement is the optimal one (Hipp and Williams, 2020).

This might suggest that examining crime at anything above this micro level is passé. However, the neighbourhood is still a useful geographic scale at which to view offending. And as mentioned, focusing on the geographic space where different neighbourhood areas meet and the relationship with crime is an area of study still in its infancy (Legewie and Schaeffer, 2016; Dean et al, 2019). These works still require the meso-level spatial area, the neighbourhood, to be present and identifiable, but the focus is then on these smaller sections of the larger spatial unit and their association with crime and disorder.

This chapter uses 2011 census LSOAs for the city of Coventry in the UK, and the 'socialFrontiers' R package to identify borders between neighbouring LSOAs based on three sociodemographic characteristics (Zhang, 2021). It follows the Bayesian conditional autoregressive regression methodology set out by previous researchers to identify those boundaries that pass a threshold to be considered social frontiers (Dean et al, 2019, Smith, 2021, Křížková et al, 2021). It then tests these frontiers and examines whether they are associated with increased amounts of crime. In addition to crime volume, crime harm will also be tested. The full dataset will also be subdivided by broad crime location.

Two tests are used to examine the association between crime volume and harm and the identified social frontiers: permutation tests at LSOA level and then more spatially specific regression analyses. This work adopts the same estimation and crime impacts approach as that used by Dean et al (2019), Smith (2021) and Křížková et al (2021) but provides novel analysis by moving the location to an unexamined medium size city, additionally investigating the association of social frontiers with crime harm and also exploring the association with covert and overt crime. While this work is not focused on methodology these tests will be conducted under different methodological constraints to test if findings hold.

This chapter is structured in the following way. Firstly, the literature is explored with an overview of neighbourhood composition and measurement. Previous work on crime and frontiers will be outlined and crime harm introduced. The area of study, data cleaning and sub setting is then described, and the method of social frontier detection and testing outlined.

Results and discussion are then given with limitations and conclusions closing the work. Table 5.1 outlines the key terminology used throughout the chapter.

Boundary	The boundary segments of individual LSOAs where two LSOAs meet
Frontier	Segments of boundary identified using the socialFrontier r package (Zhang, 2021)
Social frontier	Those frontiers that have passed the threshold
Combination frontier	Social frontiers of ANY variable
Intersectional frontier	Social frontiers that appear for EVERY social characteristic

Table 5.1: Key terminology

5.2 Literature Review

5.2.1 Neighbourhoods

Neighbourhoods have long been used as a spatial unit of analysis for research into segregation, deprivation and intergroup relations (Massey and Denton, 1988). Social frontiers as defined by Dean et al (2019) are the sharp divides that sometimes occur between neighbouring communities in terms of their socio demographic make-up. Rather than blending seamlessly these differences in race, religion and other social characteristics create “cliff edges” in the social landscape generating a length of social frontier (p.272). Despite the vast literature on residential segregation these steep differences at the boundary point between different neighbourhoods have been largely overlooked in quantitative research (Dean et al, 2019). However, there is growing interest in these boundary locations.

It is the composition of the population that social scientists usually use when referring to neighbourhoods (Logan et al, 2011). Terms such as working class or using the ethnicity of residents means that that feature is taken as the defining characteristic of the neighbourhood. They also point out that neighbourhoods described as being in transition or socially mixed are being referenced against those that are homogeneous or static in their composition (ibid).

The mechanisms by which communities and neighbourhoods organise both socially and spatially have several different origins. Neighbourhood composition can be driven by homophily which is “the principle that a contact between similar people occurs at a higher rate than among dissimilar people”, or as the well-known phrase puts it, birds of a feather flock together (McPherson et al, 2001, p,416). Homophily can lead to households being more likely to live in neighbourhoods with people of the same religion, race, ethnicity and social class (ibid).

Inequality can also cause socio-economic segregation creating an uneven distribution of different income groups across the urban area (van Ham et al, 2021). Whilst this economic segregation between high- and low-income groups living in differing neighbourhoods has increased since the 1980s (Tammaru et al, 2020), ethnic segregation in the UK has been falling (Catney et al, 2023). Rising income from globalisation, changing labour markets and the liberalisation of the economy have benefited some groups more than others and those earning the highest income are often the driver of residential segregation with their ability to purchase their housing preferences (Tammaru et al, 2020). Gentrification can also affect the socio-demographic makeup of areas with increased residential ethnic diversity as a result (Tuttle, 2020). Yet, for all the main ethnic categories (Banladeshi, Pakistani, Black Caribbean, Black African, Indian, Chinese, White), we see a marked increase in ethnic diversity, and a persistent fall in residential segregation, across most areas of the UK (Catney et al., 2023).

To examine these spaces, it is necessary to examine how neighbourhood boundaries can be drawn. Ethnographic research has found that residents tend to draw on similar social demographic characteristics to delineate their residential area. Lacy (2007), Campbell et al (2009) and Rich (2009) found residents in their US studies used both ethnicity and class to differentiate different neighbourhoods but with differing outcomes. Some were keen to see their neighbourhoods as distinct from nearby lower income areas (Lacy, 2007) while other groups drew large maps that encompassed areas of lower income and different ethnicity leading to a more diverse neighbourhood than would otherwise be the case (Campbell et al, 2009).

The question is then, what proportion of a neighbourhood needs to be of a particular ethnicity or class for it to be considered a diverse or 'characteristic here' neighbourhood? Names of neighbourhoods often relate to legacy ethnic make-up. New York's Little Italy was made up of only 8% of people with Italian ancestry in the 2012-2016 U.S Census Bureau's American Community Survey. This is not the case for Chinatown where 76% of the population gave their ethnicity as Asian and of those, 92% gave their ancestry as Chinese (Berger, 2019, Statisticalatlas, unknown a, unknown b). It is difficult to operationalise, but it is understood that a particular ethnicity or social class does not need to be in the majority for the area to be recognised as such.

There has been growing interest in recent years in establishing neighbourhood boundaries from secondary data. Logan et al (2011) use unique point-specific residential data containing socio-demographic variables for Newark New Jersey which they aggregated to street segment level. They used three different techniques to generate neighbourhoods from the racial information of residents. They reported broadly similar results from each map and concluded that there was not a single 'best' solution. With the same dataset Spielman and Logan (2013) used clustering to develop a geodemographic system based on income information and ethnicity to identify neighbourhoods.

It is, however, difficult for each researcher to undertake fieldwork to identify how and where the residents of an area would draw their neighbourhood boundary, nor is point-specific residential data readily available. As a consequence, pre-drawn administrative boundaries are an important proxy (Logan et al, 2011). However, these administrative divisions are often drawn without any theoretical considerations and are based on the limitations of available data (Dietz, 2002), they are often the only spatial unit available that incorporates official population data. They do, though, fix in place boundaries that might on the ground be considered ambiguous or fluid (Logan et al, 2011).

5.2.2 Measuring frontiers

As pre-drawn administrative boundaries are in common use in social science identifying boundary type and neighbourhood transitions is required for this areal data type. 'Wombling' (Womble, 1951) is the term used to describe the process of identifying areas of abrupt change, also known as barrier analysis or edge detection (Lu and Carlin, 2005). Wombling techniques usually require point referenced data or raster layers to generate the interpolated surface (see Jacquez et al, 2000). However techniques are available that can use areal data. These areal wombling or polygon wombling techniques can identify step change boundaries between larger pre-drawn areas (Lu and Carlin, 2005).

Different methods exist to locate and then identify the type of boundary between neighbouring areal units. Lu and Carlin (2005) and Lu et al (2007) used a polygon wombling technique that used Bayesian hierarchical models (2005) with additional variables (2007) to determine the similarity of areas based on public health data. Kramer, (2017) applied kernel density smoothing to census block administrative data with landscape features to identify persistent racial boundaries. In work relevant to this chapter Legewie and Schaeffer (2016) proposed a contested boundaries hypothesis and identified an inverted u-shaped relationship between boundaries and neighbourhood conflict using image processing edge detection algorithms.

In their 2019 work, Dean et al highlighted a gap in the literature regarding the identification and impact of social frontiers. Their paper outlined the steps necessary to identify and assess social frontiers in a robust and replicable way. Their process accounts for spatial autocorrelation which is likely present in demographic data, and they also highlight the need to be able to identify open frontiers. They explain that a social frontier might exist along a section of boundary between a community and an adjoining neighbourhood but that at other points along its circumference the boundaries between other neighbouring groups may be more gradual and diffused. The 'socialFrontiers' R package allows their work to be replicated with areal spatial data (Dean et al, 2019, Zhang, 2021).

The interest in social frontiers as potential sites for elevated amounts of crime stem from the notion that to live at a social frontier is to live at the periphery of one's own community but next to another's, which can "emphasise the physicality of segregation" (Piekut and Pryce, 2022, p21). Even without inter-group conflict these areas may see less residential mixing and a lack of social cohesiveness. Social cohesiveness, or lack thereof, is a key tenet of one of the original spatial theories of crime - *social disorganisation theory*.

5.2.3 Crime and neighbourhoods

Trying to identify and quantify the factors that contribute to an individual's propensity to commit crime had been criminology's primary focus for decades. Social disorganisation theory was one of the first that examined the 'kinds of places' that crime took place rather than taking the traditional 'kinds of people' approach (Kurbin and Whitzer, 2017, p 374). This allowed criminology to split into separate people and place branches.

Social disorganisation theory originated from the Chicago-school research undertaken by Shaw and McKay (1942). They argued that community disruption and disorganisation would occur due to three structural factors, racial heterogeneity, high levels of poverty and residential instability. These aspects accounted for the variation in crime and delinquency seen across the urban area (Sampson and Groves, 1989).

Their work was based on the Concentric Zone theory presented by human ecologists Park and Burgess (1925). Park and Burgess noted changes that occurred in the city due to rapid expansion from increased rates of urbanisation, industrialisation and inward migration. Their ecological background saw them put forward the notion that people compete over space and scarce resources in much the same way that plants and other animals do (Kubrin, 2009). Ecological terminology was used to describe the outward growth of the central business district (CDB) in terms of invasion, dominance and succession. The CBD's outward growth proceeded in successive bands with economically able residents able to move away from the areas of expansion to quieter locations on the outskirts. The properties they vacated were left uncared for or unoccupied, with the area deteriorating as a result (ibid).

It was this successive movement and changes to neighbourhood composition that Shaw and McKay (1942) examined in regard to delinquency rates in juveniles. Their work showed that commercial / industrial areas and neighbourhoods with particular social characteristics had a higher rate of delinquency. They were able to conclude that crime and delinquency is linked with other social issues such as high residential turn over, low income and the number of people out of work. In addition, they found that these high crime areas were stable over time despite the turnover of residents changing the ethnic composition of the neighbourhoods (Kubrin, 2009).

Resident turnover can be used to help describe the central principle of the theory, that of social organisation. Neighbourhoods can be described on spectrum of organisation, with disorganised neighbourhoods at one side and the socially organised on the other. The level of organisation determines the level of key elements Shaw and McKay (1942) determined could lower crime levels. Socially disorganised neighbourhoods would have low levels of solidarity, cohesion and integration and as a result, a low level of informal social control or neighbourhood self-regulation (Greenberg et al, 1982). This would be seen in neighbourhoods with high turnover as the social bonds linking neighbours would not be as well established (Sampson et al, 1997).

Informal social control and neighbourhood level self-regulation can be seen in the amount and type of engagement residents have in their neighbourhoods and is theorised as being able to mediate the effects of exogenous elements of social disorganisation such as residential instability, ethnic heterogeneity and low income (Kubrin and Weitzer, 2017). Examples of informal control include residents' willingness and ability to intervene when suspicious people or activity is noted, acting as informal surveillance of the immediate area and correcting the behaviour of misbehaving children (ibid, Greenberg et al, 1982).

These elements are also found in neighbourhoods described as being territorially distinct (Greenberg et al, 1982). In addition to having high levels of social cohesion and informal social control territorially distinct neighbourhoods also have residents with a territorial identity and close local ties. The territorial identity is a shared understanding of not only the boundary of the neighbourhood but also an agreement that the neighbourhood is distinct from adjacent areas. Close local ties: having friends and family within the neighbourhood and or taking part in local community activities goes hand in hand with social cohesion and enables informal social control to develop (ibid).

Whether a neighbourhood is described as well-organised or territorially distinct, the ability and willingness of residents to act as guardians within the neighbourhood fulfils an important role within a more recent place crime theory. Cohen and Felson's (1979) routine activity theory posits that for crime to take place three elements need to occur: a suitable target in the presence of a likely offender with the absence of a capable guardian.

This work is focused on the social characteristics of neighbourhoods and the meeting space between adjacent neighbourhood areas. It will not examine the impact of the second body of research on neighbourhood crime, defensible space, that focuses on the physical characteristics of neighbourhoods. This would be an avenue for future research.

5.2.4 Crime and social frontiers

Social frontiers may be areas of higher levels of crime and disorder due to lower levels of collective efficacy found on the outer edges of differing neighbourhoods and the subsequent lack of people willing to act as capable guardians (Legewie and Schaefer 2016; Piekut and Pryce, 2022; Reynald, 2010). This could be due to a lack of 'bridge builders', people who live at point between neighbourhoods and act to diffuse the sharp edge of frontier by connecting people from separate communities, and as a result we might expect social frontiers to be locations with a positive association with crime (Dean et al, 2019).

Dean et al (2019) used publicly available crime data (police.uk website) that anonymises the location of offences by aggregating specific crime locations to nearby public features or street centres (for full anonymisation details see Home Office, 2021). Social frontiers were generated from two demographic variables: the proportion of residents born outside the UK and the proportion of non-white residents as per the 2011 census at LSOA level. Their permutations test, at LSOA level, found that crime counts for all grouped crimes were higher at neighbourhoods joined by either social frontier compared to those joined by a non-social frontier boundary. Poisson regression analysis at a finer resolution (100m by 100m grid squares) found an association with elevated crime rates within both 100m and 200m of a social frontier (6% at both buffer distances) when the model controlled for LSOA fixed affects and unemployment (ibid).

Using spatially specific data from South Yorkshire Police, Smith (2021) also found social frontiers to be areas of elevated crime risk. His analysis used the same social frontiers package to identify social fronters for three social variables: ethnicity, religion and country of birth and assessed them against police reported crime data and offender residence. He also created a composite frontier variable that compiled the social frontiers from every variable. His work employed a slightly more stringent threshold to identify the social frontiers (ibid).

Smith (2021) conducted permutation tests for all frontiers for both Sheffield and Rotherham using residential buildings to create crime and offender rates. These initial tests found increased likelihood of crime and offenders between non UK and religious social fronted LSOAs in Sheffield but no significant results at ethnic frontiers. Rotherham had more mixed results. His regression analysis used a quasi-Poisson model with residential building per 100m grid square as an offset within the regression and also controlled for LSOA fixed effects and being within a buffered distance of any internal boundary. His headline findings were a 49% increase in crime likelihood within 100m of any Sheffield social frontier with a 38% increased likelihood of offenders residing within those buffers. In Rotherham the likelihood of an offender being within 100m of any social frontier is increased by 89% with a 28% increase in crime rate (ibid). He did find religious frontiers to associated with lower levels of public order offences in Rotherham, and country of birth frontiers to be negatively associated with violent offender residences in Sheffield.

Moving the analysis from the UK to a former socialist country, Czechia, Křížková et al (2021) used the socialFrontiers package to generate social frontiers for foreign born citizens in Pardubice (Zhang, 2021). They generated social frontiers based on not only the proportion of foreign born population but also generated social frontiers based on the cultural distance between origin countries for foreign born citizens. Their permutation test using basic settlement units as the areal neighbourhood areas tested the proportion of foreign citizens and neighbourhood conflict offences (minor crimes). Their initial permutation test found no significant results for any social frontier variable.

Their quasi-Poisson regression returned a negative result for the composite foreigner social frontiers at 100m suggesting less conflict is found there. Social frontiers generated for the subset of more distant foreign born citizens returned a positive result at 100m. They hypothesised that this result was returned as the social frontiers for more distant foreign residents are located primarily in the city centre where they overlap with ‘risky places’ (Kennedy and Caplan, 2012) such as shops, pubs and clubs as well as cheaper immigrant housing (ibid).

However, not all researchers have found social frontier areas to be places of criminal activity arising from resident difference. Legewie and Schaeffer (2016) found social frontiers (or neighbourhood boundaries) to be locations of settled difference that are uncontested when examining anti-social behaviour and nuisance, whereas ‘fuzzy’ boundaries are poorly defined and are ambiguous with regard to group rank. At census block level their findings show a curvelinear association between edge intensity and the number of complaint calls made and proposed a contested boundary theory. This aligns with Gold (1982) who stated that territorial boundaries may emerge in order to reduce or avoid conflict, “…the most important facet of territoriality is that it can create a stable and unobtrusive framework for the orderly conduct of everyday life.” (ibid, p54, 55)

These works have used neighbourhood areal units within their social frontier analysis, however, the current view in spatial criminology is that micro level analysis is preferred (Hipp and Williams, 2020). Even though social frontier work with areal spatial units is in its infancy, there is initial investigation of frontiers at this micro scale. Recent work by Kim and Hipp (2021) has moved social frontiers from neighbourhoods to street segment level by identifying boundaries between blocks on differing sides of a street within 117 US cities within Los Angeles County. Their work incorporates traditional physical boundaries and a measure of land use as well as social boundaries of comprising of socioeconomic status and racial composition. Proportions of differing variables were calculated for each side of the street segment and frontiers were identified from the squared difference. Their findings show social boundaries have a higher risk of violent and property crime.

Social frontier and crime work to date has used counts of crime and disorder and, in the case of Smith (2021) offenders. This assumes all crimes to be of equal weight when summed per spatial unit. As discussed in chapters 3 and 4 there is a growing branch of criminology that suggests that the relative harm of crimes should be included in any analysis of criminal activity.

5.2.5 Crime harm

By counting each occurrence of crime and using the summed total per geospatial unit as the basis for declaring such a unit unsafe or in need of police intervention requires that each and every crime is considered equal. That crimes are not created or considered equal is formally recognised with the use of a harm index which quantifies the harm resulting from each offence (Sherman et al, 2020). There are a number of different ways to assess the harm caused by a crime type (see Chapter 1) with the Cambridge Crime Harm Index (CCHI) used throughout this work.

This index takes the minimum sentence for each offence and converts it into the number of days. This is simple for prison sentences and community orders of unpaid work. For fines, the number of days work required to pay it (at minimum wage) is recorded (Sherman et al, 2016). This allows the index to succeed in 3 key areas that Sherman et al (2016) deem important metrics for any harm index. It is democratic as it uses the sentencing guidance passed by a democratically elected government. As such it is reliable as this guidance is available for use in generating the index and thirdly it is cost effective as this material is publicly available and once created can be shared and updated easily (ibid). It is for this reason that the UK based CCHI model has been adopted (with variations based on local sentencing practices) in numerous countries (see van Ruitenburg and Ruiter, 2023).

This CCHI was chosen for this work for these reasons and in part for the ease with which additional specific crimes could be added to the index supplied by the University of Cambridge Institute of Criminology. The publicly available resource includes a number of offences with the CCHI value given. It also has additional information outlining the reasoning behind the decision (if sentencing guidelines are not available), this allows for similar crimes to be allocated similar scores and similar factors to be taken into account (University of Cambridge, 2020). In addition, by stipulating that the starting sentence be used for the basis of the CCHI where sentencing guidelines exist, they can be used to extract this minimum sentence or apply conditions within the offence (such as victim age) to generate the appropriate tariff.

By comparison the Crime Severity Score created by the ONS uses average sentences given out in the preceding 5 – 10 years. Sherman et al (2020) raises this as a criticism as an offender's previous offending history is taken into account by the judge or magistrate and therefore factors into the sentence that is given, with previous offenders receiving longer sentences. This focuses the quantifying of harm on the offender rather than the victim. This is seen in a comparison of harm weighting for child sexual offences with the starting sentences reducing as the victim's age increases. This is reversed in the Crime severity score. This score also weights sexual offences against boys lower than girls (Sherman et al, 2020, ONS, 2023). A further reason the CSS was not used comes from a practical standpoint. It would not have been possible to easily create specific harm scores as similar crimes are grouped together and the specific crimes making up each group are not available.

In the 2020 paper Sherman and associates elaborate further on how the CCHI could be used. They explain that crimes should be analysed based on the year they occurred rather than the year they were reported to the police. Historic crimes should be collated within a Historic Offences Index. As too should crimes that are police initiated, such as drugs and weapons offences and also those detected by security officers such as shoplifting and other theft detection. These would form a Proactive Policing index and Company-Detected Crime Harm Index both of which would give an understanding of the detection rates and successes of police departments and company crime detection measures. That leaves victim-based crimes to be analysed using the CCHI. These offences, it is said, will give a truer reflection of crime experienced by members of the public who are reporting it.

Crime volume and crime harm behave differently with crime harm found to be more concentrated spatially than unweighted crime volume (Macbeth, 2015, Etheridge, 2015 Weinborn et al, 2017, Chapters 3 and 4). In her study Fenimore (2020) notes a diffusion of harm away from the city centre into a residential area that is not matched by the concentration of unweighted crime.

In summary, the study of social frontiers is a growing area of research as too is the use of crime harm as a tool to measure criminal activity. In the analysis that follows, crime volume and crime harm are both explored. If lower levels of social control and community efficacy are seen at social frontiers this could be evident in the crime and harm occurring in an outside setting within close proximity to these areas. It is less clear what effect social frontiers will have on crime occurring within a residential setting. Does living in more peripheral areas cause an increase in the likelihood of crime and harm occurring? The goal of the current paper is to contribute to the social frontiers on crime by considering the impact of proximity to social frontiers on crime volume and crime harm. To date there is no published paper exploring this topic.

5.3 Research questions

Controlling for the effects of all internal LSOA borders and the fixed effects of LSOAs is there an increased likelihood of police reported victim-based crime volume and crime harm at social frontiers?

Does the pattern hold when examined as crime within and around the home and outside?

Does examining crime harm add anything to the understanding of crime severity at social frontiers?

5.4 Methods

5.4.1 Area of study – Coventry

To test the association between social frontiers and crime in a smaller city, Coventry was selected from wider data provided by West Midlands Police. The 2021 UK City of Culture has a growing population increasing from around 317,000 counted at the 2011 census to 345,300 in 2021. It has increased to 25 (from 26) in terms of its rank in local authority areas by population size (ONS, 2022). The city's recent history has a bearing on its socio-demographic makeup. Rebuilding after sustaining substantial damage during WW2 Coventry's recovery was due to the motor industry. The 1960's saw a huge workforce employed in the manufacture of aircraft, agricultural machinery and motor vehicles and a rise in the number of Asian and West Indian immigrants living and working in the area. After the decline in manufacturing in the 1980s, Coventry now has a more diversified economy with a large portion of its income generated from its two universities (Hainey, 2018). The University of Warwick has a student population of just under 30,000 with that number again enrolled at Coventry University (Warwick 2022, Coventry University, unknown). Both universities have large international student populations which contribute to an ethnically diverse city.

The 2011 census reported that 75.8% of residents (approx. 240,100) indicated they were born in England and 73.8% identified their ethnic group as within the 'White' category. In 2021 these figures are 70.1% (242,100) and 65.5% respectively (ONS, 2022). Coventry was also chosen for this work as it is almost entirely surrounded by the West Midlands green belt reducing the impact of edge effects (Fotheringham and Rogerson, 1993).

5.4.2 Datasets Used

As noted, crime data was provided by West Midlands Police. The raw datasets included offences reported to WMP from 01/01/2015 - 10/10/2019. A date variable was created from the last point the crime was thought to have been committed and any entries occurring before 2015 were removed in keeping with Sherman et al's (2020) suggestion of an historic crime index (historic crimes should be analysed within the year they took place not the year they were reported). The 10 days of reported offences occurring in October were cut to give nine full months of data for 2019.

Entries with incorrect or incomplete spatial coordinates were removed as were any offences that took place outside Coventry's boundary. Non-notifiable and non-crime entries were removed, and the Counting Rules for Recorded Crime (Home Office) was used to identify crimes as either victim based or crimes against society. The dataset was subset to keep only victim-based offences (or those classified as both). Crimes against police personnel and commercial thefts were also removed (as per Sherman et al's 2020 methodology). This cleaned dataset had an additional count column added for future use and the corresponding CCHI scores were joined using the home office offence classification codes and description. This dataset contains all the victim-based crimes reported to have occurred within Coventry from Jan 2015 -end of sept 2019.

West Midland Police data also contains a primary and full location descriptor. The primary location column contains a single descriptor of the location of the crime. Reporting officers choose from a prepopulated list of 144 location descriptors (Appendix 2). The primary location descriptor was used to create additional dummy variables to identify offence entries taking place within a residential setting and those taking place outside. An example of a location given - 'Road', would be classified as non-residential and outside.

These dummy variables allowed the full dataset to be subset within the analysis by location; either occurring in a residential setting or in an outside location. Offences given the location descriptors: NA, Spare, Void or Other were cut from the dataset. A small proportion of offences are not analysed beyond that of the full crime dataset; those taking place within a non-residential inside setting e.g. hospital, pub, office. The full crime dataset has 98,328 entries with 36,683 residential victim-based crimes and 45,436 occurring outside between Jan 2015 and Sept 2019.

By subdividing the dataset by location, namely inside and outside locations, the dataset has been split into covert and overt crimes respectively (Felson and Eckert, 2017). Covert crime is described as crime occurring largely unseen, away from view. Overt crime by comparison takes place in public and brings more immediate police attention (ibid). The indoor crime subset is divided again by residential / non-residential locations.

There is an acknowledgement of error within the data set. Not all entries had complete location co-ordinates or locations falling within the Coventry boarder. The primary location menu available to officers is alphabetised and earlier entries maybe used in preference (abattoir is used 26 times). It is also not possible to know if the location information is precise or a nearby location, or if the location has been withheld intentionally for strategic reasons. As in previous chapters crimes have been listed as taking place within police stations. It is acknowledged that offences are committed within police stations but within this dataset serious sexual offences with a residential primary location had co-ordinates for the police station. 255 crimes with a summed harm score of 67,096 were removed from the dataset as they occurred within the vicinity of Coventry Central Police station.

5.4.3 Distribution of crime and harm

Figures 5.1 – 5.3 show the spatial distribution of crime counts and crime harm as heatmaps for the complete dataset and then subset by location (police station crime removed). The heat maps were generated in ArcGIS Pro to create a "representative surface of relative density" (ArcGIS Pro, unknown) as when a spatial dataset has many points close together a heat map symbology is advised. This allows a colour scheme to represent relative density rather than individual symbols. The kernel density method is used with ArcGIS Pro to calculate the density shown (see ArcGIS Pro, unknown 1). Using the same colour scheme and radius value (25m) the point locations of crime were input for all crime, outside locations and residential crimes, creating 3 separate heatmaps. This was replicated for crime harm. To map crime harm the same point data was used but each point was weighted by the CCHI score of the crime/s at each point. The standardised colour scheme and scale allows visual differences to be identified between all 6 maps.

These maps are based entirely on the point locations of the crimes as recorded by WMP and are not aggregated to an administration geography nor include underlying population data. Kernel density mapping to identify hot spots of crime is a popular method and has been used to predict where crime is likely to concentrate in the future (Chainey et al, 2008, Chainey and Ratcliffe, 2013) with Hu et al (2018) bringing in the temporal dimension to the maps created. These works show the sensitivity analysis undertaken regarding the parameters making up the mapping process. The maps included in this chapter have each been created under identical parameters in order to create a comparable visual aid. The use of kernel density mapping techniques incorporating a crime harm value is another area in its infancy (Fenimore, 2020).

When viewed as a complete dataset (Figure 5.1) the greatest crime volume is found in the city centre and moving out in a northeast direction, this pattern is extended when harm is viewed. This pattern is seen with outside crime and harm focused again on the city centre (Figure 5.3). Residential crime is not confined to one main geographic area, several separate residential areas are visible in both the crime volume and harm maps (Figure 5.2). As these are maps based on point data underlying residential density will influence distribution of residential crimes.

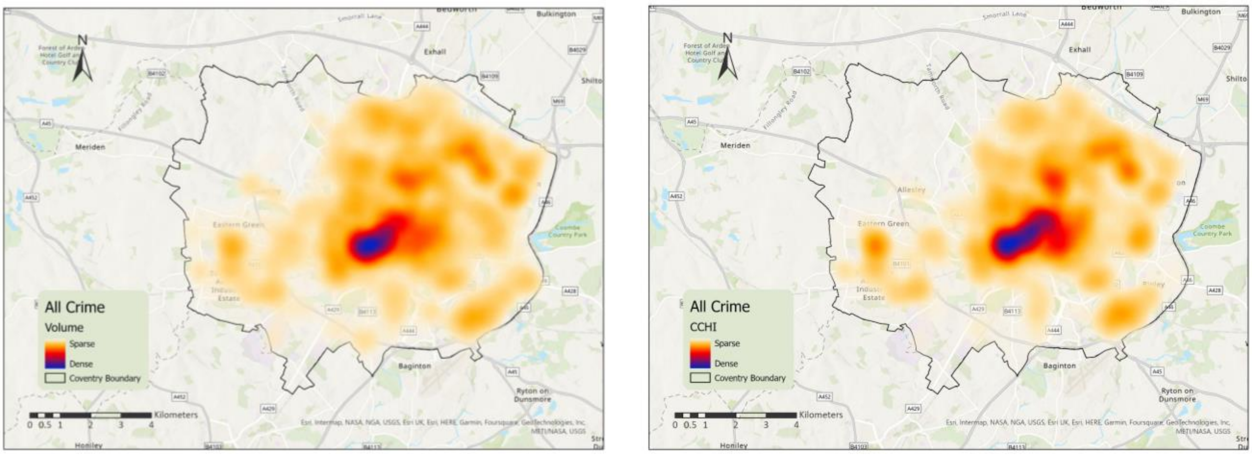


Figure 5.1: All crime volume and harm heat maps

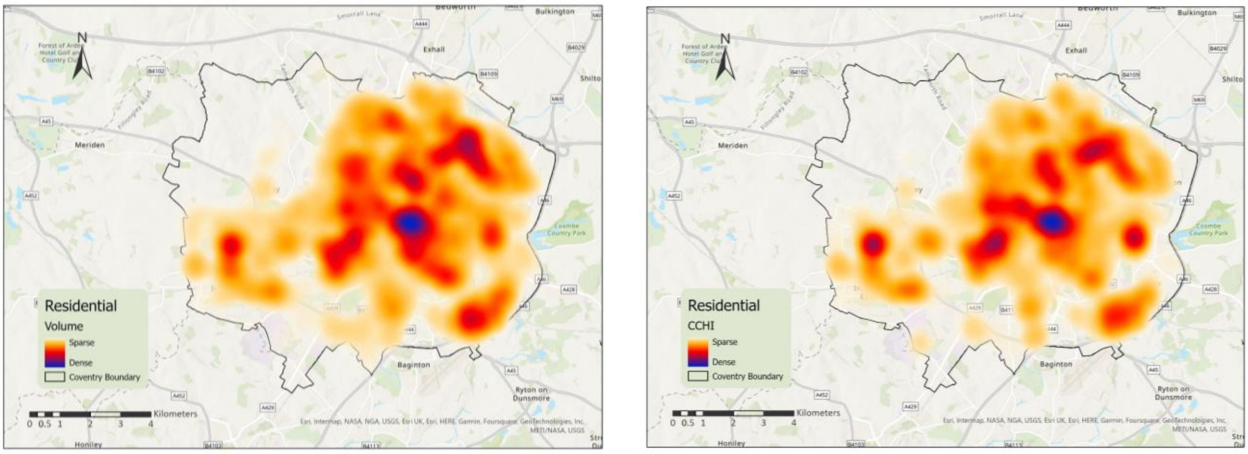


Figure 5.2: Residential crime volume and harm heat maps

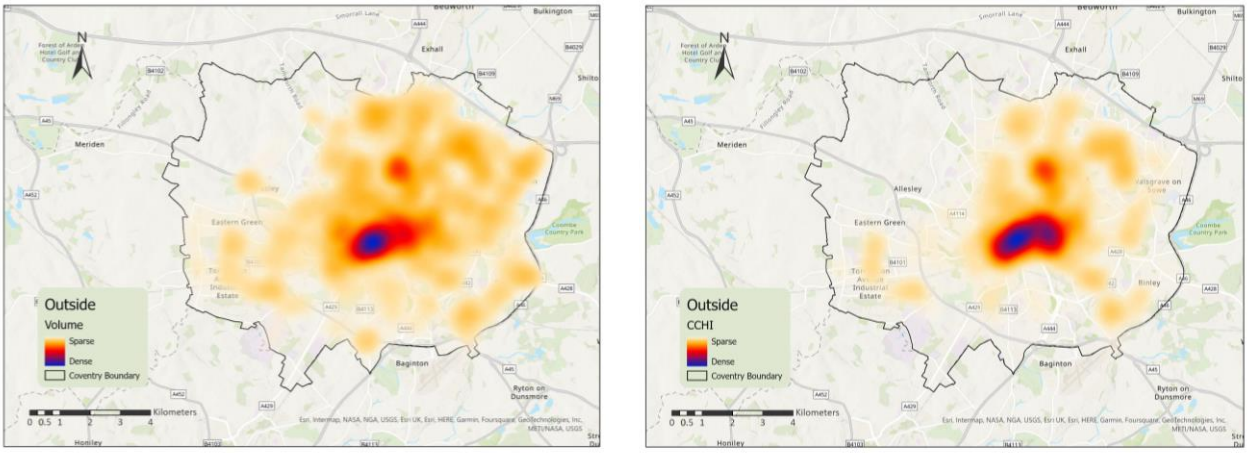


Figure 5.3 Outside crime volume and harm heat maps

5.4.4 LSOA data

This study uses 2011 LSOAs as the neighbourhood areal units on which to assess the differences between bordering pairs. Output Areas are the smallest level of geographic unit for census data and were designed especially for statistical purposes. They were first developed for the 2001 census and are based on postcode units and a number have changed shape due to population changes noted in subsequent censuses (ONS, 2016). LSOAs are made up of 4 or 5 Output Areas and have a resident population ranging from 1000- 3000 which make up around 400 to 1200 households (ONS, unknown).

Census data from 2011 was obtained for ethnicity, country of birth and religion at LSOA level for the (n = 195) LSOAs making up Coventry. Non-white and non-UK born variables were created.

Address data provided by the OS (AdressBase product) allowed for the creation of a residential building dataset for Coventry and the surrounding area. This data was used twice, one as a summed value per aerial unit and also as the basis for an inverse weighted distance interpolation layer.

5.4.5 Crime harm methods

The advice laid out by Sherman et al (2020) has been followed and a victim based CCHI created for the crimes included in the 2015 - 2019 dataset in use (Appendix 3). It contains 358 different offences with harm scores ranging from 1 - 5840. Further explanation of the score creation is found in the methodology.

5.4.6 Generating significant frontiers

The social frontiers of three socio demographic characteristics were created. Census 2011 data concerning ethnicity, country of birth and religion were downloaded for the 195 LSOAs that make up Coventry.

For the measure of ethnicity, a non-white variable was created. The country of birth dataset was used to create a non-UK born variable and the religion frontier was generated using the number of people who gave Muslim as their religion in the 2011 census. The total population per LSOA was used to generate percentages of each variable and is also a required variable within the social frontier generation process.

5.4.7 Frontier estimation

This paper follows the methodology set out in Dean et al (2019) in the creation of social frontiers using LSOAs. They apply a two-step approach to detecting frontiers in the chosen sociodemographic variable. The first step involves using Bayesian estimation of a conditional autoregressive regression to identify the location of spatial discontinuities in the residential variable examined. The second step involves identifying which pairs of adjacent neighbourhoods have a discontinuity that exceeds a given threshold. These steps are described in more detail below.

As stated, this work will use a measure of ethnicity (non-white), country of birth (non-UK) and religion (Muslim) to create the boundaries on which to measure the connection to crime. Once generated these will be merged into a combination frontier measure as seen in Smith (2021). This work will additionally create an intersectional frontier measure which will contain those social frontiers that appear for all 3 variables. The addition of this intersectional or super diverse group was highlighted as an area of interest in Dean et al (2019). They questioned whether the use of these frontiers of super diversity would add to the understanding of frontiers. “Social frontiers entail the proximity of extremes…” (Iyer and Pyrce, 2023, p.3), therefore a social frontier of multiple variables indicates the neighbourhoods on either side have multiple differences, as Iyer and Pyrce continue, “The greater the socio-cultural distance, the more difficult it may be for social connections to form.” (p. 3).

Social frontiers can be generated using any sociodemographic variable available at LSOA level. The decision to generate religious, ethnic and UK born frontiers was made in order to be able to compare findings from this analysis with previous work on frontiers, particularly those of Smith (2021) whose work indicated a strong relationship between criminal aspects and frontiers. There is precedent to use a measure of ethnicity (Legewie and Schaeffer (2016), Legewie (2018), Neil and Legewie (2023), Kramer (2017)) and or foreign born (Dean et al (2019), Křížková et al (2021), Kim and Hipp (2021), Olner et al (2023) as a measure on which to generate social frontiers. This though is an area ripe for expansion. Generating frontiers based on other variables, such as a measure of education or income, could highlight additional intersectional frontiers (borders between neighbouring areas that differ across multiple variables). It is also possible to control for differing socioeconomic variables within the regression analysis (for example Dean et al, 2019, used employment) this again presents opportunity for further sensitivity analysis in this emerging area of investigation.

The frontiers are generated using the 'socialFrontiers' R package which requires an LSOA shapefile containing both resident population and the number of people within the chosen demographic variable (Zhang, 2021).

Step one

The initial step requires finding geographic borders (LSOA borders) shared by two spatial units where the difference in the proportion of people of non-white ethnicity (or other variable of social composition) is statistically significant. This allows step changes to be identified. The mechanism for detecting these is based on Lee and Mitchells' (2013) "locally adaptive spatial conditional autoregressive model" (Dean et al, 2019, p 279) used in their work on respiratory disease risk. Initially a Poisson model, Dean et al (2019) have adapted it to model proportions by moving to a binomial distribution.

The full Bayesian model used in Dean et al (2019), Smith (2021) and Křížková (2021) is as follows:

$$Y_k \sim Binomial\ (N_k, p_k); k = 1, \dots, n$$

$$1n\left(\frac{p_k}{1 - p_k}\right) = \beta_0 + u_k$$

$$u_k \backslash u_{-k}, W, \lambda,\ \tau^2 \sim N\ \left(\frac{\sum_{k \sim l} u_l}{1 - \lambda + \lambda_{wk+}}, \frac{1}{\tau^2\ (1 -\ \lambda +\ \lambda_{wk+}}\right)$$

$$\beta_0 \sim N(0, b);\ \tau^2 \sim gamma\ (e', f')$$

$$logit(\lambda) \sim N(0{,}100)$$

Each LSOA k is indexed from 1 to n with the resident population N_k and variable count of interest Y_k used to calculate a proportion (p_k). This then undergoes logit transformation and is "set equal to a linear function of a spatial random effect" for each of the LSOAs (Dean et al, 2019, p. 279). It is assumed that the random effect (u_k) is spatially autocorrelated, that is, that the variation in the proportion of a sociodemographic variable in a particular LSOA (p_k) is influenced by the proportion of that variable in adjoining LSOAs.

The parameter affecting how the proportion of variable (Y) in a particular LSOA (k) is affected that variable in surrounding LSOAs is given as λ. The n by n spatial weights matrix W then determines if p_k is affected by the proportion of the variable in neighbouring LSOAs.

The package initially assumes that the proportion of the variable (p_k) in each of the neighbouring LSOAs has an equal effect (on the proportion of said variable in the LSOA examined). It then calculates the average effect, for each LSOA, of its neighbours. The Bayesian model then uses this average effect as the 'prior'.

Standard models fix the matrix W to values of 0 or 1 where 1 indicates neighbouring LSOAs and 0 otherwise. Unlike spatial models that assume spatial variation is smooth and symmetrical across all neighbouring geospatial units the 'socialFrontiers' package computes the average for areas only where the LSOA in question and its neighbours are similar. This is done by allowing the matrix (W) to ignore those neighbouring LSOAs where the difference is noticeably different (a statistically significant step change) i.e. there is a potential frontier between these adjacent LSOAs and allow the weight value to be 0.

The model identifies the number of borders between LSOAs and highlights those that have a statistically significant difference based on the characteristic chosen (allowing for spatial autocorrelation and small sample size).

Step two

Dean et al (2019) then propose using a threshold measure to further subset those statistically significant borders by identifying those that have a substantive difference. The supplementary material provided by Dean et al (2019) outline their frontier threshold criteria. The analysis presented in this chapter, however, will follow stricter threshold criteria used by Smith (2021) and Křížková et al (2021), where social frontiers are said to occur if and only if the absolute difference in the spatial weights either side of the neighbouring LSOA borders is greater than 1.96 SD the frontier is said to have passed the threshold of substantial difference. This will allow comparisons to be made with their work. This does present an opportunity to explore the social frontiers generated under different thresholds and how they align with the opinions of members of the communities at either side of the social frontiers identified. However, Zhang et al, (2024) found residents of Rotherham were "more likely to recognise boundaries with higher boundary values as local community borders" (page, 2) in their feasibility study of social frontiers created through areal wombling. For a more detailed explanation of the underlying mechanics with associated equations see Dean et al (2019, p279) and their supplementary material.

5.4.8 Permutation tests

The first test of association examines crime and harm rates (per 100 residential properties per LSOA) at LSOA level in a series of permutation tests. These tests compare the crime rates of mutually exclusive LSOAs either side of a social frontier with the rates of LSOAs neighbouring along a non-frontier boundary.

Each LSOA may have several neighbours, some of which are along social frontiers while others are simply borders. Due to frontier paired LSOAs being fewer in number they will occur within the tests multiple times. This creates dependency within the data which makes testing parametrically for significance difficult. To overcome this a permutation procedure is used. The dividing line between neighbouring LSOAs is randomly assigned as either social frontier or non-frontier in each permutation. This permutation procedure produces a distribution on which the statistical significance of the statistic derived from actual data can be measured.

The absolute mean difference in the crime rate found between LSOA divided with a social frontier is subtracted from the absolute mean difference in the crime rate found between LSOA bordering at non frontiers, as in the equation below. This value is then compared to the p value generated in the permutation test.

$$\frac{C_F}{N_F * P_F} - \frac{C_B}{N_B * P_B}$$

5.4.9 Regression analysis

The previous permutation tests examined the association of crime and harm rates per LSOA so there are the issues of ecological fallacy and modifiable areal unit problem to consider when interpreting the results (Openshaw, 1984a, 1984b). A more detailed examination of the relationship between social frontiers and crime and harm uses a 100m by 100m grid overlaid with point data of individual offences. This grid forms the basis of regression analyses, both linear and negative binominal, to test the association of social frontiers and crime at a finer resolution.

The number of police reported victim-based crimes falling within each grid was summed as was the CCHI harm score. This was done for all victim-based crime as well as the subsets of resident and outside crime. The five different types of social frontiers had 100m and 200m buffers added to them and dummy variables were created to indicate whether a grid square intersected with the social frontier buffer. Buffers of the same size were also created for all internal boundaries for use as a control within the regressions.

At this point a methodological decision needs to be made. Grid squares intersecting with the buffers are coded as such for use within the regression analysis. The intersection command unless otherwise specified will include all grid squares falling within the buffer to any extent. This allows a grid square with a very small proportion of its area within the buffer to be included. It is possible to specify that a grid square is included only if the centroid of the grid square falls within the buffer to allow only those grid squares where the majority of their surface are within it. Figure 5.4 highlights the difference in including all grid squares intersecting with a social frontier and those with centroids specified. Table 5.2 quantifies the differing number of grid squares included within the regression under these differing intersection conditions.

The analysis will be run twice, once with the full intersection grid square (for both social frontiers and all internal boundaries) and then with centroid only intersection. This will highlight the effect of this methodological decision on any associations.

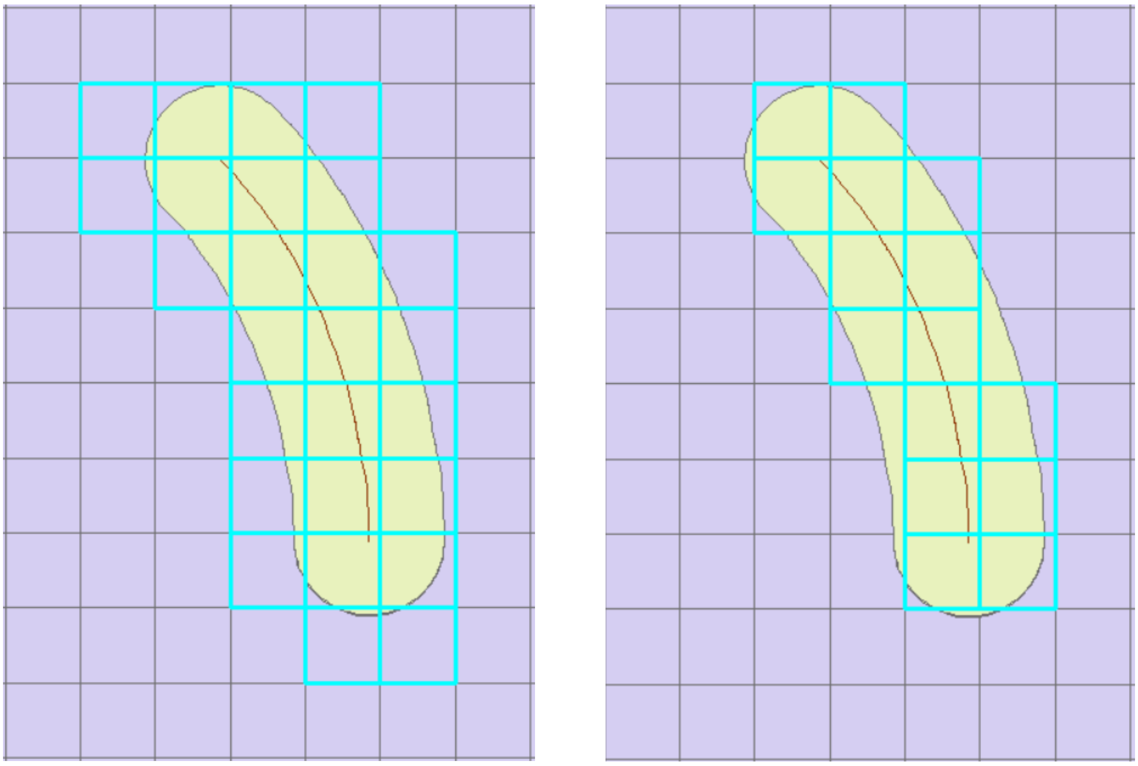


Figure 5.4: Difference in full intersect and centroid only intersect. Highlighted squares indicate inclusion.

	100m			200m		
	Centroid intersect	Full Intersect	Grid square difference	Centroid intersect	Full intersect	Grid square difference
Non-UK born	1519	2394	875	2919	3699	780
Muslim	1229	1944	715	2400	3054	654
Non-white	1451	2317	866	2885	3729	844
Composite frontiers	2374	3567	1,193	4246	5131	885
Intersectional frontier	572	979	407	1263	1728	465

Table 5.2. Difference in number of grid squares included for analysis under differing intersection conditions.

5.4.10 Underlying Population

To account for differing population counts and density both regression analyses used a measure of population within the model. For the linear regression crime and harm rates were created and within the negative binominal regression a population value per grid square was used as an offset. An inverse distance weighted interpolation surface of residential properties from the OS AddressBase product was created for use as a population proxy variable in each case.

This raster surface was created within ArcGIS and used residential property data subset from the AddressBase product supplied by the OS. Entries with a residential classification were selected for an area greater than Coventry to ensure the resulting surface covered the entire study area. This allowed detailed locational information about population to be incorporated into the analysis. This raster layer was then converted to a point file and the average value of points falling within each 100m by 100m grid square was recorded.

As mentioned, these population values were used to create a crime/harm rate per 100 residential buildings within the linear regression and as an offset within the negative binominal regression. This proxy surface can be used for all 6 crime and harm variables, but particular attention needs to be paid to the residential subset. The interpolated surface creates a layer where the minimum number of properties when averaged per grid square is 1. This is necessary for use when creating a crime/harm rate or especially as use as an offset (the offset is logged). However, as seen in chapter 4 residential crime can only occur where residential properties are listed. As per chapter 4 areal units (be it street segments or grid squares) without residential properties should be removed from the analysis as it creates false zeros within the analysis.

Using the summed value of residential properties those grid squares without residential properties were cut from the modelling. In addition, there is evidence of errors in the description of residential properties. As such any residential crimes falling in grid squares without residential properties present were removed (these points were also removed from the 'all crime' and 'all harm' datasets).

The data used in this analysis is the same count and harm data used in chapter 4 this time it is summed per 100m by 100m metre grid square. As mentioned previously it is not possible for this data to produce a negative value and as per the previous chapter, where the effects of zeros in a count dataset was explored in detail the same consideration for zero values is applied here.

The percentage of grid squares with no crime occurring was calculated. The mean and variance for each dataset was also calculated to identify if overdispersion was evident in the data. In each dataset over dispersion was identified, and to accommodate it a negative nominal regression was used (Hilbe, 2014). A denominator (referred to as an offset within r programming language) was used in each model to account for differences in resident population. This allows the differing population to be considered. Within this chapter summed residential properties per grid square and an interpolated layer are used as a proxy for population. Tables 5.3 and 5.4 outline the variables used within the analysis.

Shape type	**Variable Name**	**Description**
Polygon	Coventry grid	100m by 100m grid squares (n = 9861)
Polygon	Residential grid	100m by 100m grid squares containing residential properties (n = 5925)
Polygon	Coventry LSOA	2011 census LSOA (n = 195)
Polygon	Residential dwellings	Dwellings per 100m by 100m grid square (summed from point file)
Polygon	Population proxy	Inverse distance weighted layer based on residential properties
Polygon	SF buffer 100m	100m buffers generated for each social frontier x5
Polygon	SF buffer 200m	200m buffers generated for each social frontier x5
Polygon	Boundary buffer	100m buffers generated for each internal LSOA boundary
Polygon	Boundary buffer	200m buffers generated for each internal LSOA boundary
Line	Social frontiers	Social frontiers x5 for each variable, composite and intersectional
Line	Boundaries	Internal LSOA boundary lines segments between 2 adjacent LSOAs

Table 5.3: Shapefiles within analysis

Variable Type	Variable Name	Description	Range
Dependant	All Crime Volume	All crime volume per 100m by 100m grid square (summed from point)	0 - 556
Dependant	All crime Harm	All crime harm per 100m by 100m grid square (summed from point)	0 – 52,459
Dependant	Outside Crime Volume	Outside crime volume per 100m by 100m grid square (summed from point)	0 -276
Dependant	Outside Crime Harm	Outside crime harm per 100m by 100m grid square (summed from point)	0 – 33,341
Dependant	Residential Crime Volume	Residential crime volume per 100m by 100m grid square (summed from point) n = 5925	0 - 128
Dependant	Residential Crime Harm	Residential crime harm per 100m by 100m grid square (summed from point) n = 5925	0 – 20,272
			Coded
Independent	Social frontier (any) 100m	Dummy variable – grid squares intersecting with SF buffer 100m	1 / 0
Independent	Social frontier (any) 200m	Dummy variable – grid squares intersecting with SF buffer 200m	1 / 0
Independent	Social frontier (any) 100m - Centroid	Dummy variable – grid squares with centroids intersect with SF buffer 100m	1 / 0
Independent	Social frontier (any) 200m - Centroid	Dummy variable – grid squares with centroids that intersect with SF buffer 200m	1 / 0
Independent	Boundary control 100m	Dummy variable – grid squares intersecting with boundary buffer 100m	1 / 0
Independent	Boundary control 200m	Dummy variable – grid squares intersecting with boundary buffer 200m	1 / 0
Independent	Boundary control 100m - Centroid	Dummy variable – grid squares with centroids intersect with boundary buffer 100m	1 / 0
Independent	Boundary control 200m - Centroid	Dummy variable – grid squares with centroids that intersect with boundary buffer 200m	1 / 0

Table 5.4: Variables within analysis

5.5 Results

5.5.1 Social Frontiers

Coventry has an above average level of ethnic diversity. It has a lower than England average of people identifying their ethnic group as within the white category, a greater proportion of Muslim residents and greater proportion of people born outside the UK (proportions hold for both 2011 and 2021) (ONS, 2022).

Table 5.5 shows the number of internal boundaries identified between pairs of LSOAs, the number of those identified as having a statistically significant step change and then which of those then exceeded the threshold to be identified as social frontiers. Of the 511 internal boundaries making up the dividing lines between differing LSOAs between 23% and 28% were identified as social frontiers. The distribution of the populations making up the three social variables is varied enough that only 9.9% of social frontiers are shared by all three.

Frontiers	**Boundaries**	**Frontiers**	**Social Frontiers**
Non UK born	511	312	**144**
Muslim	511	284	**118**
Non-white	511	368	**126**
Combination			**226**
Intersectional			**51**

Table 5.5. Numbers of boundaries that are designated frontiers and from those the number that pass the threshold.

Figures 5.5 – 5.7 show the location of the significant frontiers overlaid onto a choropleth map showing the corresponding socio demographic variable (natural breaks). Figure 5.8 show the combination and intersectional frontiers.

Proportions of Non UK born populations are highest in the city centre and the southwest, possibly evidence of Coventry University and the University of Warwick’s international student population. Fig. 5.5, shows a number of social frontiers linked together enclosing the

LSOAs in the south west (Warwick's campus area). Non UK born social frontiers are also found in joined lengths around the higher proportions of non UK born residents moving northwards from the city centre.

It is interesting to note that the vast majority of social frontiers are open with a single closed religious social frontier evident in Figure 5.6 in the north east. This closed frontier encloses a single LSOA with a low percentage of Muslim residents. Muslim generated social frontiers are seen in large numbers (and linked) in the south-east of Coventry.

The distribution of non-white population is similar to that of the non UK born population with the universities evident again. The more rural areas to the northwest which form part of the West Midlands green belt have lower proportions of each demographic variable and this area has a noticeable absence of social frontiers within it (Figure 5.7).

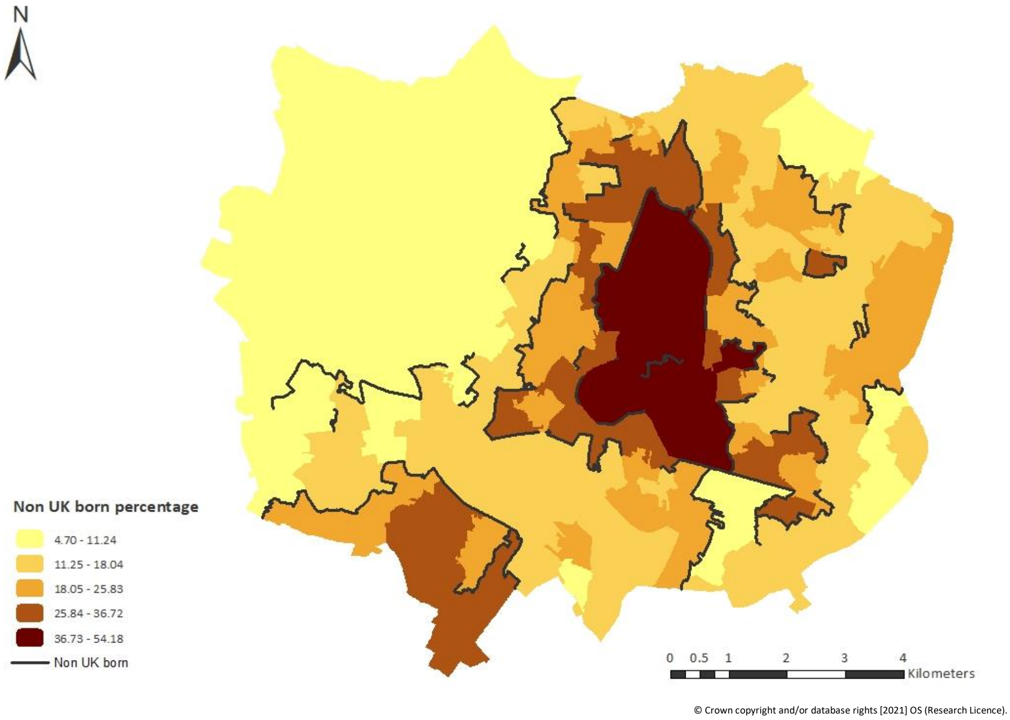


Figure 5.5: Non UK born percentage distribution and social frontiers

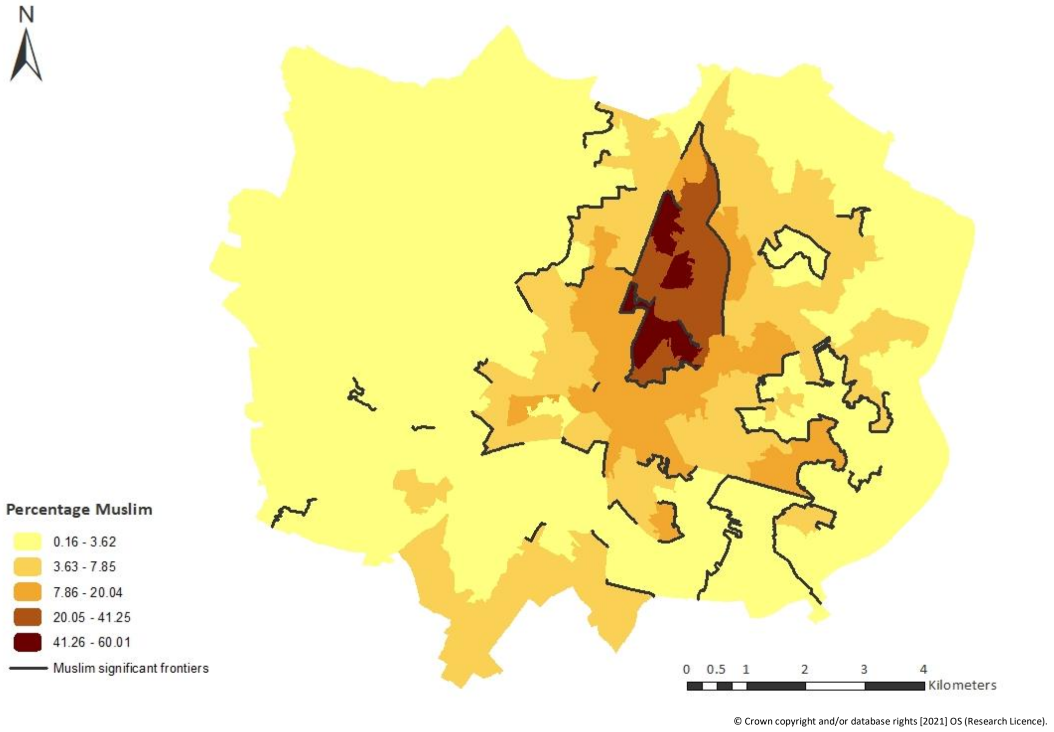


Figure 5.6: Muslim resident population percentage with religious social frontiers

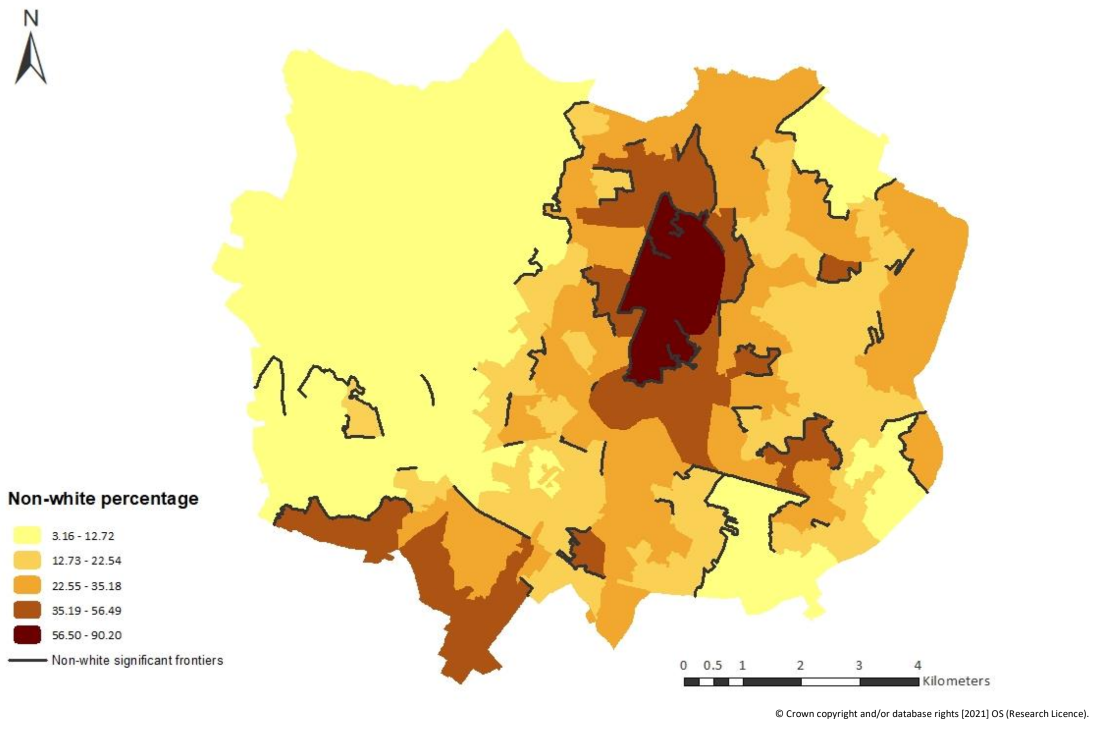


Figure 5.7: Non-white population percentage distribution and social frontiers

Figure 5.8 shows both the combined frontiers and those that occur for all three variables. The addition of LSOA boundary lines shows more clearly the number of LSOAs in the northwest whose low proportions of residents within the sociodemographic groups under study are so similar as to not create significant step changes along their borders. Combining social frontiers does not lead to the formation of any more closed frontiers. However, a single LSOA in the southeast is bordered by intersection frontiers on all but one of its boundaries.

Before moving to the regression analysis Dean et al (2019), Smith (2021) and Křížková et al (2021) all test initially for an association between the social frontiers in each grouping and crime at LSOA (or basic settlement units in the case of Křížková et al, 2021) using the permutation procedure described previously. Table 5.6 summarises the results.

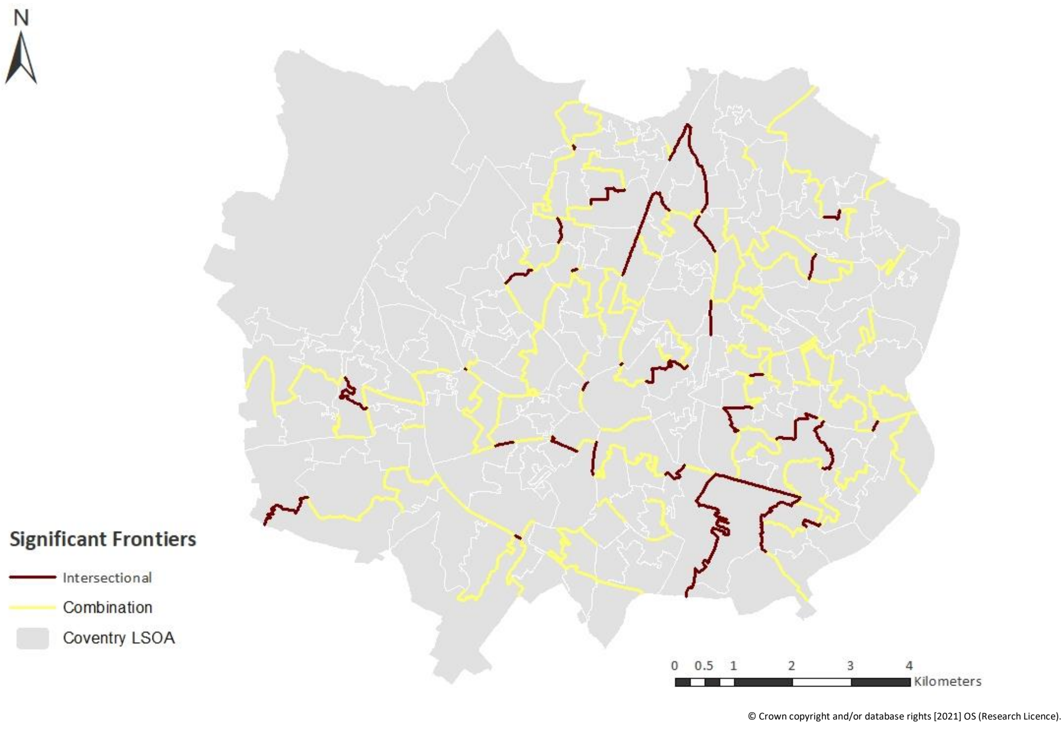


Figure 5.8: LSOA internal boundaries with Intersectional and Combination significant frontiers

5.5.2 Permutation Tests

Permutation tests were initially carried out on the complete dataset which includes all police reported victim based crime. Crime volume and crime harm were both tested. This dataset was then sub divided by location to test residential crime volume and harm and those offences occurring in an outside setting. In each instance a crime or harm rate was calculated using property data from the OS giving the rate per LSOA per 100 residential properties.

For each social variable the first column gives the difference in average mean crime/harm difference between pairs of LSOAs divided by a border and those divided by a social frontier. The second column reports the p value denoting statistical significance of each variable derived from 10,000 permutations. The negative values indicate that there is not an association between the social frontiers generated and increased levels of crime volume and harm.

The negative values are found across the complete dataset for the subsets of residential and outside locations (Table 5.6). However, as mentioned these tests examine crime and harm rates of LSOAs it should be noted that this makes the results susceptible to both the issue of ecological fallacy and the modifiable areal unit problem (Openshaw 1984a, 1984b). To account for this the following regression analyses use point specific data aggregated to smaller 100m by 100m grids.

5.5.3 Linear regression results

The crime volume and harm scores per grid square are count data for which linear regressions are not appropriate due to the possibility of negative results being returned (Hilbe, 2014). Despite this they can be used as initial analysis to understand data relationships before count based modelling is undertaken. A forward selection stepwise approach was taken to observe the impact of additional variables on model fit. The final models contain the dummy variable for the social frontier and control for all buffered internal boundaries and the fixed effects of LSOAs (neighbourhoods). This variable section differs from Dean et al (2019) who controlled for unemployment in their modelling. By controlling for internal borders and the fixed effects of LSOAs allows this work to be directly compared to Smith (2021) who used spatially specific police data.

	Social Frontiers					
Permutation test	**Non UK**		**Muslim**		**Non-white**	
Per 100 Residential Properties / LSOA	Differences as in equation (2)	*p*-values	Differences as in equation (2)	*p*-values	Differences as in equation (2)	*p*-values
All Crime Volume	-2.79	0.224	-2.3	0.31	-6.9	0.005
All Crime Harm	-599.85	0.004	-581.41	0.003	-751.93	0
Residential Crime Volume	-3.27	0	-3.06	0	-1.94	0.008
Residential Crime harm	-389.47	0.003	-254.16	0.0492	-301.0	0.02
Out Crime Volume	-1.05	0.327	-0.82	0.4659	-4.73	0
Out Crime harm	-269.16	0.013	-437.04	0	-619.89	0

Table 5.6. Permutation test results

The crime volume and harm variables are rates per 100 properties created with the interpolated population layer. Modelling was conducted on full intersection dependant variables and centroid only. Full regression results are found in appendix 6. Additional modelling on the residential subset was completed using the raw count of residential properties in the creation of the crime volume and harm rates.

All crime volume and harm

The headline results for all crime volume and harm at both full intersection and centroid only intersection are negative associations. When a social frontier returns a statistically significant result it is negative, at both 100m and 200m buffer distance, indicating that the presence of a social frontier decreases both crime volume and harm. The models are able to explain approximately 17% of the variation of crime volume and 14% of crime harm. Any positive results returned are not statistically significant.

Outside crime volume and harm

This negative effect is also seen when outside crime volume is modelled with the models explaining around 12% of the variation in outside crime. The significant results returned for outside crime harm were also negative (9%). Any positive results returned (ethnicity and composite frontiers) were not significant.

Residential crime volume and harm

The residential subset offers an opportunity to test social frontiers using different population data to create the crime volume and harm rates. As grid squares without residential properties can be identified using the summed OS residential dataset and removed from the analysis it is possible to observe the effect of a different population proxy on the results returned. This allows the modelling to be run with crime and harm rates created with the inverse distance weighted population values as well as the summed residential buildings it was created from. A summary of significant results is given in Table 5.7.

Using the inverse distance weighted population data to create the crime volume rates returns negative results for all social frontiers for both intersection methods and can explain 28% of the variation. Using the summed residential building data to create the residential crime volume rate returns one single significant result at full intersection for the composite frontier at 100m which is a positive one. This model is able to account for just under 3% of variation.

	Offset **Interpolated Distance Weighted layer values.**		**Offset** **Summed number of residential properties per grid square.**	
Residential crime volume	**Full intersection**	**Centroid only intersection**	**Full intersection**	**Centroid only intersection**
100m buffer	5 negative results	5 negative results	1 positive result	No significant result
200m buffer	5 negative results	5 negative results	No significant result	No significant result
Residential crime harm	**Full intersection**	**Centroid only intersection**	**Full intersection**	**Centroid only intersection**
100m buffer	1 negative result	3 negative results	1 positive result	No significant result
200m buffer	No significant result	3 negative results	1 positive result	No significant result

Table 5.7 Significant results returned under differing intersect and population conditions

Residential crime harm returns a similar pattern with negative results returned using the interpolated population data (centroid intersection at both 100m and 200m) and positive results from the summed property layer (intersectional frontier with full intersection at both 100m and 200m).

5.5.4 Negative binomial regression results

The total number of victim-based crimes and their associated crime harm scores were modelled as the basis on which differences and similarities in the effects found at different social frontiers could be assessed. As with the exploratory linear regression analysis the results here also control for effects of LSOA borders and LSOA fixed effect. Appendix 7 contains the full results derived from a ‘forward step’ process from null through to complete fixed effects model.

As with the linear regressions these models were conducted twice. Firstly, all social frontiers are modelled with a dependant variable (crime volume / crime harm per 100m grid square) and border control variable created from a full intersect with the 100m and 200m buffer. Secondly the same models are estimated using a dependant variable and border control variable created from a centroid only intersect. This is completed for both all crime volume and harm as well as outside crime volume and harm. With five social frontiers, two crime measures, two buffer sizes and two intersect variations this returns 40 results for each location. Full results are listed in appendix 7.

A number of results are available for interpretation in this result section. Significant results generated using full intersection methodology will be presented initially with the corresponding centroid intersection results following. All datasets were modelled using the interpolated population layer as the offset. The significant results are collated by crime measure and buffer size in tables 5.7 – 5.15.

Again, as with the linear regression the residential crime subset offers an additional methodological option to explore. In addition to changing the intersect parameter it is also possible to assess the impact of the offset used within the regression by comparing the result of the interpolated layer with a summed number of residential properties per grid square. A summary of significant results for the residential analysis is given in table 5.16.

Key findings

Social frontiers are associated with a reduction in the likelihood of both crime volume and crime harm when all victim based crime is modelled with both full and centroid intersect.

Social frontiers are also associated with a reduced likelihood of crime and harm occurring in outside settings within both 100m and 200m of the frontier when the centroid intersect method of grid square selection is used. When the full intersect grid selection method is used outside crime volume shows a reduced likelihood at both buffer sizes but outside crime harm produces a varying result. At full intersection at 100m there is a crime harm reduction but the likelihood of crime harm at 200m is said to increase at two social frontier types (non-UK and the composite frontier).

When residential crime and harm are modelled using the interpolated layer as the offset value (with property free grid squares removed from the analysis) there is also a crime reductive effect of social frontiers on both residential crime volume and harm (with both intersection approaches). There is a single exception: when using the full intersection parameter there is an increased likelihood of residential crime harm occurring within 100m of Non UK born social frontiers.

Negative binomial	**Crime Volume, FULL intersect using IDW layer as offset**					
	100m					
	All crime		**Outside**		**Residential**	
	Significant	**AIC**	**Significant**	**AIC**	**Significant**	**AIC**
Non-UK born **Standard error**	/	/	/	/	/	/
Muslim **Standard error**	-0.1212* 0.0494	55672	-0.0962 . 0.0508	43596	-0.1193 ** 0.0399	32736
Non-white **Standard error**	-0.1026* 0.0449	55673	-0.0974* 0.0464	43595	/	/
Composite frontiers **Standard error**	/	/	/	/	/	/
Intersectional frontier **Standard error**	-0.2104*** 0.0606	55667	-0.1861*** 0.0625	43591	-0.2002 *** 0.0513	32731
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’						

Table 5.8: Crime volume at 100m full intersect

Negative binomial	Crime Volume, centroid intersect using IDW layer as offset					
	100m					
	All crime		Outside		Residential	
	Significant	AIC	Significant	AIC	Significant	AIC
Non-UK born **Standard error**	-0.0929 . 0.0511	55696	/	/	-0.0745. 0.0422	32742
Muslim **Standard error**	-0.2459*** 0.0561	55682	-0.2276 *** 0.0578	43601	-0.2183*** 0.0456	32723
Non-white **Standard error**	-0.121* 0.0520	55694	-0.1063 * 0.0536	43611	-0.1153** 0.0434	32738
Composite frontiers **Standard error**	-0.0918 . 0.0473	55696	/	/	-0.1154** 0.0383	32736
Intersectional frontier **Standard error**	-0.3142*** 0.0742	55683	-0.3284 *** 0.0767	43598	-0.2554*** 0.0648	32731
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'						

Table 5.9: Crime volume at 100m centroid intersect

Negative binomial	Crime volume, FULL intersect using IDW layer as offset					
	200m					
	All crime		Outside		Residential	
	Significant	AIC	Significant	AIC	Significant	AIC
Non-UK born **Standard error**	-0.07281 . 0.04384	55569	/	/	-0.0620 . 0.0371	32740
Muslim **Standard error**	-0.0864 . 0.0482	55568	-0.0987* 0.0497	43494	-0.0844 * 0.0389	32738
Non-white **Standard error**	/	/	/	/	-0.0684 . 0.0358	32739
Composite frontiers **Standard error**	/	/	/	/	/	/
Intersectional frontier **Standard error**	-0.1676** 0.0523	55561	-0.1737** 0.0540	43488	-0.1269 ** 0.0428	32734
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'						

Table 5.10: Crime volume at 200m full intersect

Negative binomial	Crime volume, centroid intersect using IDW layer as offset					
	200m					
	All crime		**Outside**		**Residential**	
	Significant	**AIC**	**Significant**	**AIC**	**Significant**	**AIC**
Non-UK born **Standard error**	-0.0776 . 0.0438	55678	/	/	-0.0827* 0.0366	32737
Muslim **Standard error**	-0.1281 ** 0.0480	55674	-0.0959 . 0.0494	43607	-0.1425*** 0.0388	32729
Non-white **Standard error**	/	/	/	/	-0.0996** 0.0360	32734
Composite frontiers **Standard error**	/	/	/	/	-0.0910* 0.0364	32736
Intersectional frontier **Standard error**	-0.2282 *** 0.0560	55666	-0.2007 *** 0.0578	43600	-0.2047*** 0.0467	32724
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'						

Table 5.11: Crime volume at 200m centroid intersect

Negative binomial	Crime harm, FULL intersect using IDW layer as offset					
	100m					
	All crime		**Outside**		**Residential**	
	Significant	**AIC**	**Significant**	**AIC**	**Significant**	**AIC**
Non-UK born **Standard error**	/	/	/	/	0.1567* 0.0700	73524
Muslim **Standard error**	/	/	-0.1611 . 0.093	77961	-0.1450 . 0.0749	73525
Non-white **Standard error**	-0.1872* 0.0773	103391	-0.3153*** 0.0842	77953	/	/
Composite frontiers **Standard error**	/	/	/	/	/	/
Intersectional frontier **Standard error**	-0.2714** 0.1048	103390	-0.3147* 0.1141	77958	-0.2316* 0.0969	73523
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'						

Table 5.12: Crime harm at 100m full intersect

Negative binomial	**Crime harm, centroid intersect using IDW layer as offset**					
	100m					
	All crime		**Outside**		**Residential**	
	Significant	**AIC**	**Significant**	**AIC**	**Significant**	**AIC**
Non-UK born **Standard error**	/	/	/	/	/	/
Muslim **Standard error**	-0.2728 ** 0.0970	103395	-0.1857 . 0.1058	77982	-0.3480*** 0.0856	73507
Non-white **Standard error**	-0.2008 * 0.0897	103398	-0.2302 * 0.0977	77981	/	/
Composite frontiers **Standard error**	/	/	/	/	/	/
Intersectional frontier **Standard error**	-0.3129 * 0.1279	103397	-0.2596 . 0.1394	77982	-0.3501** 0.1215	73514
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'						

Table 5.13: Crime harm at 100m centroid intersect

Negative binomial	**Crime harm, FULL intersect using IDW layer as offset**					
	200m					
	All crime		**Outside**		**Residential**	
	Significant	**AIC**	**Significant**	**AIC**	**Significant**	**AIC**
Non-UK born **Standard error**	/	/	0.2209** 0.0824	77956	/	/
Muslim **Standard error**	/	/	/	/	/	/
Non-white **Standard error**	/	/	/	/	/	/
Composite frontiers **Standard error**	/	/	0.2932*** 0.0851	77952	/	/
Intersectional frontier **Standard error**	/	/	-0.2288* 0.0989	77957	/	/
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'						

Table 5.14: Crime harm at 200m full intersect

Negative binomial	Crime harm, centroid intersect using IDW layer as offset					
	200m					
	All crime		Outside		Residential	
	Significant	AIC	Significant	AIC	Significant	AIC
Non-UK born **Standard error**	/	/	/	/	/	/
Muslim **Standard error**	/	/	-0.1513 . 0.0904	77969	/	/
Non-white **Standard error**	/	/	/	/	/	/
Composite frontiers **Standard error**	/	/	/	/	/	/
Intersectional frontier **Standard error**	-0.2359 * 0.0968	103400	-0.2629 * 0.1054	77966	-0.2150* 0.0881	73525
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'						

Table 5.15: Crime harm at 200m centroid intersect

	Offset **Interpolated Distance Weighted layer values.**		**Offset** **Summed number of residential properties per grid square.**	
Residential crime volume	**Full intersection**	**Centroid only intersection**	**Full intersection**	**Centroid only intersection**
100m buffer	2 negative results	5 negative results	4 positive results	No significant result
200m buffer	4 negative results	5 negative results	No significant result	No significant result
Residential crime harm	**Full intersection**	**Centroid only intersection**	**Full intersection**	**Centroid only intersection**
100m buffer	1 positive result 2 negative results	2 negative results	3 positive results	1 positive result
200m buffer	No significant result	1 negative results	5 positive results	1 positive result

Table 5.16: Significant results returned under differing intersect and population conditions for residential models.

5.6 Discussion

This study has followed the methodology set out by Dean et al (2019) in generating and testing the association of crime and social frontiers. It set out to add to this emerging area of research by adding an intersectional social frontier which tests the association of social frontiers that appear for every social characteristic. By adding the CCHI score to each incident of reported victim-based crime it aimed to contribute to the growing study of crime harm by exploring the impact of social frontiers on crime harm in addition to unweighted crime volume, at the time of writing the first study to do so. Additionally, these crime and harm datasets where subset by broad location allowing testing of both overt (outside) and covert (residential) crime locations. However, the main finding to come from this chapter is the need to more fully explore the impact of differing methodological choices that can be made during the analysis.

Dean et al (2019) stated that as social frontiers are a growing area of interest there should be a robust and reliable way to identify and quantify them. This would ensure that measures would be replicable and allow comparisons to be made. They then set out a means to do this. Their work used a publicly available r package 'socialFrontiers' (Zhang, 2021) and suggested a threshold for determining between those frontiers that are statistically significant but do not represent a significant step change. Changes have already been made by researchers to the suggestions they put forward.

In the supplementary material provided with their 2019 paper Dean et al outlined the threshold value used within their work. They identified social frontiers using the mean multiplied by one standard deviation of absolute values to determine those frontiers that were not only statistically significant but represented a significant step change. This benchmark has been revised in the work that has followed. Smith (2021) and Křížková et al (2021) adopted 1.96 * the SD as the threshold, as has this work, which suggests this could become the standard threshold for future works.

If future researchers utilise the publicly available socialFrontiers R package and adopt a grid square or similar areal unit of analysis, there additionally needs to be clarity of language when discussing the method of intersection used to select those areal units falling within the buffered distance around social frontiers. Using the term intersect, either within a programming language such as R or Python or within a selection process within a GIS without qualification allows any areal unit to be included as part of the dependent variable within the analysis. Even if only a small part of its area falls within the buffer.

It is not clear whether Dean et al (2019) stipulated that the centroid needed to fall within the buffer when selecting grids in their work. The supplementary code supplied with Smith (2021) notes the intersection term used within R but no mention of centroid. Křížková et al (2021), however, who also built on the work of Dean et al (2019), did make clear their use of the grid centroid.

This chapter, on being presented with this data selection decision modelled both options as an opportunity to note the impact of changing the inclusion parameter. Figure 5.4 showed this graphically while Table 5.4 showed the effect of this on the number of grid squares included in the different sets of regressions. Focusing on the results from the negative binomial regressions the impact of the intersection choice firstly has an effect on the number of significant results returned and secondly it can affect the strength and direction of the relationship.

For the complete crime dataset for both crime volume and harm the centroid intersection models returned a greater number of significant results. The direction of the relationships did not change with all significant results indicating a negative association between social frontiers and crime volume and harm.

For outside crime the effects are different for crime volume and harm. Outside crime volume sees one additional significant result returned at the 100m buffer and stronger effects returned from the centroid regressions. Outside crime harm is interesting, at full intersect at 100m three social frontiers are negatively associated with crime harm but at the 200m buffer two social frontiers see a positive association with crime (non UK born and the composite frontier) with one negative (intersectional). When the centroid regressions are run the positive association between harm and social frontiers (indicating an increased likelihood of crime) is lost and a single (significant) negative result is returned. A negative association between social frontiers and crime volume, but a positive association between social frontiers and harm, could indicate low volume, high harm offences being committed.

Arguably a factor having a greater impact on results is the population data chosen for use as an offset within the regression. In this work ‘all crime’ and ‘outside crime’ regressions used the same offset values derived from the interpolated surface generated from residential properties. As the exact number of residential properties per grid could be calculated this value was used initially for use in the residential subset regressions. However, as the number of grid squares without properties is known, and those grid squares can be removed from the analysis it was possible, as with the intersection, to run the regressions with a different population proxy parameter. The residential subset allowed the effect of differing offset values to be examined. Within this residential subset the change in offset had the effect of changing the direction of association the social frontiers had on crime volume and giving mixed results with crime harm. The intersection choice again had an impact on the number of significant results returned.

As a result, it is not possible to establish conclusive answers to the research questions this chapter set out to investigate without clarifying the methodological ambiguities raised in the present study. Results for the centroid intersect were described showing a negative association between crime and social frontiers. These results differ from the findings of both Dean et al (2019), Smith (2021) and Křížková et al (2021) all of whom found and least a single positive association between crime and social frontiers. These differences may, however, be due to substantive factors (such as human agency) that cause different communities to respond in different ways to social frontiers (Iyer and Pryce, 2023; Staples et al, 2023).

5.7 Limitations

This paper has used LSOAs as the basis for the neighbourhood analysis and the 100m by 100m grid square for the regression analysis. Both of these have necessitated the aggregation of crime data and as a result there is a loss of the specific locations at which these crimes were recorded and precision associated with it.

The literature review outlined the necessity of using pre-drawn administrative boundaries as a proxy for neighbourhoods and may not reflect the neighbour boundaries residents would draw if asked. As a result of this future research could be affected by changes to LSOA boundaries from one census cycle to the next. An argument can be made for identifying social frontiers using other administrative spatial divisions, parishes or postcode zones. With different units of analysis available to researchers choosing the most appropriate can be a difficult task (Hipp, 2007).

5.8 Further Avenues

There are further avenues for investigating the effect of neighbour boundaries on crime. Asymmetry in frontiers is an area examined in house price (Myatt et al, 2023) and household mobility (Olner et al, 2023) but has yet to be examined in analysis concerning crime. In property research it is noted that different sides of the social frontier exhibit different behaviours with regard to the variable (house price, moving rate) examined (ibid). As this chapter has not examined sides of the social frontiers separately it is not possible to know if one side is driving the results, or if significant differences are being masked as one side cancels the effect of the other. This is an area that requires additional investigation. It may become apparent that crime/harm is occurring on one side but not the other of a particular frontier.

Another area that requires attention regards the offences making up the crime data. This analysis followed the methodology put forward by Sherman et al (2020) that victim based crimes better reflect the crime and harm experienced by a population. Police derived crime is more a reflection of their budgets and targeted focus. It would be interesting to examine the association of police generated crime and social frontiers particularly if sides of the frontier were examined. Are social frontiers areas of heavier proactive policing and is there an asymmetry to that coverage?

This may also be a possible explanation for the differing results found in this chapter with previous published work. Dean et al (2019) used a measure of all crime in their analysis which would have included police identified crime. Smith (2021) examined violent offences and public order crimes. Křížková et al (2021) examined neighbourhood conflict (minor crimes). Each analysis differs in the offences examined. It should also be noted that social frontiers do not exist in a vacuum. The operationalised crime pattern theory variables created for use in chapter 4 are still present in the environment creating situational opportunities for crime. Future work will also need to consider these elements.

5.8 Conclusion

This work set out to add to the limited literature on social frontiers and crime by adding two elements of novelty to the analysis namely the addition of crime harm and the sub setting of crime by broad location to consider differences in both overt and covert crime. As Dean et al (2019) note frontiers can be generated using any socio demographic difference measure. As with previous work examining crime and social frontiers, the frontiers generated for examination in this chapter have focused on the impact of ethnicity, religious difference and country of origin. Additional novelty within this work was achieved by creating a composite frontier of all social frontier sections and an intersectional frontier including only those frontier sections that appear for every variable.

In the process of examining these aspects it became apparent that there is sensitivity within the area of social frontiers to methodological decisions concerning: 1) the threshold used to identify social frontiers 2) the inclusion of data within buffers, and 3) the population data used to create crime rates and for use as offset within regression analysis. These findings potentially open up new avenues for future research into the impacts of social frontiers.

References

ArcGIS Pro, 2023, *Create heat maps in ArcGIS Pro using the Density toolset* [Online].[Accessed 01 September 2023] Available at: https://support.esri.com/en-us/knowledge-base/how-to-create-heat-maps-in-arcgis-pro-using-the-density-000021710

ArcGIS Pro, Unknown, *Heat map symbology* [Online].[Accessed 01 September 2023] Available at: https://pro.arcgis.com/en/pro-app/latest/help/mapping/layer-properties/heat-map.htm

Berger, J., (2019) *Neighborhoods of New York Demographics* [Online].[Accessed 01 September 2023] Available at: https://eportfolios.macaulay.cuny.edu/neighborhoodsofnyc/little-italy/culture/

Campbell, E., Henly, J.R., Elliott, D.S. and Irwin, K., 2009. Subjective constructions of neighborhood boundaries: lessons from a qualitative study of four neighborhoods. *Journal of Urban Affairs*, *31*(4), pp.461-490.

Catney, G., Lloyd, C.D., Ellis, M., Wright, R., Finney, N., Jivraj, S. and Manley, D., 2023. Ethnic diversification and neighbourhood mixing: A rapid response analysis of the 2021 Census of England and Wales. *The Geographical Journal*, *189*(1), pp.63-77.

Chainey, S. and Ratcliffe, J., 2013. *GIS and crime mapping*. John Wiley & Sons.

Chainey, S., Tompson, L. and Uhlig, S., 2008. The utility of hotspot mapping for predicting spatial patterns of crime. Security journal, 21(1-2), pp.4-28.

Cohen, L. and Felson, M., 1979. Social change and crime Rate Trends. *A Routine Activity Approach American Sociological Review*, *44*.

Coventry University, unknown. *Coventry. Your city, your university* [Online].[Accessed 01 September 2023] Available at: https://www.coventry.ac.uk/the-university/about-coventry-university/history/coventry-polytechnic-became-coventry-university/

Dean, N., Dong, G., Piekut, A. and Pryce, G., 2019. Frontiers in residential segregation: understanding neighbourhood boundaries and their impacts. *Tijdschrift voor economische en sociale geografie*, *110*(3), pp.271-288.

Dietz, R.D., 2002. The estimation of neighborhood effects in the social sciences: An interdisciplinary approach. *Social science research*, *31*(4), pp.539-575.

Etheridge, P., 2015. An exploratory study of the application of the Cambridge Harm Index (CHI) to crime data in South Yorkshire. *Police Executive Programme, Cambridge University (Unpublished)*.

Felson, M. and Eckert, M.A., 2017. *Introductory criminology: The study of risky situations*. Routledge.

Fenimore, D.M., 2020. *Investigating the spatiotemporal distribution and environmental risk factors of harm-weighted crime*. Texas State University-San Marcos.

Fotheringham, S.A. and Rogerson, P.A., 1993. GIS and spatial analytical problems. *International Journal of Geographical Information Science*, *7*(1), pp.3-19.

Gold, J.R., 1982. Territoriality and human spatial behaviour. *Progress in Human Geography*, *6*(1), pp.44-67.

Greenberg, S.W., Rohe, W.M. and Williams, J.R., 1982. Safety in urban neighborhoods: A comparison of physical characteristics and informal territorial control in high and low crime neighborhoods. *Population and environment*, *5*, pp.141-165.

Hainey, F, 2018, Coventry Telegraph. This is how much Coventry University is worth to the city [online]. [Accessed 01 September 2023]. Available at: https://www.coventrytelegraph.net/news/coventry-news/how-much-coventry-university-worth-14430533

Hilbe, J.M., 2014. *Modeling count data*. Cambridge University Press.

Hipp, J.R. and Williams, S.A., 2020. Advances in spatial criminology: The spatial scale of crime. *Annual Review of Criminology*, *3*, pp.75-95.

Hipp, J.R., 2007. Block, tract, and levels of aggregation: Neighborhood structure and crime and disorder as a case in point. *American sociological review*, *72*(5), pp.659-680.

Home Office. 2021. Location Anonymisation – Police.uk [online]. data.police.uk. [Accessed 01 September 2023]. Available from: https://data.police.uk/about/#location-anonymisation

Hu, Y., Wang, F., Guin, C. and Zhu, H., 2018. A spatio-temporal kernel density estimation framework for predictive crime hotspot mapping and evaluation. *Applied geography*, *99*, pp.89-97.

Iyer A, Pryce G., 2023. Theorising the Causal Impacts of Social Frontiers: The Social and Psychological Implications of Discontinuities in the Geography of Residential Mix, Urban Studies. Sage, In preparation.

Jacquez, G.M., Maruca, S. and Fortin, M.J., 2000. From fields to objects: a review of geographic boundary analysis. *Journal of Geographical Systems*, *2*, pp.221-241.

Johnson, S.D., 2010. A brief history of the analysis of crime concentration. *European Journal of Applied Mathematics*, *21*(4-5), pp.349-370.

Kennedy, L.W. and Caplan, J.M., 2012. A theory of risky places. *Newark, NJ: Rutgers Center on Public Security. Accessed February*, *12*, p.2021.

Kim, Y.A. and Hipp, J.R., 2021. Both sides of the street: Introducing measures of physical and social boundaries based on differences across sides of the street, and consequences for crime. *Journal of Quantitative Criminology*, pp.1-29.

Kramer, R., 2017. Defensible spaces in Philadelphia: Exploring neighborhood boundaries through spatial analysis. *RSF: The Russell Sage Foundation Journal of the Social Sciences*, *3*(2), pp.81-101.

Křížková, I., Le Zhang, M., Olner, D. and Pryce, G., 2021. Social Frontiers: Estimating the Spatial Boundaries Between Residential Groups and Their Impacts on Crime. *Urban Inequality and Segregation in Europe and China: Towards a New Dialogue*, pp.285-304.

Kubrin, C.E., 2009. Social disorganization theory: Then, now, and in the future. *Handbook on crime and deviance*, pp.225-236.

Kubrin, C.E., and Weitzer, R., 2017. New directions in social disorganization theory. In Recent developments in criminological theory (pp. 265-294). Routledge.

Lacy, K.R., 2007. *Blue-chip black: Race, class, and status in the new black middle class*. Univ of California Press.

Lee, D. and Mitchell, R., 2013. Locally adaptive spatial smoothing using conditional auto-regressive models. *Journal of the Royal Statistical Society Series C: Applied Statistics*, *62*(4), pp.593-608.

Legewie, J. & M. Schaeffer., (2016), Contested Boundaries: Explaining Where Ethnoracial Diversity Provokes Neighborhood Conflict. American Journal of Sociology 122, pp. 125–161.

Legewie, J., 2018. Living on the edge: neighborhood boundaries and the spatial dynamics of violent crime. *Demography*, *55*(5), pp.1957-1977.

Logan, J.R., Spielman, S., Xu, H. and Klein, P.N., 2011. Identifying and bounding ethnic neighborhoods. *Urban Geography*, *32*(3), pp.334-359.

Lu, H. and Carlin, B.P., 2005. Bayesian areal wombling for geographical boundary analysis. *Geographical Analysis*, *37*(3), pp.265-285.

Lu, H., Reilly, C.S., Banerjee, S. and Carlin, B.P., 2007. Bayesian areal wombling via adjacency modeling. *Environmental and ecological statistics*, *14,* pp.433-452.

Macbeth, E. (2015). Evidence-based vs. experience-based targeting of crime and harm hotspots in Northern Ireland. Master thesis. University of Cambridge.

Massey, D.S. and Denton, N.A., 1988. The dimensions of residential segregation. *Social forces*, *67*(2), pp.281-315.

McPherson, M., Smith-Lovin, L. and Cook, J.M., 2001. Birds of a feather: Homophily in social networks. *Annual review of sociology*, *27*(1), pp.415-444.

Myatt, A., Osland, L. and Lindgren, U. (2023) Housing Price Impacts of Social Frontiers in Oslo, Paper presented at the Life at the Frontier Symposium, Sheffield, June 2023

Neil, R. and Legewie, J., 2024. Policing neighborhood boundaries and the racialized social control of spaces. *Law & Society Review, 58*(2), pp.192-215.

Office for National Statistics, 2016, *Output areas Introduction to Output Areas - the building block of Census geography.* [Online].[Accessed 01 September 2023] Available at:

https://www.ons.gov.uk/census/2001censusandearlier/dataandproducts/outputgeography/outputareas

Office for National Statistics, 2022, *How the population changed in Coventry: Census 2021*. [Online].[Accessed 01 September 2023] Available at: https://www.ons.gov.uk/visualisations/censuspopulationchange/E08000026/

Office for National Statistics, 2023, *Crime Severity Score (Experimental Statistics)* [Online].[Accessed 01 September 2023] Available at: https://www.ons.gov.uk/peoplepopulationandcommunity/crimeandjustice/datasets/crimeseverityscoreexperimentalstatistics

Office for National Statistics, Unknown. *Census 2021 geographies* [Online].[Accessed 01 September 2023] Available at: https://www.ons.gov.uk/methodology/geography/ukgeographies/censusgeographies/census2021geographies#lower-layer-super-output-areas-lsoas

Olner, D., Pryce, G., van Ham, M. and Janssen, H., 2023. The conflicting geographies of social frontiers: Exploring the asymmetric impacts of social frontiers on household mobility in Rotterdam. *Environment and Planning B: Urban Analytics and City Science*, p.23998083231173696.

Openshaw, S., 1984a. Ecological fallacies and the analysis of areal census data. *Environment and planning A*, *16*(1), pp.17-31.

Openshaw, S., 1984b. The modifiable areal unit problem. *Concepts and techniques in modern geography*.

Park, R. E., Burgess, E. W., & McKenzie, R. D. (1925). The city. Chicago: University of Chicago Press.

Piekut, A. and Pryce, G., 2022. Life at the Social Frontier: Re-conceptualisation, synthesis, and future directions. *NordForsk Life at the Frontier Working Paper (in preparation)*.

Reynald, D.M., 2010. Guardians on guardianship: Factors affecting the willingness to supervise, the ability to detect potential offenders, and the willingness to intervene. *Journal of Research in Crime and Delinquency, 47*(3), pp.358-390.

Rich, M.A., 2009. “It Depends on How You Define Integrated”: Neighborhood Boundaries and Racial Integration in a Baltimore Neighborhood 1. In *Sociological Forum* (Vol. 24, No. 4, pp. 828-853). Oxford, UK: Blackwell Publishing Ltd.

Sampson, R.J., Raudenbush, S.W. and Earls, F., 1997. Neighborhoods and violent crime: A multilevel study of collective efficacy. *science, 277*(5328), pp.918-924.

Sampson, Robert J., and W. Byron Groves. 1989. Community structure and crime: Testing social disorganization theory. American Journal of Sociology 94, no. 4: 774-802.

Shaw, C. R., & McKay, H. D. (1942). *Juvenile delinquency and urban areas*. Chicago: University of Chicago Press.

Sherman, L.W, Neyroud, P.W. and Neyroud, E., 2016. The Cambridge crime harm index: Measuring total harm from crime based on sentencing guidelines. *Policing: a journal of policy and practice*, *10*(3), pp.171-183.

Sherman, L.W. and Cambridge University associates, 2020. How to count crime: the Cambridge harm index consensus. *Cambridge Journal of Evidence-Based Policing*, *4*, pp.1-14.

Sherman, L.W., Gartin, P.R. and Buerger, M.E., 1989. Hot spots of predatory crime: Routine activities and the criminology of place. Criminology, 27(1), pp.27-56.

Smith, J. (2021) Crime and offending in South Yorkshire: understanding neighbourhood effects of social frontiers [MA Thesis, University of Sheffield]. University of Sheffield (MA Thesis, University of Sheffield).

Spielman, S.E. and Logan, J.R., 2013. Using high-resolution population data to identify neighborhoods and establish their boundaries. *Annals of the Association of American Geographers*, *103*(1), pp.67-84.

Staples H, Piekut A, Pryce G (2023) Questioning the ‘conflict hypothesis’: an alternative perspective on intergroup collaboration along neighbourhood social frontiers, NordForsk Life at the Frontier Working Paper

StatisticalAtlas, unknown a, *Ancestry in Chinatown, New York, New York* [Online].[Accessed 01 September 2023] Available at: https://statisticalatlas.com/neighborhood/New-York/New-York/Chinatown/Ancestry

StatisticalAtlas, unknown b, *Race and Ethnicity in Chinatown, New York, New York* [Online].[Accessed 01 September 2023] Available at: https://statisticalatlas.com/neighborhood/New-York/New-York/Chinatown/Race-and-Ethnicity

Tammaru, T., Marcin´ Czak, S., Aunap, R., van Ham, M. and Janssen, H., 2020. Relationship between income inequality and residential segregation of socioeconomic groups. *Regional Studies*, *54*(4), pp.450-461.

Tuttle, S., 2020. Producing diverse and segregated spaces: Local businesses and commercial gentrification in two Chicago neighborhoods. *City & Community*, *19*(4), pp.845-869.

University of Cambridge, 2020 *Institute of Criminology The Cambridge Crime Harm Index* [Online]. [Accessed 01 September 2023] Available from: https://www.crim.cam.ac.uk/research/thecambridgecrimeharmindex

Van Ham, M., Tammaru, T., Ubarevičienė, R. and Janssen, H., 2021. *Urban socio-economic segregation and income inequality: A global perspective* (p. 523). Springer Nature.

van Ruitenburg, T. and Ruiter, S., 2023. The adoption of a crime harm index: A scoping literature review. *Police Practice and Research*, *24*(4), pp.423-445.

Warwick, 2022, *About People* [Online].[Accessed 01 September 2023] Available at: https://warwick.ac.uk/about/profile/people/

Weinborn, C., Ariel, B., Sherman, L. W., & O'Dwyer, E. (2017). Hotspots vs. harmspots: Shifting focus from counts to harm in the criminology of place. *Applied Geography, 86*, 226–244.

Weisburd, D., Groff, E., & Yang, S. (2012). The criminology of place: Street segments and our understanding of the crime problem. Oxford: Oxford University Press.

Womble, W.H., 1951. Differential systematics. *Science*, *114*(2961), pp.315-322.

Zhang, M. (2021). *socialFrontiers* [online]. Github. [Accessed 1 January 2023]. Available from: https://github.com/MengLeZhang/socialFrontiers

Zhang, M., Piekut, A., Rasool, Z., Warden, L., Staples. H and Pryce, G (2024) Using residents and experts to evaluate the validity of areal wombling for detecting social boundaries: a small-scale feasibility study (working paper)

Chapter 6. Conclusion

6.1 Introduction

The current thesis aimed to better understand the use and utility of crime harm in the analysis of victim based crimes from police data. To accomplish this aim, police data from two police forces were combined with various publicly available datasets (e.g. OS open roads and paths, AddressBase, Points of Interest, ONS deprivation domains) and analysed using quantitative methods (descriptive, route analysis and regressions) over three empirical papers.

The use of harm as a measure of crime originated with Sellin and Wolfgang (1964) and their work developing a ranking of crime seriousness from surveying public perception. Since that point other authors have contributed both rationale for the need for a weighted measure of crime and methods for operationalising one. More recently harm measures have started to be integrated with the more well known analytical process of hot spot mapping and the wider work on crime concentration. In a similar scale to the early ~~work~~ of Pierce et al (1988) and Sherman et al (1989) in the late 1980s, this thesis has used crime and other environmental variables recorded at the micro-scale and sou~~g~~ht to explain the non-random spatial distribution of crime using environmental criminology theories. These theories and processes can be applied to harm at the micro-scale and it can be examined in the same manner.

This concluding chapter presents a summary of the preceding work and reiterates the answers to the research questions posed and makes clear the contribution of the thesis. The impact of COVID will be addressed before a discussion of the limitations of the thesis which will highlight areas for further consideration when interpreting the results of the dissertation as a whole. Policy implications will be discussed before the final conclusions are drawn.

6.2 Research Questions and Key Findings

The three research questions were addressed as separate chapters 3 to 5.

Q1: Acknowledging both day of week and police shift, to what extent is it useful to combine police reported crime volume and crime harm to police patrol routing?

Chapter 3, using data from SYP, sought to answer this question by using the five level classification of crime volume and harm devised by Weinborn et al (2017) and applying it to the study area of Rotherham. This classification uses both summed crime volume and crime harm per street segment to identify micro areas of crime concentration. This five level division of street segments by crime volume and harm was then used in a preventative patrol route analysis.

Initial descriptive statistics examining the cleaned dataset for Rotherham by both crime volume and harm indicated that different classes of crime are driving high amounts of crime volume and harm. Theft offences are the most numerous crimes but the most harm comes from crime involving violence against the person. This is in keeping with the findings of Weinburn et al (2017), Norton et al (2017) and Fenimore (2020). As theft offences are less harmful, they are fifth in terms of their summed harm. Both crime volume and harm peak on Friday and Saturdays, and the highest crime volume and harm occur during the afternoon policing shift, with a higher percentage of volume to harm. Lower amounts of crime volume are seen during the night shift but the associated harm from those crimes is higher indicating more serious crimes.

Analysis by street segment showed approximately 45% of Rotherham's street segments were crime free. 50% of crime volume is concentrated on 6.3% of street segments which falls outside the bandwidth set by Weisburd (2015). Crime harm was more concentrated with 50% of harm located on 2.6% of segments; again this is in line with findings from Macbeth (2015) and Weinborn et al (2017).

The five point classification was used as a cost impediment within a route analysis conducted within the network analyst extension of ArcGIS. The priority street segments were given the lowest value. This allocated street segments a value that allowed the route analysis algorithms to route the journey with the lowest cost impediment which prioritised street segments in the order of the classification. This would allow patrols to travel along higher crime streets in preference and be a visible deterrent. In addition to analysing the data set as a whole this chapter recognised the temporal nature of crime and harm as highlighted in Norton et al's (2017) work and subset the data by weekday and weekend and also again by policing shift. This does reduce the number of offences within each dataset but allows temporal hot and harm spots to become visible that would otherwise be masked within the complete dataset. The routing exercise was then completed for differing days and shifts to highlight the different requirements of patrol at alternate times.

The contribution of this chapter, therefore, is to lay out the means for police forces to route non-emergency responding vehicles through the force area. It highlights the utility of combining measures of both crime volume and crime harm to identify areas of policing priority and is then the first analysis to make use of these identified priority areas by using them as a cost measure within a network routing analysis. It also recognises that the areas of policing priority change over the course of both days and weeks. By identifying those changes and generating routes for the appropriate day and shift ensures areas receive policing attention at the most suitable time and alleviates under or over utilisation of particular routes that may be present due to behavioural bias (Davies and Bowers, 2019). This chapter presents a testable methodology for increased efficiency from the routine movement of police vehicles.

Q2: To what extent are variables pertaining to situational crime theory associated with police reported victim based crime volume and harm? Does this association differ when crime volume and harm are subset by broad location and does this have implications for policing?

This chapter used data from WMP as a result of the COVID pandemic and the lack of continued access to SYP offices. Examining variables operationalised from situational crime theories, namely guardianship and motivated offenders from routine activity theory and crime generators and attractors from crime pattern theory, this analysis first examined the association with the complete dataset. It then partitioned the data by broad location to allow crime occurring outside (overt crime) to be analysed separately to crimes occurring in and around residential properties (covert crime) (Felson and Eckert, 2017). The location subsets were based on a scene location variable contained within the WMP data.

Rather than examining crime by offence type, as had been seen traditionally in spatial criminology and the creation of hot spots (see Braga et al, 2019), the location variable allowed broad location to be a factor of analysis. Crime types that are not limited to certain locations (such as burglary) would be examined within the broad setting (outside or residential) they occurred.

Following a more detailed methodology set out by Sherman et al (2020) regarding the inclusion and exclusion of offences, this chapter used a dataset of police reported victim based crimes (and those offences classified as jointly victim and crimes against the state) as defined by the

Notifiable Offences list 2020 for the city of Coventry. Additional offences were removed as outlined within the chapter.

This chapter, again at the street segment level, found crime harm to be more concentrated than crime volume, 50% of harm occurring on 1.71% of street segments compared with 3.74% of crime volume. The more interesting descriptive statistic discovered was the amount of harm occurring in and around residential properties. Higher amounts of harm from lower crime volume indicates higher harm (more serious) crimes taking place in residential settings.

The results from the negative binomial regressions (Table 4.4) indicated that streetlights increase the likelihood of crime volume and harm occurring in outside locations which is at odds with the literature (Welsh et al, 2022), however it was not a focused analysis of streetlights nor the timing of crime which would have a bearing on this result. The greatest impact on increased residential crime volume and harm coming from bus stops directly located on the street segment. Bus stops are recognised as a feature with the potential to increase crime and it is interesting to see this effect on crime in a residential setting (Ceccato et al, 2022). The crime reductive power of police and fire stations was evident but as noted these are fixed locations and unlikely to grow in number.

These findings answer the research question set and shows the novel contribution of the analysis. Crime volume and harm are associated to different extents with elements within the environment and those associations further change when offences are subset by their location. The main finding is the greater amount of harm in a residential setting given the lower volume of crime occurring. This answers the question posed by Fenimore (2020) and further shows the use of not only incorporating crime harm but also the importance of identifying the location of offences. This highlights it as an area for further research.

Q3: *To what extent is crime harm, in addition to crime volume, associated with social frontiers? Does this association differ when crime volume and harm are subset by broad location and does this have implications for policing?*

Using the same cleaned point data from WMP for Coventry, this chapter moved the analysis from the micro-scale of street segments to using LSOA and 100m by 100m grid areal units. Social frontiers are areas described as abrupt dividing lines between adjacent neighbourhoods with regard to the social makeup of the resident populations on either side.

Social frontiers for three social variables (ethnicity, religion and country of birth) were created with a composite measure which included social frontiers of any characteristic and an intersectional variable which identified those social frontiers that appear for every social variable. Permutation tests at the LSOA level, exploratory linear regressions and negative binomial regressions indicated a negative association between social frontiers and crime volume and harm. This was found for all subsets. These findings were unexpected as previous research using the same analytic techniques found at least some indication of increased crime at social frontier locations. The negative association between police reported victim based crimes and social frontiers, once methodological decisions have been discussed, has raised the question that the positive association identified in previous studies may be driven by crimes proactively policed. This is an area for further examination with attention paid to the distribution of crimes on either side of the social frontier.

More interestingly, methodological choices within the analysis had not only an impact on the number of significant results returned but in some cases the direction of the relationship between crime and social frontiers. While it was not possible to address the research question clearly, Chapter 5 makes suggestions for future researchers examining the effect of social frontiers and crime to establish their methodological parameters so findings can be compared.

6.3 Contributions of the Thesis

The traditional methods for identifying areas of concentrated crime have focused on the use of calls for service or the use of police reported crime. Calls for service and police reported crimes can be filtered to identify crimes of particular type or calls relating to particular offence types. Within the work included in the most recent iteration of Braga et al's (2019) systematic review is evidence of hot spots being created based on offence type criteria. The point made in earlier chapters, that the location the crime occurs is often secondary to the crime type or intervention, is given here as explicit evidence of the contribution of this work. Subsetting all police reported victim based crimes by their broad location has allowed crimes that occur in multiple settings to be analysed within the broad location they were committed. This has revealed that while the overall volume of crime is lower in residential settings when compared to outside locations, the overall harm from those crimes is greater. This indicates that higher harm offences are being committed in and around residential properties in a covert setting (Felson and Eckert, 2017). This setting is not as susceptible to general guardianship as supplied by the public nor is visible policing likely to be a deterrent.

The identification of elements of the environment that increase the likelihood of crime volume and harm have also been found to differ when the locations of the offences are acknowledged. Street lights increase the likelihood of crime outside but do not return a significant result for residential crime and harm.

This thesis also clearly shows the benefit of combining both crime volume and crime harm to identify areas of concentrated serious crimes. This allows these areas to be the focus of limited police resources. The practical implications of this work concern resource allocation and the identification of areas for targeted problem-oriented policing or visible patrol.

Combining both crime volume and harm expands the notion of hot spot policing and in so doing, highlights where improvements to efficiency may be made. Problem-oriented policing of areas that experience both high volume and high harm coupled with targeted policing that additionally acknowledges the temporal element of the distribution of crime volume and harm concentration could see greater crime reductive results. Using a crime harm metric in the reporting of crime statistics will also allow police forces the ability to highlight any reductions in high harm crime.

The identification of residential properties as the sites of greater amounts of victim based harm from a lower volume of crime that occurs in outside settings has implications for neighbourhood policing teams rather than then hot spot strategies. In addition, this thesis has also highlighted that using a harm measure with police reported victim based crime without also examining the harm associated with crimes making up the accompanying Proactive Policing Index raises questions when comparing findings to previous crime research.

This thesis has also examined crime harm in relation to social frontiers. At the time of writing this is the first work to do so. In examining the relationship between social frontiers and crime volume and harm it became necessary to make a number of methodological choices. These choices effect the outcome of social frontier modelling and are an area ripe for further exploration.

To summarise, the overall contribution of the thesis is found initially in the application of a crime harm value to location specific police data from two separate police forces. This has allowed the descriptive analysis of harm to be generated at the micro scale, street segments, and produced findings in keeping with emerging work that finds harm to be more concentrated in space than crime volume. It has then presented three novel papers that include harm within each analysis in parallel with the tradition crime measure of volume which allows comparisons to be made between the two measures. The first showing how volume and harm can be incorporated to generate increased visibility and efficiencies of movement through non-emergency routing of police vehicles to high volume and harm areas which are temporally appropriate. The second, by additionally portioning the data by broad location categories, examined the differing influence of environmental context on both crime volume and harm. This analysis suggested areas for future investigation particularly around the differing influence of elements traditionally viewed as guardian features, such as streetlights, on crime taking place outside. The third, examined crime volume and harm, with the addition of location based analysis, in relation to the emerging field of social frontiers. This field was additionally expanded with the creation of an intersectional frontier. This analysis again presented areas for further investigation particularly related to methodological choices. The sensitivity analysis presented in the final paper showing the necessity of clearly documenting the decision pathway. The complete thesis shows the need to include a measure of crime harm alongside crime volume in order to fully recognise the complexity of the spatial distribution of ‘crime’.

6.4 Impact of COVID

This thesis was started pre pandemic in September 2018. Initial access to data provided by South Yorkshire Police was delayed due to issues related to international work and the number of years present in the UK available for vetting. Once access was granted analysis began working as a visitor in South Yorkshire Police headquarters in Carbrook. Chapter 3 was completed in January 2020. March 2020 saw the first lockdown and access to Carbrook headquarters became difficult to impossible with various levels of restrictions in place for the remainder of the year.

Data from West Midlands Police was made available online from December 2020. This data contained different variables for a different part of the country. While not starting from the beginning this new data required investigation and preprocessing. The new data allowed analysis to move in a different direction with the addition of location information. This thesis is reflective of the time it was written using the data available.

6.5 Limitations

This section will expand on limitations highlighted within each chapter and discuss limitations that apply to the thesis overall. A discussion of the limitations of using police reported data in criminology research will be followed with an overview of possible errors present within that data. Issues surrounding the compilation and use of the CCHI are also explored.

6.5.1 Police data as a measure of crime

The crime survey for England and Wales has shown that only 4 in 10 crimes are reported to the police (Verian, 2023). This relates directly to this thesis as offences analysed in this work are victim based crimes, reported to the police, rather than crime uncovered through proactive policing. The ‘dark figure of crime’ is a term used to describe “occurrences that by some criteria are called crime yet that are not registered in the statistics of whatever agency was the source of the data being used”, put simply, unreported crime (Biderman and Reiss, 1967, p 2).

Designing preventive policing measures based on geocoded police reported crime must acknowledge the risk that using this data presents. Just as reported crime is unequally distributed across space so must the assumption be that unreported crime is also unequally distributed (Buil-Gil et al, 2021). Tarling and Morris (2010) note that crime reporting rates differ for differing groups. The elderly are more likely to report crime than younger crime victims with women more likely to report than men. There are no clear reporting rates for particular ethnic groups (ibid).

There are also differences based on location and social economic factors. Urban and rural residents report crime slightly more than people living in suburban areas (Langton et al, 2012), additionally people with higher educational qualifications, the employed, especially those with higher household incomes, and those living in the least deprived areas are more likely to report their victimisation (Tarling and Morris, 2010). Having a favourable attitude towards the police is also more likely to increase crime reporting (ibid).

Crime type also affects the rate at which that crime is reported (Buil-Gil et al, 2021). The more serious the crime the more likely it is to be reported, this is particularly true of high value property crime where the reporting may be necessary for the release of insurance monies. Reporting rates also increase as severity of injury increases and the presence of a weapon also increases reporting rates (Tarling and Morris, 2010). These factors interplay with the rational victim, who, like the rational offender, assesses the cost and benefits of reporting the crime they have experienced (ibid, 2010, Clarke and Cornish, 1985). It is acknowledged that the crimes analysed within this thesis are a fraction of the crimes that occurred within the areas of Rotherham and Coventry in the timeframes examined.

Police data provided by any police force is a snapshot in time. The offences held within that dataset are static within any analysis but on the policing system they can and do change. Data extracted in the future for the same time period, from the same system may not contain the same offences in the same numbers. Individual offences may change classification due to police findings at a later date.

This thesis also uses data from two different police forces each of which contained different variables. The data cleaning decisions differ for each dataset as the methodological stance regarding the inclusion of crime types was made more explicit by Sherman et al (2020). For the sake of consistency it would be useful to use the same methodology for the Rotherham analysis, however, this is evidence of the evolution of the methodology concerning the use of crime harm and its use for analysis of victim based crimes.

6.5.2 Within data errors

It should also be acknowledged that error is present within the data provided for analysis and could be added during variable creation. Error within the police datasets has been noted for both SYP and WMP. Incomplete coordinates or coordinates that place the offence outside the police boundary are examples of spatial error found early in the data cleaning process (shoplifting location given as shop headquarters, for example). However, the need to remove the street segment housing the publicly facing police stations in both data sets is an interesting similarity between datasets. Table 6.1, shows the number of crimes by volume and the amount of associated harm located at each police station. In the case of the Rotherham data, this street segment had the highest number of offences in the dataset. For Coventry, a number of the crimes located at the station have the highest harm score (rape by multiple offenders). It is acknowledged that some offences will be committed within police stations but this highlights an issue with the geocoding of crime. Have crimes been geocoded to the police stations intentionally or has this occurred because the victim of crime has attended the police station to report the crime, either way it highlights errors within the data.

Police force	Crime volume	CCHI score
South Yorkshire	296	59,580
West Midlands	255	67,096

Table 6.1: Crime volume and harm located at police stations

6.5.3 Spatial joining error

Each crime location had information relating to the nearest street segment joined to it (line to point) to prevent duplication. This was also done for all other point based data including residential property data provided within the OS AddressBase product. There is the possibility of error at this stage. The line to point spatial joins could link an incorrect street segment to the offence or other variable as it is nearer, this is possible at a road junction, for example.

A non-spatial join was then performed based on a shared unique street segment identifier. The assumption is that the location of each offence has been correctly input to the police system. With the exception of burglary, that should by definition be linked to a particular address, other offences may not have a specific address location and therefore there is no way of confirming that the correct coordinates are given. As a result there may be additional geographical unreliability within the police data provided.

Property data from AddressBase used in both chapters 4 and 5 also has a characteristic worth commenting on. Individual addresses within large buildings such as high rise flats and student accommodation are given the same spatial location rather than coordinates that show the relative position of the multiple units making up that building. This has the impact of condensing multiple addresses to a single location which are then linked to a single street segment. However, this data was still able to provide a more spatially specific measure of residential distribution for use as a population proxy measure. Data input error in listing the location information from the dropdown menu was also commented on within chapters 4 and 5 with reference to the WMP data.

6.5.4 Crime harm index

The CCHI as a measure of harm passes the three tests Sherman et al (2016) stated were necessary for a measure to be formally adopted. It is democratic, reliable and cost effective. From a practical point of view the use of the CCHI has become easier over the duration of this thesis. The partially completed resource available at the start of this thesis is now a more fully accessible tool. This means that a number of offences present in the datasets provided by SYP and WMP were not listed within the early versions of the resource provided and needed to be added. This was completed based on the reasoning given within the resource, but there is an acknowledgement that scores used within this work may not align perfectly with scores that have been added subsequently.

There is also the issue of attempted crime. Attempted crimes in Chapter 3 had their CCHI score reduced to reflect that the crime had been stopped before completion. Based on discussion between members of the Cambridge Centre for Evidence Based Policing, attempted crimes in Chapters 4 and 5 had the full CCHI score. This is an inconsistency between the chapters. An additional inconsistency is the inclusion of the high harm crime of homicide in Chapters 4 and 5. While it is acknowledged that the inclusion of infrequent high harm offences can create ephemeral harm spots as 55% of homicides occur in and around residential properties (year ending 2019) it was decided to include them as evidence of the harm occurring within this setting (ONS, 2020). The limitation therefore is that these papers present results derived from different data preparation methods.

6.6 Conclusion

The thesis adds to the growing literature on crime harm. It has shown that in line with previous findings crime harm is more concentrated at the micro-scale than crime volume (Chapters 3 and 4). High harm areas, harm spots, can occur alongside areas with high crime volume. These areas should be prioritised for police attention. Harm spots areas can also occur in areas with low crime volumes indicating that serious offences have occurred.

Analysing crime by where it occurs rather than by offence type has revealed residential crime to be higher in harm than crime taking place outside. This has implications for policing as covert crime is not susceptible to the crime reductive influence of guardianship. Further research using the location of crime is suggested.

The creation of a police reported victim based dataset highlighted the need to analyse proactively policed crimes especially in light of the negative association of crime volume and harm with social frontiers. This unused portion of data could also be used within other analysis as a means to create crime generators. However, the key use of a crime harm index is alongside the volume measure of those same offences. By having access to crime data in both forms allows a greater understanding of the distribution of criminal activity and offers the most efficient and effective use of crime data (Harinam et al, 2022).

This thesis shows that a measure of crime harm, be it the Cambridge Crime Harm Index or another relative measure of crime seriousness, is a useful metric by which to assess the criminality of an area and the identification of areas to receive targeted police strategies. These findings have policing implications and have raised additional questions for future criminological research.

References

Biderman, A.D. and Reiss Jr, A.J., 1967. On exploring the" dark figure" of crime. The Annals of the American Academy of Political and Social Science, 374(1), pp.1-15.

Braga, A.A., Turchan, B.S., Papachristos, A.V. and Hureau, D.M., 2019. Hot spots policing and crime reduction: An update of an ongoing systematic review and meta-analysis. *Journal of experimental criminology*, *15*, pp.289-311.

Buil-Gil, D., Medina, J. and Shlomo, N., 2021. Measuring the dark figure of crime in geographic areas: Small area estimation from the crime survey for England and Wales. The British Journal of Criminology, 61(2), pp.364-388.

Ceccato, V., Gaudelet, N. and Graf, G., 2022. Crime and safety in transit environments: a systematic review of the English and the French literature, 1970–2020. Public Transport, 14(1), pp.105-153.

Clarke, R.V. and Cornish, D.B., 1985. Modeling Offenders' Decisions-A Framework for Research and Policy (From Crime and Justice-An Annual Review of Research, Volume 6, P 147-185, 1985, Micheal Tonry and Norval Morris, ed.-See NCJ-98380).

Davies, T. and Bowers, K., 2019. Patterns in the supply and demand of urban policing at the street segment level. *Policing and society*.

Felson, M. and Eckert, M.A., 2017. Introductory criminology: The study of risky situations. Routledge.

Fenimore, D.M., 2020. *Investigating the spatiotemporal distribution and environmental risk factors of harm-weighted crime*. Texas State University-San Marcos.

Harinam, V., Bavcevic, Z. and Ariel, B., 2022. Spatial distribution and developmental trajectories of crime versus crime severity: do not abandon the count-based model just yet. *Crime Science*, *11*(1), pp.1-15.

Langton, L., Berzofsky, M., Krebs, C.P. and Smiley-McDonald, H., 2012. Victimizations not reported to the police, 2006-2010 (p. 18). Washington, DC: US Department of Justice, Office of Justice Programs, Bureau of Justice Statistics.

Macbeth, E., 2015. Evidence-based vs. experience-based targeting of crime and harm hotspots in Northern Ireland. Masters thesis. University of Cambridge.

Norton, S., Ariel, B., Weinborn, C. and O'Dwyer, E., 2018. Spatiotemporal patterns and distributions of harm within street segments: the story of the "harmspot". Policing: An International Journal, 41(3), pp.352-371.

Office for National Statistics (2020) *Homicide in England and Wales: year ending March 2019* [Online].[Accessed on 15 September 2023] Available at: https://www.ons.gov.uk/peoplepopulationandcommunity/crimeandjustice/articles/homicideinenglandandwales/yearendingmarch2019

Pierce, G.L., Spaar, S. and Briggs, L.R., 1988. *The character of police work: Strategic and tactical implications*. Center for Applied Social Research, Northeastern Unviersity.

Sellin, T., & Wolfgang, M. E. (1964). The measurement of delinquency. Wiley.

Sherman, L. W., Neyroud, P. W., & Neyroud, E. C. (2016). The Cambridge crime harm Index: Measuring total harm from crime based on sentencing guidelines. Policing, 1e13.

Sherman, L.W. and Cambridge University associates, 2020. How to count crime: the Cambridge harm index consensus. *Cambridge Journal of Evidence-Based Policing*, *4*, pp.1-14.

Sherman, L.W., Gartin, P.R. and Buerger, M.E., 1989. Hot spots of predatory crime: Routine activities and the criminology of place. Criminology, 27(1), pp.27-56.

Tarling, R. and Morris, K., 2010. Reporting crime to the police. The British Journal of Criminology, 50(3), pp.474-490.

Verian (2023) *About the Crime Survey for England and* [Online].[Accessed on 27 March 2024] Available at: https://www.crimesurvey.co.uk/en/AboutTheSurvey.html

Weinborn, C., Ariel, B., Sherman, L.W. and O'Dwyer, E., 2017. Hotspots vs. harmspots: Shifting the focus from counts to harm in the criminology of place. *Applied geography*, *86*, pp.226-244.

Weisburd, D., 2015. The law of crime concentration and the criminology of place. *Criminology*, *53*(2), pp.133-157.

Welsh, B.C., Farrington, D.P. and Douglas, S., 2022. The impact and policy relevance of street lighting for crime prevention: A systematic review based on a half-century of evaluation research. Criminology & Public Policy, 21(3), pp.739-765.

Appendix Section

Appendix 1: Offences and harm scores for Rotherham

OTHER CRIMES AGAINST SOCIETY	
DRUG OFFENCES	
Attempted - Having possession of a controlled drug - Class A - Cocaine	2.4
Attempted - Possession of a controlled drug with intent to supply - Class B - Cannabis	5
Having possession of a controlled drug - Class A - Cocaine	3
Having possession of a controlled drug - Class A - Crack	3
Having possession of a controlled drug - Class A - Heroin	3
Having possession of a controlled drug - Class A - Other	3
Having possession of a controlled drug - Class B - Amphetamine	2
Having possession of a controlled drug - Class B - Cannabis	2
Having possession of a controlled drug - Class B - Ketamine	2
Having possession of a controlled drug - Class B - Other	2
Having possession of a controlled drug - Class B - Synthetic cannabinoid receptor agonists	2
Having possession of a controlled drug - Class C - GHB	1
Having possession of a controlled drug - Class C - Other	1
Having possession of a controlled drug - Class unspecified	1
Possess a psychoactive substance with intent to supply	5
Possession of a controlled drug with intent to supply - Class A - Cocaine	547.5
Possession of a controlled drug with intent to supply - Class A - Crack	547.5
Possession of a controlled drug with intent to supply - Class A - Heroin	547.5
Possession of a controlled drug with intent to supply - Class A - Methadone	547.5
Possession of a controlled drug with intent to supply - Class A - Other	547.5
Possession of a controlled drug with intent to supply - Class B - Amphetamine	5

Possession of a controlled drug with intent to supply - Class B - Cannabis	5
Possession of a controlled drug with intent to supply - Class B - Ketamine	3
Possession of a controlled drug with intent to supply - Class C - Anabolic steroids	5
Possession of a controlled drug with intent to supply - Class C - Gamma-butyrolactone (GBL) and 1,4-butanediol (1,4-BD)	5
Possession of a controlled drug with intent to supply - Class unspecified	5
Possession of a controlled drug with intent to supply a class A controlled drug	547.5
Possession of a controlled drug with intent to supply a class B controlled drug	5
Possession of a controlled drug with intent to supply a class C controlled drug	5
Production or being concerned in production of a controlled drug - Class B - Cannabis	3
Supplying or offering to supply a controlled drug - Class A - Cocaine	547.5
Supplying or offering to supply a controlled drug - Class A - MDMA	547.5
Supplying or offering to supply a controlled drug - Class A - Other	547.5
Supplying or offering to supply a controlled drug - Class B - Cannabis	5
Supplying or offering to supply a controlled drug - Class unspecified	5
Unlawful importation of a drug controlled under the Misuse of Drugs Act 1971- Class A	1642.5

MISC CRIMES AGAINST SOCIETY	
Absconding from lawful custody	6.25
Acquisition, use & possession of criminal property	5
Arrangements - concerned in arrangement, knows or suspects, facilitates acquisition, retention, use or control of criminal property by, or on behalf of another person	5
Assist offender (Offences triable on indictment only)	120
Attempted - Pass etc counterfeit coin or note as genuine	1.5
Attempted - Possess false instrument or materials to make false instrument	1.5
Attempted - Rendering food injurious to health	2.4
Attempted - Take or to make or to distribute indecent photographs or pseudo- photographs, of children	438

Attempting to Pervert the Course of Public Justice	42
Bigamy	14
Dangerous Driving	10
Depositing, causing the deposition or permitting the deposition treating, keeping or disposing of controlled (but not special) waste in or on land without a licence	1.5
Failure to comply with conditions of Listed Building consent	2
Forgery of a drug prescription or copying a false drug prescription	3.25
Fraud, forgery etc associated with driving licence	1.5
Fraudulently obtaining credit	2
Going equipped for stealing etc	3
Harming or threatening to harm a witness	126
Intimidating a juror or witness or person assisting in investigation of offence	42
Intimidating or intending to intimidate a witness	42
Making counterfeit coin or note	3.25
Offences relating to offering, promising or giving bribes	10
Offences relating to requesting, agreeing to receive and accepting bribes	10
Pass etc counterfeit coin or note as genuine	1.5
Possess / control a false / improperly obtained / another persons identity document	3.25
Possess counterfeit coin or note	1.5
Possess/control artcile(s) for use in fraud(s)	2
Possessing prohibited images of children	91
Possession of an indecent or pseudo indecent photo of a child	18.75
Possession of extreme pornographic image - a person performing an act of intercourse or oral sex with an animal (whether dead or alive) (bestiality)	365
Receiving stolen goods	2
Send/attempt to send false/misleading message by wireless telegraphy likely to endanger personal safety/ship/aircraft/vehicle	2
Soliciting another for the purpose of obtaining their sexual services as a prostitute in a street or public place	0.1
Take or to make or to distribute indecent photographs or pseudo-photographs, of children	547.5
Threats to destroy or damage property	3
Triable Either Way Offences under: Communications Act 2003 except Sec 125, 126	2

Undertaking or assisting in the retention, removal, disposal or realisation of stolen goods or arranging to do so	2
Unlawful eviction of Occupier	91.25
Unlawful harassment of Occupier	182.5
Unlawful interception of a postal public or private telecommunication scheme	182.5
Using a false drug prescription or a copy of a false drug prescription	1.5
Using a false instrument or a copy of a false instrument	1.5

POSSESS WEAPON OFFENCES

Carrying a loaded or unloaded or imitation firearm or air weapon in public place	6.25
Having an article with a blade or point in a public place	18.75
Having an article with a blade or point on school premises	42
Possessing air weapon or imitation firearm with intent to cause fear of violence	913
Possessing etc firearms or ammunition without firearm certificate	182.5
Possessing firearm or imitation firearm with intent to cause fear of violence	1825
Possessing firearm or imitation firearm with intent to commit indictable offence or resist arrest	1825
Possessing firearm or imitation while committing or being arrested for offences in Schedule 1 Firearms Act 1968	1825
Possessing or distributing firearm designed as other object	1825
Possessing or distributing prohibited weapons designed for discharge of noxious substances etc	1825
Possessing or distributing prohibited weapons or ammunition	1825
Possessing shotgun or imitation firearm with intent to cause fear of violence	1825
Possessing shotgun or imitation firearm with intent to commit indictable offence or resist arrest	1825
Possession of firearms by persons previously convicted of crime (Group I)	182.5
Possession of firearms by persons previously convicted of crime (Group III)	182.5
Possession of offensive weapon without lawful authority or reasonable excuse	18.75
Purchase / acquire prohibited weapon / ammunition for sale / transfer.	2

Selling etc., firearm to person without a certificate.	182.5
Threaten with a blade or sharply pointed article in a public place	182.5
Threaten with a blade or sharply pointed article on school premises	182.5
Threaten with an offensive weapon in a public place	182.5
Trespassing with firearm or imitation firearm in a building (Group II)	2

PUBLIC ORDER OFFENCES

Affray	10
Breach a sexual risk order / risk of harm order etc. or fail to comply with requirement under Sec 122 c (4)	10
Breach of a criminal behaviour order	10
Breach of a Restraining Order issued on acquittal	5
Breach of non-molestation order	5
Breach SHPO / interim SHPO / SOPO / interim SOPO / Foreign travel order or fail to comply with a requirement under Sec 103D (4)	10
Causing intentional harassment, alarm or distress	3
Committing or conspiring to commit, an act outraging public decency	6.25
Communicating false information alleging presence of bomb	365
Fail to comply with requirements re notification of changes under Sec 109(1) or 6(b)	1.5
Failure to comply with (Sexual Offence) Notification Order	10
Fear or provocation of violence	3
Harassment, alarm or distress (S5 POA)	1
Hoaxes involving noxious substances or things	182.5
Public Nuisance	3.25
Publishing or distributing written material (Acts intended to stir up racial hatred)	3.25
Racially or religiously aggravated fear or provocation of violence	42
Racially or religiously aggravated harassment, alarm or distress	42
Racially or religiously aggravated intentional harassment, alarm or distress	42
Use of words or behaviour or display of written material (Acts intended to stir up religious hatred/sexual hatred)	365
Use of words or behaviour or display or written material (Acts intended to stir up racial hatred)	3.25
Violent disorder	182

VICTIM BASED

DAMAGE AND ARSON OFFENCES

Arson endangering life	730
Arson not endangering life	5
Attempted - Arson endangering life	584
Attempted - Arson not endangering life	4
Attempted - Other criminal damage to a building other than a dwelling (Under £5,000)	1.6
Attempted - Other criminal damage to a dwelling (£5,000 and over)	84
Attempted - Other criminal damage to a dwelling (Under £5,000)	1.6
Attempted - Other criminal damage to a vehicle (£5,000 and over)	84
Attempted - Other criminal damage to a vehicle (Under £5,000)	1.6
Attempted - Other criminal damage, other (Under £5,000)	1.6
Attempted - Racially or religiously aggravated criminal damage	4
Criminal damage to a building other than a dwelling endangering life	730
Criminal damage to a dwelling endangering life	730
Criminal damage to a vehicle endangering life	730
Other criminal damage to a building other than a dwelling (£5,000 and over)	84
Other criminal damage to a building other than a dwelling (Under £5,000)	2
Other criminal damage to a dwelling (£5,000 and over)	84
Other criminal damage to a dwelling (Under £5,000)	2
Other criminal damage to a vehicle (£5,000 and over)	84
Other criminal damage to a vehicle (Under £5,000)	2
Other criminal damage, other (£5,000 and over)	84
Other criminal damage, other (Under £5,000)	2
Racially or religiously aggravated criminal damage	5

ROBBERY

Assault with intent to rob (Of Personal Property)	365
Attempted - Robbery (of a Business Property)	292
Attempted - Robbery (of Personal Property)	292
Robbery (of a Business Property)	365
Robbery (of Personal Property)	365

SEXUAL OFFENCES

Assault of a female child under 13 by penetration	1460
Assault of a male child under 13 by penetration	1460
Assault on a female by penetration	730
Assault on a male by penetration	730

Attempted - Arranging or facilitating the commission of a child sex offence	8
Attempted - Causing a child under 13 to watch a sexual act by an offender over 18 years of age	8
Attempted - Causing a person to engage in sexual activity without consent: Male person no penetration	15
Attempted - Causing or inciting a child under 13 to engage in sexual activity by an offender under 18 years of age: Female child no penetration	145.6
Attempted - Causing or inciting a child under 13 to engage in sexual activity: Female child no penetration	584
Attempted - Causing or inciting a female child under 16 to engage in sexual activity No Penetration - Offender 18 or over	15
Attempted - Causing or inciting a female child under 16 to engage in sexual activity No Penetration - Offender Under 18	15
Attempted - Engage in sexual communication with a child	2.6
Attempted - Meeting a female child following sexual grooming etc (Offender is aged 18 or over and victim is under 16)	438
Attempted - Meeting a male child following sexual grooming etc (Offender is 18 or over and victim is under 16)	438
Attempted - Sexual assault on a female	15
Attempted rape of a female aged 16 or over	1825
Attempted rape of a female aged under 16	1825
Attempted rape of a female child under 13 by a male	2920
Attempted rape of a male aged 16 or over	1825
Causing a child under 13 to watch a sexual act by an offender over 18 years of age	10
Causing a child under 13 to watch a sexual act by an offender under 18 years of age	10
Causing a child under 16 to watch a sexual act - Offender aged 18 or over	10
Causing a child under 16 to watch a sexual act - Offender aged Under 18	10
Causing a person to engage in sexual activity without consent: Female person	730
Causing a person to engage in sexual activity without consent: Male person	730
Causing a person to engage in sexual activity without consent: Male person no penetration	18.75

Causing or inciting a child under 13 to engage in sexual activity by an offender under 18 years of age: Female child - penetration	2920
Causing or inciting a child under 13 to engage in sexual activity by an offender under 18 years of age: Female child no penetration	182
Causing or inciting a child under 13 to engage in sexual activity by an offender under 18 years of age: Male child no penetration	182
Causing or inciting a child under 13 to engage in sexual activity: Female child - penetration	2920
Causing or inciting a child under 13 to engage in sexual activity: Female child no penetration	730
Causing or inciting a child under 13 to engage in sexual activity: Male child no penetration	730
Causing or inciting a female child under 16 to engage in sexual activity No Penetration - Offender 18 or over	18.75
Causing or inciting a female child under 16 to engage in sexual activity No Penetration - Offender Under 18	18.75
Causing or inciting a male child under 16 to engage in sexual activity by Penetration - Offender 18 or over	730
Causing or inciting a male child under 16 to engage in sexual activity by Penetration - Offender Under 18	730
Causing or inciting a male child under 16 to engage in sexual activity No Penetration - Offender 18 or over	18.75
Causing or inciting a male child under 16 to engage in sexual activity No Penetration - Offender Under 18	18.75
Causing or inciting a person with a mental disorder impeding choice to engage in sexual activity: Male person	2920
Engage in sexual communication with a child	3.25
Engaging in sexual activity in the presence of a child under 13 by an offender over 18 years of age	182
Engaging in sexual activity in the presence of a child under 13 by an offender under 18 years of age	182
Exposure	10
Meeting a female child following sexual grooming etc (Offender is aged 18 or over and victim is under 16)	547.5
Meeting a male child following sexual grooming etc (Offender is 18 or over and victim is under 16)	547.5
Paying for sexual service of a child: Male child under 18	182
Rape (multiple undefined offenders) of a female aged 16 or over	3650
Rape (multiple undefined offenders) of a female under 16	3650

Rape of a female aged 16 or over	1825
Rape of a female aged under 16	1825
Rape of a female child under 13 by a male	1825
Rape of a male aged 16 or over	1825
Rape of a male aged under 16	1825
Rape of a male child under 13 by a male	2920
Sex with an adult relative - Penetration (Offender aged 16 or over relative aged 18 or over)	10
Sexual activity with a child family member - Female - Victim aged 13-17 - 18 or over - penetration	1277.5
Sexual activity with a child family member - Female - Victim Under 13 - 18 or over - no penetration	10
Sexual activity with a child family member - Female - Victim Under 13 - 18 or over - penetration	2190
Sexual activity with a child family member - Male - Victim aged 13-18 - 18 or over - no penetration	10
Sexual activity with a child under 13 by an offender under 18 years of age: Female child - penetration	2920
Sexual activity with a child under 13 by an offender under 18 years of age: Female child no penetration	182
Sexual activity with a child under 13 by an offender under 18 years of age: Male child - penetration	2920
Sexual activity with a child under 13 by an offender under 18 years of age: Male child no penetration	182
Sexual activity with a female child under 16 by Penetration - Offender 18 or over	730
Sexual activity with a female child under 16 by Penetration - Offender Under 18	730
Sexual activity with a female child under 16 No penetration - Offender 18 or over	18.75
Sexual activity with a female child under 16 No penetration - Offender Under 18	18.75
Sexual activity with a male child under 16 by Penetration - Offender 18 or over	730
Sexual activity with a male child under 16 by Penetration - Offender Under 18	730
Sexual activity with a male child under 16 No penetration - Offender 18 or over	18.75
Sexual assault of a female child under 13	182
Sexual assault on a female	18.75
Sexual assault on a male	18.75
Sexual assault on a male child under 13	182
Voyeurism	10
Voyeurism (upskirting) (offence from 12/04/19) Record image under clothing to observe another without consent	18.75

THEFT OFFENCES

(DO NOT USE from 01/04/19) Aggravated vehicle taking where the only aggravating factor is criminal damage of £5000 or under	10
Abstracting electricity	1
Aggravated Burglary Business and Community	730
Aggravated Burglary Residential	730
Aggravated vehicle taking	126
Aggravated vehicle taking (driving / carried) and vehicle / property damage under £5000	10
Attempted - Blackmail	292
Attempted - Making off without payment	0.8
Attempted - Theft from automatic machine or meter	1.6
Attempted - Theft from shops and stalls	1.6
Attempted - Theft from the person of another	1.6
Attempted - Theft if not classified elsewhere	1.6
Attempted - Theft or Unauthorised Taking of a Pedal Cycle	1.6
Attempted Burglary- Business and Community	8
Attempted-Burglary Residential	15
Attempted-Distraction Burglary Residential	292
Blackmail	365
Burglary- Business and Community	10
Burglary Residential	18.75
Distraction Burglary Residential	365
Interference with a motor vehicle	3
Making off without payment	1
Take or ride a pedal cycle without consent etc	2
Tampering with motor vehicles	2.5
Theft by an Employee	5
Theft from a motor vehicle	2
Theft from automatic machine or meter	2
Theft from shops and stalls	2
Theft from the person of another	2
Theft from vehicle other than a motor vehicle	2
Theft if not classified elsewhere	2
Theft in a dwelling other than from automatic machine or meter	2
Theft of a motor vehicle	5
Theft of conveyance other than a motor or pedal cycle	2
Theft of Mail	2
Theft or Unauthorised Taking of a Pedal Cycle	2
Unauthorised taking of a motor vehicle (does not include 'driving or being carried knowing motor vehicle has been taken ')	5

Unauthorised taking of conveyance other than a motor vehicle or pedal cycle (does not include being found with a conveyance that has already been stolen)	5

VIOLENCE AGAINST THE PERSON

Arrange or facilitate travel of another person with a view to exploitation	182.5
Assault or assault by beating of a Constable	2
Assault or assault by beating on an emergency worker (except a Constable)	2
Assault with Injury - Administering poison with intent to injure or annoy	182.5
Assault with Injury - Assault occasioning actual bodily harm	10
Assault with Injury - Malicious wounding: wounding or inflicting grievous bodily harm (Minor wound or equivalent)	18.75
Assault with Injury: Wounding with intent to do grievous bodily harm on a Constable (GBH S18)	1460
Assault with Intent to cause Serious Harm - Torture	1460
Assault with Intent to cause Serious Harm - Wounding with intent to do grievous bodily harm	1460
Assault without Injury - Common assault and battery	1
Assault without Injury on a Constable - Assaults a designated person or his assistant in the exercise of a relevant power	2
Assault without Injury on a Constable - Assaults an officer of Revenue or Customs	2
Assault without Injury on a Constable - Vagrant violently resisting a constable	2
Assault without injury on a constable (Police Act offence)	2
Attempted - Assault with Intent to cause Serious Harm - Wounding with intent to do grievous bodily harm	1168
Attempted - Child Abduction - Abduction of child by other persons	438.4
Attempted - Kidnapping - Destroying, damaging or endangering safety or aircraft	548
Attempted - Kidnapping - Kidnapping	438.4
Attempted murder	3285
Care provider breach duty of care resulting in ill-treatment/neglect of individual	6.25
Care worker ill-treat /wilfully neglect an individual	6.25
Causing death by dangerous driving	1095
Causing serious injury by dangerous driving	547.5
Child Abduction - Abduction of child by other persons	548

Commit offence other than kidnapping or false imprisonment with intention of arranging travel with view to exploitation	182
Conspiracy to Murder - Assisting offender by impeding his apprehension or prosecution In a case of murder	548
Cruelty to Children/Young Persons - Cruelty to and neglect of children	84
Disclose private sexual photographs and films with intent to cause distress	10
Endangering Life - Causing danger to road-users	1.5
Endangering Life - Causing explosions, sending explosive substance or throwing corrosive fluids with intent to do grievous bodily harm	4380
Engage in controlling/coercive behaviour in an intimate / family relationship.	182.5
Harassment	10
Harassment - Breach of a restraining order	5
Harassment - Breach of conditions of injunction against harassment	5
Harassment - Pursue course of conduct in breach of Sec 1 (1) which amounts to stalking	42
Harassment - Putting people in fear of violence	42
Harassment - Stalking involving fear of violence	182.5
Harassment - Stalking involving serious alarm/distress	182.5
Harassment etc. of a person in his home	5
Hold person in slavery or servitude	365
Kidnapping - False imprisonment	548
Kidnapping - Forced marriage offences under	548
Kidnapping - Kidnapping	548
Malicious wounding: wounding or inflicting grievous bodily harm	1460
Murder - of persons aged 1 year or over	5475
Owner or person in charge allowing dog to be dangerously out of control in any place in England or Wales (whether or not a public place) injuring any person or assistance dog	1
Possession of air weapon with intent to endanger life	1278
Possession of firearm with intent to endanger life	2555
Racially or religiously aggravated assault or assault occasioning actual bodily harm	182
Racially or religiously aggravated common assault or beating	10
Racially or religiously aggravated Harassment or stalking with fear of violence	126
Racially or religiously aggravated Harassment or stalking without violence	42

Racially or religiously aggravated wounding or grievous bodily harm	547.5
Require person to perform forced or compulsory labour	365
Sending letters etc with intent to cause distress or anxiety	10
Threats to kill	10

Appendix 2: Location description – Coventry

Primary Location	Inside	Private	Residential
Abattoir	1	1	0
Airfield	0	0	0
Airport	1	1	0
Airside	0	1	0
Alley	0	0	0
Alleyway	0	0	0
Allotment	0	0	0
Armoury	1	1	0
Auction	1	0	0
Bakery	1	0	0
Bank	1	0	0
Betting Office	1	0	0
Bicycle Shed	0	0	0
Bridge	0	0	0
Building Site	0	0	0
Building Society	1	0	0
Bungalow - Dwelling	1	0	1
Bus	1	0	0
Bus Shelter	0	0	0
Bus Station	1	0	0
Bus Stop	0	0	0
Camp Site	0	0	0
Car Park	0	0	0
Caravan Mobile Home	1	1	1
Caravan Site	0	0	0
Care Home	1	1	1
Cash Machine	0	0	0
Casino	1	0	0
Cemetery	0	0	0
Changing Room	1	0	0
Childrens Home	1	1	1
Childrens Nursery	1	1	0
Club - Social	1	0	0

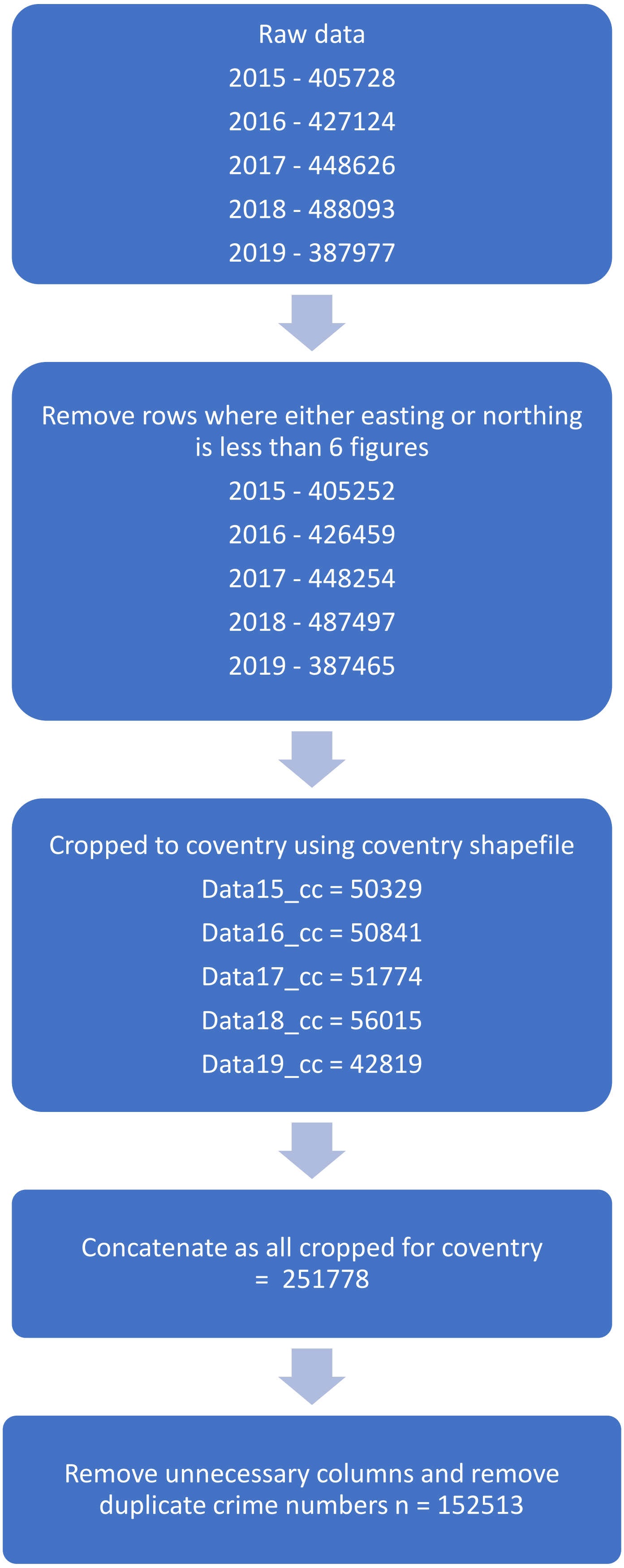
Coach / Trailer Park	0	0	0
Communal Area	1	0	0
Community Centre	1	0	0
Compound	0	0	0
Conservatory	1	1	1
Conveyance	1	1	0
Council Owned	0	0	0
Countryside	0	0	0
Court	1	0	0
Cricket Ground	0	0	0
Dairy	1	1	0
Day Care Centre	1	1	0
Derelict	0	0	0
Detached - Dwelling	1	1	1
Drive/Driveway	0	1	0
Educational	1	1	0
Entertainment Indoor	1	0	0
Entertainment Outdoor	0	0	0
Estate Agent	1	0	0
Exhibition Centre	1	0	0
Factory	1	1	0
Farm Building - Not Dwelling	1	1	0
Farmhouse - Dwelling	1	1	1
Fast Food Outlet	1	0	0
Fire Station	1	1	0
Flat - Dwelling	1	1	1
Football Ground	0	1	0
Foyer	1	0	0
Function Room	1	0	0
Garage Commercial	1	0	0
Garage Domestic	1	1	1
Garden	0	1	0
Garden Centre	1	0	0
Golf Course	0	0	0
Government Building	1	0	0

Greenhouse	1	1	0
Gymnasiums	1	0	0
Halls Of Residence - Dwelling	1	1	1
Health Centre	1	0	0
Hospital	1	0	0
Hostel - Dwelling	1	1	1
Hotel	1	1	0
Houseboat - Dwelling	1	1	1
Industrial Estate	0	0	0
Kiosk	1	0	0
Landside	0	0	0
Launderette	1	0	0
Lavatory / Toilet	1	0	0
Leisure Complex	1	0	0
Library	1	0	0
Lorry Park	0	0	0
Maisonette - Dwelling	1	1	1
Market	0	0	0
Military Establishment	1	1	0
Motorway	0	0	0
Museum	1	0	0
Na	NA	NA	NA
Nightclub	1	0	0
Nursing Home	1	1	1
Off Licence - Licensed Premises	1	0	0
Office	1	1	0
Old People Home - Dwelling	1	1	1
Other	NA	NA	NA
Outbuilding	1	1	0
Outside Address	0	0	0
Park	0	0	0
Patio	0	1	0
Petrol Station	0	0	0
Place Of Worship	1	0	0
Playing Field	0	0	0

Police Establishment	1	0	0
Porch	1	1	1
Portacabin	1	1	0
Post Office	1	0	0
Prison	1	1	0
Public Footpath	0	0	0
Public House - Licensed Premises	1	0	0
Quarry	0	0	0
Railway Property	1	1	0
Rear Of Premises	0	0	0
Restaurant / Cafe	1	0	0
Road	0	0	0
Security Vehicle	1	1	0
Semi Detached - Dwelling	1	1	1
Sewage Treatment Works	1	1	0
Shed	1	0	0
Sheltered/Warden Controlled - Dwelling	1	1	1
Shop	1	0	0
Shopping Complex	1	0	0
Spare	NA	NA	NA
Sports Club	1	0	0
Subway	0	0	0
Supermarket	1	0	0
Surgery	1	0	0
Swimming Baths (Pool)	1	0	0
Taxi	1	0	0
Telephone Kiosk	1	0	0
Terminal 1	1	1	0
Terminal 2	1	1	0
Terrace - Dwelling	1	1	1
Town House - Dwelling	1	1	1
Tram Station	0	0	0
Underpass	0	0	0
Village Hall	1	0	0
Void	NA	NA	NA

Warehouse	1	1	0
Waste Ground	0	0	0
Waterway / Canal / Towpath	0	0	0
Wharf	0	0	0
Woodland	0	0	0
Yard	0	0	0

Appendix 3 – Data cleaning flow chart - Coventry



Remove historic crimes

- last date less than 2014 but keep na's- n=151611

- date first less than 2014 n = 150735

Remove non-notifiable and crimes that are not victim based

Victim = 100870

Add primary location and delete Void, Spare, Other and na = 1459

Victim_harm with location added = 99411

Remove those dates that fall in oct 2019 as not a full month - 563 - 98848

Add offence class column - no change

Remove the cuc = 70 by id = x2. N = 98846

Cut residential crime count on non residential road - 279

Cut residential crime harm on non residential road -76635

Remove police station street segment - TOID osgb5000005180411401

Police road 255 count / 67096 harm

(16 offences are residential on non residential rd)

↓

Crime volume = 98,328

Crime harm = 7,631,172

Appendix 4: Offences and harm scores for Coventry

Arson And Criminal Damage	
056/01 / Arson - Recklessly Endanger Life	365
056/01 / Arson W/I To Endanger Life	730
056/01 / Attempt Arson W/I To Endanger Life	730
056/02 / Arson	5
056/02 / Attempt Arson	5
058/04 / Attempt Criminal Damage Other Building	2
058/04 / Criminal Damage To Other Building	2
058/05 / Attempt Criminal Damage To Vehicle	2
058/05 / Criminal Damage To Vehicle	2
058/06 / Attempt Criminal Damage Other	2
058/06 / Cause Explosion To Damage - Other	2
058/06 / Other Criminal Damage	2
058/13 / Racially Aggravated Criminal Damage To A Dwelling	2
058/14 / Racially Aggravated Damage Other Building	2
058/15 / Racially Aggravated Criminal Damage To Vehicle	2
058/16 / Racially Aggravated Other Criminal Damage	2
Burglary	
028/03 / BURGLARY DWELLING	19
028/03 / BURGLARY DWELLING CONSPIRE	19
028/04 / DISTRACTION BURGLARY DWELLING	365
028/05 / ATTEMPT BURGLARY DWELLING	19
028/07 / BURGLARY RESIDENTIAL	19
028/08 / ATTEMPT BURGLARY RESIDENTIAL	19
028/09 / DISTRACTION BURGLARY RESIDENTIAL	365
028/10 / ATTEMPT DISTRACTION BURGLARY RESIDENTIAL	365
029/00 / AGGRAVATED BURGLARY DWELLING	730
029/00 / ATTEMPT AGGRAVATED BURGLARY DWELLING	730
029/01 / AGGRAVATED BURGLARY RESIDENTIAL	730
029/01 / ATTEMPT AGGRAVATED BURGLARY RESIDENTIAL	730
030/02 / BURGLARY OTHER BUILDING	10
030/03 / ATTEMPT BURGLARY OTHER BUILDING	10

030/04 / BURGLARY BUSINESS AND COMMUNITY	10
030/05 / ATTEMPT BURGLARY BUSINESS AND COMMUNITY	10
031/00 / AGGRAVATED BURGLARY OTHER BUILDING	730
031/01 / AGGRAVATED BURGLARY BUSINESS AND COMMUNITY	730
031/01 / ATTEMPT AGGRAVATED BURGLARY BUSINESS AND COMMUNITY	730
CRIMINAL DAMAGE	
057/03 / CRIMINAL DAMAGE END.LIFE TO VEHICLE	365
057/04 / OTHER CRIMINAL DAMAGE ENDANGERING LIFE	365
058/03 / ATT CRIMINAL DAMAGE-DWELLING	2
058/03 / CRIMINAL DAMAGE TO DWELLING	2
MISCELLANEOUS CRIMES AGAINST SOCIETY	
026/00 / BIGAMY	4
059/11 / THREATEN DAMAGE OWN PROP ENDANGER LIFE	19
059/11 / THREATEN TO DAMAGE PROPERTY	2
059/12 / MAKE EXPLOSIVE SUBST UNDER SUSP CIRCUMSTANCES	1460
086/14 / POSSESS EXTREME PORNOGRAPHIC IMAGES - BESTIALITY	4
086/15 / POSSESSING PROHIBITED IMAGES OF CHILDREN	19
087/02 / HARASS OCCUP W/I CAUSE LEAVE PREMISES	7
802/00 / DANGEROUS DRIVING	10
PUBLIC ORDER OFFENCES	3
066/91 / RACIALLY/RELIGIOUSLY AGGRAVATED FEAR/PROVOCATION OF VIOLENCE (S4)	10
125/09 / CAUSE INT HARASSMENT/ALARM/DISTRESS	3
125/11 / FEAR/PROVOCATION OF VIOLENCE	5
ROBBERY	365
034/01 / ATTEMPT ROBBERY-BUSINESS PROPERTY	365
034/01 / CONSPIRACY TO ROB-BUSINESS PROPERTY	365
034/01 / ROBBERY-BUSINESS PROPERTY	365
034/02 / ASSAULT W/I TO ROB-BUSINESS PROPERTY	365
034/03 / ATTEMPTED ROBBERY-PERSONAL PROPERTY	365
034/03 / ROBBERY-PERSONAL PROPERTY	365

034/04 / ASSAULT W/INT TO ROB-PERSONAL PROPERTY	365
SEXUAL OFFENCES	
017/13 / ASSAULT ON A MALE 13+ BY PENETRATION	730
017/14 / ASSAULT ON A MALE CHILD U13 BY PENETRATION	1460
017/15 / SEXUAL ASSAULT ON A MALE 13+	19
017/16 / SEXUAL ASSAULT ON A MALE CHILD U13	182
019/07 / RAPE OF FEMALE CHILD AGED 13-15	2555
019/08 / RAPE OF FEMALE 16 OR OVER	1825
019/09 / RAPE OF MALE CHILD AGED 13-15	2555
019/10 / RAPE OF MALE 16 OR OVER	1825
019/11 / ATTEMPT RAPE OF FEMALE CHILD AGED 13-15	2555
019/12 / ATTEMPT RAPE OF FEMALE 16 OR OVER	1825
019/13 / ATTEMPT RAPE OF MALE AGED 13-15	2555
019/14 / ATTEMPT RAPE MALE 16 OR OVER	1825
019/16 / RAPE OF FEMALE CHILD UNDER 13 BY A MALE	2920
019/17 / RAPE OF MALE CHILD UNDER 13 BY A MALE	2920
019/18 / ATTEMPT RAPE OF FEMALE CHILD UNDER 13 BY A MALE	2920
019/19 / ATTEMPT RAPE OF MALE CHILD UNDER 13 BY A MALE	2920
019/20 / MULTIPLE UNDEFINED OFFENDERS - RAPE OF FEMALE CHILD UNDER 13 BY A MALE	5840
019/22 / MULTIPLE UNDEFINED OFFENDERS - RAPE OF FEMALE CHILD AGED 13-15	5110
019/23 / MULTIPLE UNDEFINED OFFENDERS - RAPE OF FEMALE 16 OR OVER	3650
020/03 / ASSAULT ON A FEMALE 13+ BY PENETRATION	730
020/04 / ASSAULT ON FEMALE CHILD UNDER 13 BY PENETRATION	1460
020/05 / SEXUAL ASSAULT ON A FEMALE 13 OR OVER	19
020/06 / SEXUAL ASSAULT ON FEMALE CHILD UNDER 13	182
021/02 / CAUSE FEMALE CHILD U13 TO ENGAGE IN SEXUAL ACTIVITY	2190
021/03 / CAUSE FEMALE U13 ENGAGE IN SEXUAL ACTIVITY - NO PENETRATION	730
021/04 / CAUSE MALE U13 ENGAGE IN SEXUAL ACTIVITY	2190

021/05 / CAUSE MALE U13 TO ENGAGE IN SEXUAL ACTIVITY - NO PENETRATION	730
021/10 / ENGAGE IN SEXUAL ACTIVITY IN PRESENCE OF CHILD U13 - OFFENDER 18+	10
021/11 / CAUSE CHILD U13 TO WATCH SEXUAL ACT - OFFENDER 18+	10
021/12 / SEXUAL ACTIVITY WITH FEMALE U13 - OFFENDER UNDER18	1460
021/13 / SEXUAL ACTIVITY WITH MALE U13 - OFFENDER U18	1460
021/14 / CAUSE FEMALE CHILD U13 TO ENGAGE IN SEXUAL ACTIVITY - OFFENDER U18 - PENETRATION	2190
021/15 / CAUSE MALE U13 TO ENGAGE IN SEXUAL ACTIVITY - OFFENDER U18 - PENETRATION	2190
021/16 / ENGAGE IN SEXUAL ACTIVITY IN THE PRESENCE OF CHILD U13 - OFFENDER U18	10
021/22 / SEXUAL ACTIVITY WITH FEMALE CHILD U13 - NO PENETRATION - OFFENDER U18	730
021/23 / SEXUAL ACTIVITY WITH MALE CHILD U13 - NO PENETRATION - OFFENDER U18	730
021/24 / CAUSE FEMALE CHILD U13 TO ENGAGE IN SEXUAL ACTIVITY-OFFENDER U18- NO PENETRATION	730
021/25 / CAUSE MALE CHILD U13 TO ENGAGE IN SEXUAL ACTIVITY- OFFENDER U18 - NO PENETRATION	730
022/02 / CAUSE FEMALE 16+ TO ENGAGE IN SEXUAL ACTIVITY W/O CONSENT	730
022/03 / CAUSE MALE 16+ TO ENGAGE IN SEXUAL ACTIVITY W/O CONSENT	730
022/04 / CAUSE FEMALE 16+ TO ENGAGE IN SEXUAL ACTIVITY - NO PENETRATION	19
022/05 / CAUSE MALE 16+ TO ENGAGE IN SEXUAL ACTIVITY - NO PENETRATION	19
022/06 / SEXUAL ACTIVITY WITH FEMALE U16 - OFFENDER 18+ PENETRATION	365
022/07 / SEXUAL ACTIVITY WITH MALE U16 - OFFENDER 18+	365
022/08 / CAUSE SEXUAL ACTIVITY FEMALE U16 - OFFENDER 18+	365
022/09 / CAUSE SEXUAL ACTIVITY MALE U16 - OFFENDER 18+	365
022/10 / ENGAGE IN SEXUAL ACTIVITY IN PRESENCE OF CHILD 13-15 - OFFENDER 18+	10
022/11 / CAUSE CHILD U16 TO WATCH SEXUAL ACT - OFFENDER 18+	10

022/12 / SEXUAL ACTIVITY WITH FEMALE U16 - OFFENDER U18	365
022/13 / SEXUAL ACTIVITY WITH MALE U16 - OFFENDER U18	365
022/14 / CAUSE SEXUAL ACTIVITY FEMALE U16 - OFFENDER U18	365
022/15 / CAUSE SEXUAL ACTIVITY MALE U16 - OFFENDER U18	365
022/16 / ENGAGE IN SEXUAL ACTIVITY IN PRESENCE OF CHILD U16 - OFFENDER U18	10
022/17 / CAUSE CHILD U16 TO WATCH SEXUAL ACT - OFFENDER U18	10
022/18 / SEXUAL ACTIVITY WITH FEMALE CHILD U16 - NO PENETRATION - OFFENDER 18 OR OVER	10
022/19 / SEXUAL ACTIVITY WITH MALE CHILD U16 - NO PENETRATION - OFFENDER 18 OR OVER	10
022/20 / CAUSE FEMALE U16 TO ENGAGE IN SEXUAL ACTIVITY - NO PENETRATION - OFFENDER 18+	10
022/21 / CAUSE MALE U16 TO ENGAGE IN SEXUAL ACTIVITY - NO PENETRATION - OFFENDER 18+	10
022/22 / SEXUAL ACTIVITY WITH FEMALE CHILD U16 - NO PENETRATION - OFFENDER U18	10
022/23 / SEXUAL ACTIVITY WITH MALE CHILD U16 - NO PENETRATION - OFFENDER U18	10
022/24 / CAUSE FEMALE U16 TO ENGAGE IN SEXUAL ACTIVITY - NO PENETRATION - OFFENDER U18	10
022/25 / CAUSE MALE CHILD U16 SEX. ACTIVITY-NO PENETRATION-OFFENDER U18	10
023/04 / SEXUAL ACTIVITY WITH FEMALE FAMILY MEMBER 13-17,OFFENDER 18+	1278
023/14 / SEXUAL ACTIVITY WITH FEMALE FAMILY MEMBER U13 - OFFENDER 18+	2555
023/17 / SEXUAL ACTIVITY WITH MALE FAMILY MEMBER U13, OFFENDER U18	365
023/21 / INCITE SEXUAL ACTIVITY WWITH MALE FAMILY MEMBER U13, OFFENDER U18	365
023/24 / SEXUAL ACTIVITY WITH FEMALE FAMILY MEMBER U13, OFF 18+ NO PENETRATION	365
070/04 / SEXUAL ACTIVITY WITH FEMALE MENTAL PATIENT - NO PENETRATION	183
070/05 / CAUSE SEXUAL ACTIVITY WITH MALE MENTAL PATIENT	2920
071/01 / ARRANGING OR FACILITATING THE COMMISSION OF A CHILD SEX OFFENCE	183

071/01 / ATTEMPT TO ARRANGE / FACILITATE THE COMMISSION OF A CHILD SEX OFFENCE	183
071/08 / CAUSE/INCITE CHILD PROSITUTION OR PORNOGRAPHY 13-17	365
071/09 / CONTROL CHILD 13-17 PROSTITUTE OR INVOLVED IN PORNOGRAPHY	365
071/10 / ARRANGE/FACILITATE CHILD 13-17 PROSTITUTION OR PORNOGRAPHY	365
071/11 / CAUSING OR INCITING CHILD PROSTITUTION OR PORNOGRAPHY U13	730
071/17 / ENGAGE IN SEXUAL COMMUNICATION WITH A CHILD	10
073/08 / ABUSE OF TRUST: SEXUAL ACTIVITY WITH MALE 13-17 OFFENDER 18+	10
088/01 / MEETING A FEMALE U16 FOLLOWING SEXUAL GROOMING, OFFENDER 18+	548
088/03 / INTERCOURSE WITH AN ANIMAL BY A MALE	19
088/05 / ADMINISTERING A SUBSTANCE WITH INTENT	730
088/07 / TRESPASS WITH INTENT TO COMMIT A SEXUAL OFFENCE	730
088/09 / EXPOSURE	10
088/10 / VOYEURISM	10
088/12 / VOYEURISM ADDITIONAL OFFENCES UPSKIRTING	19
THEFT	
035/00 / ATTEMPT BLACKMAIL	365
035/00 / BLACKMAIL	365
039/00 / ATTEMPT THEFT FROM PERSON	2
039/00 / THEFT FROM PERSON	2
040/00 / ATTEMPT THEFT DWELLING NOT MACH/METER	2
040/00 / THEFT DWELLING NOT MACHINE/METER	2
041/00 / ATTEMPT THEFT BY EMPLOYEE	19
041/00 / THEFT BY EMPLOYEE	19
042/00 / ATTEMPT THEFT MAIL BAG/POST PACKET	2
042/00 / THEFT MAIL BAG/POST PACKET	2
043/00 / ABSTRACT ELECTRICITY	1
044/00 / ATTEMPT THEFT OF P/CYCLE	2
044/00 / THEFT OF P/CYCLE	2
045/11 / ATT THEFT FROM OTHER VEH	2
045/11 / THEFT FROM OTHER VEHICLE	2
047/00 / ATTEMPT THEFT FROM AUTO MACH/METER	2

047/00 / THEFT FROM AUTO MACH/METER	2
049/10 / ATTEMPT THEFT OTHER	2
049/10 / THEFT OTHER	2
049/12 / THEFT CONVEYANCE NOT M/VEH OR P/CYCLE	10
053/25 / MAKE OFF W/O PAYMENT	1
137/18 / RIDE P/CYCLE TAKE W/O CONSENT TWOC	2
137/18 / TAKE P/CYCLE W/O CONSENT TWOC	2
VEHICLE OFFENCES	
037/02 / AGG VEH TAKE DRIVE - NOT CAUSE DEATH	10
045/10 / ATTEMPT THEFT FROM MOTOR VEHICLE	2
045/10 / THEFT FROM MOTOR VEHICLE	2
048/01 / ATTEMPT THEFT OF MOTOR VEHICLE	10
048/01 / THEFT OF MOTOR VEHICLE	10
048/02 / TAKE CONVEYANCE W/O CONSENT	5
048/02 / TAKE MOTOR/VEH W/O OWNER CONSENT	5
126/00 / INTERFERE WITH VEHICLE	3
825/06 / TAMPER WITH M/VEHICLE	3
VIOLENCE AGAINST THE PERSON	
001/01 / MURDER-VICTIM 1 YR OLD OR OVER	5475
001/02 / MURDER VICTIM UNDER 1 YR OLD	5475
002/00 / ATTEMPT MURDER VICTIM UNDER 1 YR OLD	3285
002/00 / ATTEMPT MURDER-VICTIM 1 YR OLD OR OVER	3285
003/01 / THREATS TO KILL	10
004/04 / CAUSE DEATH BY DANGEROUS DRIVING	1095
004/06 / DEATH BY CARELESS DRIVE-EXCESS ALCOHOL	548
004/07 / CAUSE/ALLOW DEATH OF CHILD OR VULNERABLE PERSON	730
004/08 / CAUSE DEATH CARELESS OR INCONSIDERATE DRIVING	10
004/11 / CAUSE/ALLOW CHILD/VULNERABLE PERSON TO SUFFER SERIOUS PHYSICAL HARM	270
004/12 / CAUSE SERIOUS INJURY BY DANGROUS DRIVING	365
005/01 / ATTEMPT TO CAUSE GBH W/I TO DO GBH	1460
005/01 / CAUSE GBH WITH INTENT	1460
005/10 / ADMINISTER NOXIOUS THING TO INFLICT GBH	2190
005/10 / CAUSE POISON ADMINISTERED-ENDANGER LIFE	3285

005/11 / CAUSE DANGER-ITEM TO BE ON ROAD	10
005/14 / POSSESS FIREARM WITH INTENT TO ENDANGER LIFE	1825
005/14 / POSSESS IMITATION F/ARM W/I ENDANGE LIFE	1825
005/15 / POSSESS S/GUN W/I ENDANGER LIFE	1825
005/27 / TORTURE	548
008/02 / ADMINISTER NOXIOUS THING W/I	548
008/02 / ADMINISTER POISON W/I	548
008/02 / CAUSE NOXIOUS THING TO BE TAKEN W/I	548
008/04 / CAUSE BODILY HARM WANTON/FURIOUS DRIVING	84
008/06 / ASSAULT OCCASION ABH	10
008/21 / OWN/ IN CHARGE OF DOG DANGEROUSLY OUT OF CONTROL CAUSING INJURY ASSISTANCE DOG	2
008/21 / OWNER/ PERSON IN CHARGE OF DOG DANGEROUSLY OUT OF CONTROL CAUSING INJURY PERSON	2
008/30 / PUTTING PEOPLE IN FEAR OF VIOLENCE	5
008/52 / EXCISE/INFIBULATE/OTHERWISE MUTILATE FEMALE GENITALIA	1460
008/55 / RACIALLY/RELIGIOUSLY AGGRAVATED INTENTIONAL HARASSMENT,ALARM OR DISTRESS	5
008/56 / RACIALLY/RELIGIOUSLY AGGRAVATED HARASSMENT WITHOUT VIOLENCE S2	10
008/57 / RACIALLY/RELIGIOUSLY AGGRAVATED COMMON ASSAULT	10
008/58 / RACIALLY/RELIGIOUSLY AGGRAVATED HARASSMENT WITH FEAR OF VIOLENCE	10
008/59 / RACIALLY/RELIGIOUSLY AGGRAVATED INFLICTING GBH WITHOUT INTENT	357
008/60 / RACIALLY/RELIGIOUSLY AGGRAVATED S47 ASSAULT AND MALICIOUS WOUNDING	19
008/61 / THREATEN PERSON WITH OFFENSIVE WEAPON IN A PUBLIC PLACE	183
008/62 / THREATEN PERSON WITH A BLADE/SHARPLY POINTED ARTICLE ON SCHOOL PREMISES	548
008/63 / THREATEN A PERSON WITH AN OFFENSIVE WEAPON ON SCHOOL PREMISES	548
008/64 / THREATEN PERSON WITH A BLADE/SHARPLY POINTED ARTICLE IN A PUBLIC PLACE	183
008/65 / STALKING INVOLVING FEAR OF VIOLENCE	84

008/66 / STALKING INVOLVING SERIOUS ALARM/DISTRESS	252
008/67 / ENGAGE IN CONTROLLING/COERCIVE BEHAVIOUR IN AN INTIMATE/FAMILY RELATIONSHIP	84
008/69 / CARE WORKER ILL-TREAT/WILFULLY NEGLECT AN INDIVIDUAL	19
008/71 / DISCLOSE PRIVATE SEXUAL PHOTOGRAPHS AND FILMS WITH INTENT TO CAUSE DISTRESS	5
008/72 / SEND COMMUNICATION/ARTICLE CONVEYING A THREATENING MESSAGE	2
008/75 / ASSAULT BY BEATING OF AN EMERGENCY WORKER (EXCEPT A CONSTABLE) - NO INJURY	2
008/76 / COMMON ASSAULT OF AN EMERGENCY WORKER (EXCEPT A CONSTABLE) - NO INJURY	2
008/81 / ATTEMPT TO INFLICT GBH WITHOUT INTENT	19
008/81 / INFLICTING GBH WITHOUT INTENT	19
008/91 / ATTEMPT MALICIOUS WOUNDING	548
008/91 / MALICIOUS WOUNDING	548
011/03 / WILFUL ABANDON YOUNG PERSON UNDER 16	10
011/03 / WILFULLY ASSAULT YOUNG PERSON UNDER 16	10
011/03 / WILFULLY EXPOSE YOUNG PERSON UNDER 16	10
011/03 / WILFULLY ILL-TREAT YOUNG PERSON UNDER 16	10
011/03 / WILFULLY NEGLECT YOUNG PERSON UNDER 16	10
013/01 / ABDUCTION OF A CHILD BY PARENT	19
013/02 / ABDUCTION OF CHILD BY OTHER PERSON	1460
036/01 / ATTEMPT KIDNAPPING	1460
036/01 / KIDNAPPING	1460
036/03 / FALSE IMPRISONMENT	1460
036/05 / USE VIOLENCE/THREATS/A FORM OF COERCION TO CAUSE PERSON TO ENTER INTO MARRIAGE	2190
036/06 / HOLD PERSON IN SLAVERY OR SERVITUDE	182
036/07 / REQUIRE PERSON TO PERFORM FORCED OR COMPULSORY LABOUR	182
036/08 / ARRANGE OR FACILITATE TRAVEL OF ANOTHER PERSON WITH A VIEW TO EXPLOITATION	1095

036/10 / COMMIT OFFENCE OTHER THAN KIDNAP/FALSE IMPRISON. W/I TO COMMIT HUMAN TRAFFICKING	182
036/11 / COMMIT OFFENCE OF KIDNAP/FALSE IMPRISONMENT W/I TO COMMIT HUMAN TRAFFICKING	1460
037/01 / AGG-TAKE M/VEH W/O CONSENT CAUSE DEATH	1825
098/06 / ILL TREAT/ WILFUL NEGLECT A PERSON LACKING CAPACITY BY CARER	5
105/01 / COMMON ASSAULT	1
195/12 / PURSUE COURSE OF CONDUCT IN BREACH OF S1(1) WHICH AMOUNTS TO STALKING	10
195/94 / HARASSMENT	10

Appendix 5: Complete negative binomial results, chapter 4

	Complete dataset		Outside subset		Residential subset	
	Volume	**Harm**	**Volume**	**Harm**	**Volume**	**Harm**
Guardians						
Streetlights	0.017** 0.006	0.024. 0.013	0.031*** 0.007	0.04** 0.015	-0.009 0.006	-0.023 0.015
Police and fire stations within 200m	-0.268** 0.084	-0.568*** 0.153	-0.354*** 0.100	-0.639*** 0.181	-0.117 0.093	-1.177*** 0.211
Police and fire stations within 400m	0.044 0.046	0.188* 0.086	0.034 0.054	0.146 0.102	-0.031 0.047	0.329** 0.111
Motivated Offenders						
NCDI	0.204*** 0.005	0.303*** 0.011	0.075*** 0.006	0.097*** 0.013	0.099*** 0.003	0.156*** 0.009
Crime Generators						
Retail/Office	0.048*** 0.002	0.065*** 0.005	0.037*** 0.002	0.048*** 0.006	-0.003 0.003	-0.003 0.005
Retail/Office within 200m	-0.0005** 0.0002	-0.001** 0.0003	-0.0005* 0.0002	-0.001. 0.0004	-0.001*** 0.0003	-0.002** 0.001
Crime generators within 200m	0.041* 0.016	0.046 0.031	0.038* 0.019	0.058 0.036	0.003 0.017	-0.026 0.039
Crime generators within 400m	0.015. 0.009	0.088*** 0.016	0.034*** 0.010	0.15*** 0.019	0.0001 0.009	-0.014 0.021
Crime Attractors						
Transport on street segment	0.195*** 0.036	0.305*** 0.075	0.141*** 0.041	0.359*** 0.088	0.171*** 0.028	0.309*** 0.071
Transport within 200m	0.042*** 0.005	0.034*** 0.009	0.042*** 0.005	0.026* 0.010	0.034*** 0.006	0.029* 0.013
Transport within 400m	-0.012*** 0.002	-0.003 0.004	-0.012*** 0.003	0.0004 0.005	-0.028*** 0.003	-0.022*** 0.006
Crime attractors within 200m	0.038*** 0.003	0.056*** 0.007	0.033*** 0.004	0.055*** 0.008	0.004 0.004	0.021* 0.01
Crime attractors within 400m	0.012*** 0.002	0.010*** 0.003	0.013*** 0.002	0.01** 0.003	0.002 0.002	0.001 0.005
Social context						
Number of residences	0.007*** 0.0003	0.011*** 0.001	0.002*** 0.0003	0.001 0.001		
Income Decile	-0.061*** 0.007	-0.081*** 0.014	-0.072*** 0.009	-0.104*** 0.016	-0.133*** 0.008	-0.061*** 0.018
Health Decile	0.006 0.011	0.013 0.020	0.008 0.012	-0.017 0.023	0.006 0.011	-0.106*** 0.024

Barriers to Housing Decile	-0.006 0.005	-0.052*** 0.010	0.004 0.006	-0.058*** 0.012	-0.0001 0.006	0.015 0.013
Living Decile	-0.008 0.006	-0.025* 0.010	-0.016* 0.007	-0.057*** 0.012	0.008 0.006	-0.026* 0.013
Intercept	-3.306*** 0.043	0.869*** 0.079	-3.846*** 0.050	0.47*** 0.093	-1.058*** 0.047	3.566*** 0.104
AIC	115344	220492	84552	150982	50142	119633
Std. errors are presented below the coefficients Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

Appendix 6: Complete linear regression results, chapter 5

ALL Crime - Order of tables

All crime volume – full intersect – IDW interpolated layer

All crime volume – centroid intersect – IDW interpolated layer

All crime harm – full intersect – IDW interpolated layer

All crime harm – centroid intersect – IDW interpolated layer

All Crime volume – full intersect– IDW interpolated layer

	Frontiers only			Frontiers and all boundaries		
	coefficient	**Std error**	**R^2 / Adjusted R^2**	**coefficient**	**Std error**	**R^2 / Adjusted R^2**
Model Intercept	617.01	15.60	0.004186	240.7116	24.9876	0.0396
Religious frontier	226.20 ***	35.14	0.004085	-0.5658	36.5025	0.0394
Model Intercept	592.87	16.04	0.007617	240.71	24.98	0.0398
Country of Birth	283.13 ***	32.55	0.007516	49.64	34.50	0.0396
Model Intercept	589.09	15.95	0.008849	240.71	24.98	0.04013
Ethnicity	308.62 ***	32.90	0.008749	81.53 *	34.76	0.03994
Model Intercept	524.40	17.38	0.01717	240.71	24.97	0.041
Composite	379.32 ***	28.90	0.01707	124.71 ***	32.86	0.0408
Model Intercept	649.99	14.76	0.0006324	240.71	24.98	0.03995
Intersectional	116.97 *	46.83	0.000531	-89.36 .	47.04	0.03975
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1						

	Frontiers, boundaries and fixed effects at 100m			Frontiers, boundaries and fixed effects at 200m		
	coefficient	**Std error**	**R^2 / Adjusted R^2**	**coefficient**	**Std error**	**R^2 / Adjusted R^2**
Model Intercept	507.373	184.727	0.1921	460.37	189.37	0.1921
Religious frontier	-167.996 ***	41.246	0.1757	-138.22 ***	40.37	0.1757
Model Intercept	485.3076	184.7966	0.1912	428.715	188.982	0.1916
Country of Birth	-89.4624 *	37.4159	0.1748	-92.380 *	36.537	0.1752
Model Intercept	455.715	184.353	0.1917	372.184	187.808	0.1911
Ethnicity	-130.191 ***	37.360	0.1753	4.295	35.240	0.1747
Model Intercept	469.175	184.986	0.1908	376.644	188.417	0.1911
Composite	-31.785	36.026	0.1744	-8.241	33.925	0.1747
Model Intercept	486.593	184.355	0.1926	439.562	188.070	0.1929
Intersectional	-242.107 ***	50.590	0.1763	-205.906 ***	43.867	0.1766
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1						

All Crime Volume – Centroid intersect– IDW interpolated layer

	Frontiers only			Frontiers and all boundaries		
	coefficient	**Std error**	**R^2 / Adjusted R^2**	**coefficient**	**Std error**	**R^2 / Adjusted R^2**
Model Intercept	645.15	14.97	0.0009833	393.88	20.26	0.03299
Religious	132.05 **	42.39	0.0008819	-149.46 ***	44.53	0.03279
Model Intercept	628.71	15.21	0.003072	393.88	20.27	0.03216
Country of Birth	213.56	38.75	0.002971	-69.72 .	41.58	0.03196
Model Intercept	623.16	15.14	0.004428	393.88	20.27	0.03189
Ethnicity	261.29 ***	39.46	0.004327	-10.40	42.17	0.03169
Model Intercept	591.28	16.01	0.008061	393.88	20.27	0.0319
Composite	292.11 ***	32.63	0.00796	-15.60	37.81	0.0317
Model Intercept	660.74	14.43	6.239e-06	393.88	20.25	0.03345
Intersectional	14.86	59.93	-9.519e-05	-242.58 ***	60.55	0.03326
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1						

	Frontiers, boundaries and fixed effects at 100m			Frontiers, boundaries and fixed effects at 200m		
	coefficient	Std error	R^2 / Adjusted R^2	coefficient	Std error	R^2 / Adjusted R^2
Model Intercept	533.900	182.896	0.1935	516.828	186.398	0.1922
Religious frontier	-268.937 ***	46.802	0.1771	-173.362***	40.060	0.1758
Model Intercept	520.1272	183.1196	0.1917	486.098	186.202	0.1914
Country of Birth	-144.8057 ***	42.5645	0.1753	-115.616	**36.426	0.175
Model Intercept	489.551	182.952	0.192	441.139	185.706	0.1907
Ethnicity	-167.051 ***	43.297	0.1756	-44.825	35.797	0.1743
Model Intercept	520.1129	183.1610	0.1916	453.411	185.881	0.1908
Composite	-123.3995 **	39.3495	0.1752	-58.156 .	34.907	0.1744
Model Intercept	511.315	182.832	0.1932	493.09	185.67	0.1932
Intersectional	-334.390 ***	61.712	0.1768	-260.30 ***	46.72	0.1768
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

All Crime Harm – Full Intersect - IDW interpolated layer

	Frontiers only			Frontiers and all boundaries		
	coefficient	Std error	R^2 / Adjusted R^2	coefficient	Std error	R^2 / Adjusted R^2
Model Intercept	44287	1509	0.004446	14815	2432	0.02767
Religious frontier	22549 ***	3398	0.004345	4788	3552	0.02747
Model Intercept	42226	1551	0.007295	14815	2431	0.02814
Country of Birth	26800 ***	3148	0.007194	8625 *	3357	0.02794
Model Intercept	41845	1542	0.008534	14815	2430	0.02866
Ethnicity	29313 ***	3182	0.008433	11693 ***	3382	0.02847
Model Intercept	36858	1684	0.01375	14815	2430	0.02913
Composite	32828 ***	2800	0.01365	13044 ***	3198	0.02893
Model Intercept	47380	1427	0.0009164	14815	2432	0.02752
Intersectional	13619 **	4529	0.000815	-2799	4579	0.02733
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

	Frontiers, boundaries and fixed effects at 100m			Frontiers, boundaries and fixed effects at 200m		
	coefficient	Std error	R^2 / Adjusted R^2	coefficient	Std error	R^2 / Adjusted R^2
Model Intercept	53438.7	18227.2	0.1591	51112.9	18688.7	0.1588
Religious frontier	-12000.9**	4069.8	0.1421	-8529.2 *	3984.1	0.1417
Model Intercept	50721.7	18231.6	0.1584	49197.65	18647.55	0.1586
Country of Birth	-2799.0	3691.4	0.1414	-5763.37	3605.23	0.1415
Model Intercept	49776	18192	0.1586	45349.1	18527.5	0.1584
Ethnicity	-6273 .	3687	0.1416	2590.9	3476.5	0.1414
Model Intercept	50049.7	18246.1	0.1584	45119.6	18588.1	0.1584
Composite	-561.6	3553.4	0.1413	1254.1	3346.8	0.1413
Model Intercept	52105.5	18191.7	0.1596	50188.9	18565.2	0.1593
Intersectional	-18527.4	4992.1	0.1425	-13815.7	4330.3	0.1422
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

All Crime Harm – Centroid Intersect– IDW interpolated layer

	Frontiers only			Frontiers and all boundaries		
	coefficient	**Std error**	**R^2 / Adjusted R^2**	**coefficient**	**Std error**	**R^2 / Adjusted R^2**
Model Intercept	47055	1447	0.001091	27714	1971	0.02136
Religious frontier	13456 **	4100	0.0009902	-8213 **.**	4332	0.02116
Model Intercept	45577	1471	0.003021	27714	1971	0.02101
Country of Birth	20485***	3748	0.00292	-1063	4044	0.02081
Model Intercept	45162	1464	0.004083	27714	1971	0.02108
Ethnicity	24267***	3817	0.003982	3592	4101	0.02088
Model Intercept	42717	1550	0.006305	27714	1971	0.02102
Composite	24986 ***	3159	0.006204	1600	3677	0.02083
Model Intercept	48494	1396	5.081e-05	27714	1971	0.02173
Intersectional	4103	5796	-5.061e-05	-15944	5892	0.02153
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

	Frontiers, boundaries and fixed effects at 100m			Frontiers, boundaries and fixed effects at 200m		
	coefficient	**Std error**	**R^2 / Adjusted R^2**	**coefficient**	**Std error**	**R^2 / Adjusted R^2**
Model Intercept	56371	18049	0.1604	54583.2	18393.8	0.1591
Religious frontier	-22694***	4619	0.1434	-12122.6**	3953.1	0.142
Model Intercept	54495.38	18070.10	0.1586	51672.7	18372.4	0.1585
Country of Birth	-8020.92**.**	4200.23	0.1415	-6200.2 **.**	3594.1	0.1414
Model Intercept	52730	18054	0.1589	49168.13	18318.20	0.1582
Ethnicity	-11267 **	4272	0.1418	-37.03	3531.06	0.1412
Model Intercept	54890.1	18071.2	0.1587	50233.88	18334.97	0.1584
Composite	-8820.4 *	3882.3	0.1417	-4419.62	3443.18	0.1413
Model Intercept	54447.4	18042.2	0.1601	53121.0	18326.1	0.1597
Intersectional	-27845.2 ***	6089.82	0.1431	-19160.7	4611.5	0.1427
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

OUTSIDE Crime - Order of tables

Outside crime volume – full intersect – IDW interpolated layer
Outside crime volume – centroid intersect – IDW interpolated layer
Outside crime harm – full intersect – IDW interpolated layer
Outside crime harm – centroid intersect – IDW interpolated layer

Out Crime volume – full intersect– IDW interpolated layer

	Frontiers only			Frontiers and all boundaries		
	coefficient	**Std error**	**R^2 / Adjusted R^2**	**coefficient**	**Std error**	**R^2 / Adjusted R^2**
Model Intercept	284.061	8.348	0.003286	117.528	13.447	0.02753
Religious frontier	107.191***	18.801	0.003185	6.833	19.644	0.02734
Model Intercept	277.637	8.591	0.00428	117.528	13.447	0.02754
Country of Birth	113.506***	17.436	0.004179	7.349	18.568	0.02734
Model Intercept	269.935	8.534	0.007314	117.53	13.44	0.02825
Ethnicity	150.056***	17.606	0.007213	50.71 **	18.71	0.02805
Model Intercept	244.338	9.322	0.01181	117.53	13.44	0.02845
Composite	168.233***	15.500	0.01171	54.42 **	17.69	0.02826
Model Intercept	299.233	7.892	0.0005824	117.53	13.45	0.02767
Intersectional	60.037*	25.047	0.0004811	-31.57	25.32	0.02748
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

	Frontiers, boundaries and fixed effects at 100m			Frontiers, boundaries and fixed effects at 200m		
	coefficient	**Std error**	**R^2 / Adjusted R^2**	**coefficient**	**Std error**	**R^2 / Adjusted R^2**
Model Intercept	258.7278	101.6244	0.1451	244.206	104.139	0.1457
Religious frontier	-57.5350*	22.6909	0.1278	-67.326**	22.200	0.1284
Model Intercept	256.907	101.610	0.1451	232.171	103.914	0.1455
Country of Birth	-48.699*	20.573	0.1277	-50.584*	20.090	0.1281
Model Intercept	241.025	101.403	0.145	201.6604	103.2683	0.1449
Ethnicity	-45.866*	20.550	0.1277	-0.8569	19.3774	0.1276
Model Intercept	248.331	101.713	0.1446	205.461	103.603	0.1449
Composite	-17.835	19.809	0.1273	-8.355	18.654	0.1276
Model Intercept	252.004	101.436	0.1454	230.0178	103.4593	0.1461
Intersectional	-86.119**	27.836	0.1281	-87.7966***	24.1315	0.1288
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1						

Out Crime Volume – Centroid intersect

	Frontiers only			Frontiers and all boundaries		
	coefficient	**Std error**	**R^2 / Adjusted R^2**	**coefficient**	**Std error**	**R^2 / Adjusted R^2**
Model Intercept	296.024	8.003	0.001067	183.69	10.89	0.02343
Religious	73.573**	22.670	0.0009658	-52.28*	23.93	0.02323
Model Intercept	290.349	8.137	0.002187	183.69	10.89	0.02317
Country of Birth	96.368***	20.732	0.002086	-32.30	22.34	0.02297
Model Intercept	284.337	8.094	0.004556	183.69	10.89	0.02306
Ethnicity	141.741***	21.101	0.004455	22.47	22.65	0.02286
Model Intercept	269.842	8.568	0.007122	183.69	10.89	0.023
Composite	146.841***	17.461	0.007021	12.54	20.31	0.0228
Model Intercept	304.028	7.719	3.986e-05	183.69	10.88	0.02382
Intersectional	20.093	32.050	-6.156e-05	-96.00**	32.54	0.02362
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1						

	Frontiers, boundaries and fixed effects at 100m			Frontiers, boundaries and fixed effects at 200m		
	coefficient	**Std error**	**R^2 / Adjusted R^2**	**coefficient**	**Std error**	**R^2 / Adjusted R^2**
Model Intercept	267.575	100.658	0.1459	272.125	102.544	0.1452
Religious frontier	-93.760***	25.758	0.1286	-68.201**	22.038	0.1279
Model Intercept	263.217	100.711	0.1452	264.6273	102.3988	0.1451
Country of Birth	-53.097*	23.409	0.1279	-56.8423**	20.0319	0.1277
Model Intercept	252.4464	100.6413	0.1451	242.435	102.118	0.1444
Ethnicity	-48.9381*	23.8175	0.1278	-19.798	19.685	0.1271
Model Intercept	260.125	100.742	0.1449	242.315	102.226	0.1444
Composite	-29.753	21.643	0.1276	-2.743	19.197	0.127
Model Intercept	260.0629	100.6028	0.1459	263.1234	102.1722	0.1458
Intersectional	-124.2407***	33.9567	0.1286	-104.0384***	25.7101	0.1285
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1						

Out Crime Harm – Full intersect

	Frontiers only			Frontiers and all boundaries		
	coefficient	**Std error**	**R^2 / Adjusted R^2**	**coefficient**	**Std error**	**R^2 / Adjusted R^2**
Model Intercept	16346.4	782.9	0.00279	5292	1269	0.01494
Religious frontier	9260.5***	1763.4	0.002688	2599	1854	0.01474
Model Intercept	15743.3	805.8	0.003781	5292	1269	0.01505
Country of Birth	10004.3***	1635.4	0.00368	3075.	1752	0.01485
Model Intercept	15410.1	801.1	0.005105	5292	1269	0.0156
Ethnicity	11754.7***	1652.7	0.005004	5159**	1766	0.0154
Model Intercept	13835.2	876.3	0.006821	5292	1269	0.01541
Composite	11989.4***	1457.1	0.00672	4322**	1670	0.01521
Model Intercept	17402.9	739.8	0.001103	5292	1269	0.01479
Intersectional	7747.8***	2348.0	0.001002	1642	2390	0.01459
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1						

	Frontiers, boundaries and fixed effects at 100m			Frontiers, boundaries and fixed effects at 200m		
	coefficient	**Std error**	**R^2 / Adjusted R^2**	**coefficient**	**Std error**	**R^2 / Adjusted R^2**
Model Intercept	12561.47	9687.55	0.1165	12377.50	9931.91	0.1162
Religious frontier	-3154.00	2163.06	0.09855	-2032.95	2117.28	0.09832
Model Intercept	11784.91	9686.80	0.1163	11996.32	9909.16	0.1162
Country of Birth	-538.87	1961.29	0.09836	-1498.11	1915.79	0.09829
Model Intercept	11600.9	9666.5	0.1163	10671.1	9843.3	0.1164
Ethnicity	-1422.6	1959.0	0.09841	3019.2	1847.0	0.09849
Model Intercept	11463.17	9694.25	0.1163	10572.61	9876.43	0.1162
Composite	389.74	1887.97	0.09836	1101.24	1778.29	0.09827
Model Intercept	12231.91	9670.46	0.1166	12697.7	9867.2	0.1166
Intersectional	-5039.09.	2653.72	0.09869	-4959.4*	2301.5	0.09867
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1						

Out Crime Harm – Centroid intersect

	Frontiers only			Frontiers and all boundaries		
	coefficient	**Std error**	**R^2 / Adjusted R^2**	**coefficient**	**Std error**	**R^2 / Adjusted R^2**
Model Intercept	17235.5	750.4	0.001266	9779.4	1026.6	0.01247
Religious frontier	7515.0***	2125.6	0.001165	-838.5	2256.5	0.01227
Model Intercept	16782	763	0.002183	9779.4	1026.6	0.01247
Country of Birth	9028 ***	1944	0.002081	580.9	2106.1	0.01226
Model Intercept	16552.6	759.5	0.003124	9779	1026	0.01265
Ethnicity	11005.7***	1980.0	0.003023	2980	2136	0.01245
Model Intercept	15530.9	804.4	0.004521	9779	1026	0.01257
Composite	10970.7***	1639.5	0.00442	2005	1915	0.01237
Model Intercept	17824.8	723.7	0.0004024	9779	1027	0.01249
Intersectional	5986.0*	3004.8	0.000301	-1775	3069	0.01229
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1						

	Frontiers, boundaries and fixed effects at 100m			Frontiers, boundaries and fixed effects at 200m		
	coefficient	**Std error**	**R^2 / Adjusted R^2**	**coefficient**	**Std error**	**R^2 / Adjusted R^2**
Model Intercept	13153.321	9598.296	0.1168	13286.1	9776.4	0.1163
Religious frontier	-5028.863*	2456.145	0.09885	-3007.2	2101.1	0.0984
Model Intercept	12505.6	9601.5	0.1164	12639.2	9762.4	0.1162
Country of Birth	-411.0	2231.8	0.09846	-1724.0	1909.8	0.09829
Model Intercept	12361.4	9593.9	0.1165	11921.1	9732.5	0.1161
Ethnicity	-2079.0	2270.5	0.09854	537.4	1876.1	0.09822
Model Intercept	12341.00	9602.75	0.1164	11507.7	9741.8	0.1162
Composite	475.91	2063.01	0.09846	1800.3	1829.4	0.0983
Model Intercept	12761.60	9592.94	0.1168	13021.8	9743.1	0.1166
Intersectional	-6900.76*	3237.93	0.09888	-5230.6*	2451.7	0.09864
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1						

RESIDENTIAL Crime

Order of tables

Residential crime volume – full intersect – IDW interpolated layer
Residential crime volume – centroid intersect – IDW interpolated layer
Residential crime volume – full intersect – Sum of Residential buildings
Residential crime volume – centroid intersect – Sum of Residential buildings

Residential crime harm – full intersect – IDW interpolated layer
Residential crime harm – centroid intersect – IDW interpolated layer
Residential crime harm – full intersect – Sum of Residential buildings
Residential crime harm – centroid intersect – Sum of Residential buildings

Residential crime volume – full intersect – IDW interpolated layer

	Frontiers only			Frontiers and all boundaries		
	coefficient	**Std error**	**R^2 / Adjusted R^2**	**coefficient**	**Std error**	**R^2 / Adjusted R^2**
Model Intercept	436.505	8.416	0.0009759	261.278	18.579	0.01942
Religious frontier	41.455*	17.234	0.0008072	-2.753	17.582	0.01909
Model Intercept	425.996	8.698	0.003206	261.28	18.57	0.0198
Country of Birth	70.669***	16.191	0.003038	25.38	16.68	0.01947
Model Intercept	417.909	8.576	0.006828	261.28	18.56	0.02173
Ethnicity	105.146***	16.478	0.00666	63.41***	16.93	0.0214
Model Intercept	405.707	9.852	0.006396	261.28	18.57	0.02025
Composite	90.964***	14.731	0.006229	35.48*	15.84	0.01992
Model Intercept	445.772	7.765	1.028e-05	261.28	18.58	0.01971
Intersectional	5.927	24.023	-0.0001586	-32.21	24.04	0.01938
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1						

	Frontiers, boundaries and fixed effects at 100m			Frontiers, boundaries and fixed effects at 200m		
	coefficient	Std error	R^2 / Adjusted R^2	coefficient	Std error	R^2 / Adjusted R^2
Model Intercept	293.178	79.366	0.3046	272.106	84.092	0.3037
Religious frontier	-74.093***	18.369	0.2808	-48.613 **	17.882	0.2798
Model Intercept	291.544	79.397	0.3042	273.3814	83.9511	0.304
Country of Birth	-60.890***	17.153	0.2804	-55.0358**	16.9997	0.2802
Model Intercept	272.946	79.315	0.3037	246.055	83.590	0.3031
Ethnicity	-52.097**	17.260	0.2799	-28.593.	16.339	0.2793
Model Intercept	288.51885	79.49679	0.3033	257.374	83.750	0.3033
Composite	-38.58055*	16.34344	0.2795	-32.112*	15.518	0.2794
Model Intercept	284.851	79.171	0.3064	262.592	83.574	0.3049
Intersectional	-131.576***	23.678	0.2826	-82.853***	19.761	0.2811
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

Residential crime volume – centroid intersect – IDW interpolated layer

	Frontiers only			Frontiers and all boundaries		
	coefficient	Std error	R^2 / Adjusted R^2	coefficient	Std error	R^2 / Adjusted R^2
Model Intercept	447.855	7.956	3.884e-05	363.28	12.78	0.01189
Religious frontier	-9.953	20.750	-0.00013	-62.47**	21.55	0.01155
Model Intercept	439.86	8.12	0.0006012	363.28	12.79	0.01058
Country of Birth	35.97.	19.05	0.0004325	-14.93	20.07	0.01024
Model Intercept	434.721	8.039	0.002136	363.28	12.79	0.01071
Ethnicity	70.202 ***	19.716	0.001968	24.16	20.66	0.01038
Model Intercept	432.193	8.748	0.001503	363.28	12.79	0.01055
Composite	48.044**	16.092	0.001334	-11.57	17.95	0.01022
Model Intercept	449.182	7.568	0.0003976	363.28	12.78	0.01194
Intersectional	-48.350	31.501	0.0002288	-93.95**	31.80	0.01161
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

	Frontiers, boundaries and fixed effects at 100m			Frontiers, boundaries and fixed effects at 200m		
	coefficient	Std error	R^2 / Adjusted R^2	coefficient	Std error	R^2 / Adjusted R^2
Model Intercept	306.512	78.162	0.3065	277.1226	80.5586	0.3053
Religious frontier	-121.881***	20.975	0.2828	-77.5939***	17.8454	0.2815
Model Intercept	303.0427	78.3324	0.3039	276.6210	80.5323	0.3054
Country of Birth	-66.9422***	19.3801	0.2801	-75.2922***	16.8276	0.2816
Model Intercept	286.6805	78.3049	0.3037	249.936	80.441	0.304
Ethnicity	-64.5055**	19.9964	0.2799	-47.670**	16.497	0.2802
Model Intercept	305.858	78.331	0.3043	265.599	80.478	0.3046
Composite	-67.577***	17.578	0.2804	-57.531***	15.706	0.2808
Model Intercept	292.202	78.152	0.3061	264.9169	80.3093	0.3067
Intersectional	-162.537***	29.764	0.2823	-119.6240***	21.5651	0.283
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

Residential crime volume – full intersect – Sum of Residential buildings

	Frontiers only			Frontiers and all boundaries		
	coefficient	**Std error**	**R^2 / Adjusted R^2**	**coefficient**	**Std error**	**R^2 / Adjusted R^2**
Model Intercept	22.3226	0.9314	0.0002752	23.792	2.075	0.0003812
Religious frontier	2.4352	1.9073	0.0001064	2.806	1.964	4.356e-05
Model Intercept	22.3251	0.9637	0.0002106	23.792	2.075	0.0003181
Country of Birth	2.0035	1.7938	4.176e-05	2.407	1.864	-1.951e-05
Model Intercept	21.8807	0.9517	0.0007191	23.792	2.075	0.0009004
Ethnicity	3.7749	1.8285	0.0005504	4.284*	1.893	0.000563
Model Intercept	21.629	1.093	0.0005126	23.792	2.075	0.0007665
Composite	2.849 .	1.634	0.0003439	3.680*	1.769	0.000429
Model Intercept	22.5742	0.8589	0.0002372	23.792	2.075	0.0003073
Intersectional	3.1500	2.6573	6.84e-05	3.402	2.686	-3.028e-05
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1						

	Frontiers, boundaries and fixed effects at 100m			Frontiers, boundaries and fixed effects at 200m		
	coefficient	**Std error**	**R^2 / Adjusted R^2**	**coefficient**	**Std error**	**R^2 / Adjusted R^2**
Model Intercept	20.40538	10.20236	0.06107	19.101941	10.804117	0.0608
Religious frontier	0.62935	2.36127	0.02894	0.632078	2.297414	0.02866
Model Intercept	20.06817	10.20246	0.06118	19.79889	10.78884	0.0608
Country of Birth	1.92896	2.20411	0.02906	-0.73912	2.18468	0.02866
Model Intercept	20.7299	10.1881	0.06131	19.45554	10.73504	0.06089
Ethnicity	2.7448	2.2170	0.02919	1.65589	2.09827	0.02875
Model Intercept	19.43240	10.20716	0.06152	18.62176	10.75590	0.06102
Composite	3.55133 .	2.09845	0.02941	2.38065	1.99295	0.02889
Model Intercept	20.51757	10.19026	0.06106	19.4626	10.7471	0.06078
Intersectional	0.47214	3.04771	0.02893	-0.1340	2.5412	0.02865
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1						

Residential crime volume – centroid intersect – Sum of Residential buildings

	Frontiers only			Frontiers and all boundaries		
	coefficient	**Std error**	**R^2 / Adjusted R^2**	**coefficient**	**Std error**	**R^2 / Adjusted R^2**
Model Intercept	22.5769	0.8801	0.0001579	23.333	1.422	0.0002353
Religious frontier	2.2203	2.2954	-1.086e-05	2.690	2.398	-0.0001023
Model Intercept	22.8414	0.8986	4.407e-06	23.3331	1.4222	3.801e-05
Country of Birth	0.3407	2.1086	-0.0001644	0.6675	2.2324	-0.0002997
Model Intercept	22.4300	0.8901	0.0002871	23.333	1.422	0.000399
Ethnicity	2.8470	2.1831	0.0001183	3.429	2.297	6.144e-05
Model Intercept	22.2635	0.9684	0.0002493	23.333	1.422	0.0004275
Composite	2.1650	1.7814	8.054e-05	3.090	1.996	8.99e-05
Model Intercept	22.8541	0.8374	1.011e-05	23.3331	1.4222	3.944e-05
Intersectional	0.8529	3.4856	-0.0001587	1.1072	3.5388	-0.0002983
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1						

	Frontiers, boundaries and fixed effects at 100m			Frontiers, boundaries and fixed effects at 200m		
	coefficient	**Std error**	**R^2 / Adjusted R^2**	**coefficient**	**Std error**	**R^2 / Adjusted R^2**
Model Intercept	18.7511	10.0628	0.06085	17.31814	10.36215	0.06078
Religious frontier	-0.2971	2.7004	0.02871	-0.57824	2.29544	0.02865
Model Intercept	18.70160	10.06562	0.06085	17.0911	10.3598	0.06078
Country of Birth	0.09838	2.49031	0.02871	0.1403	2.1647	0.02864
Model Intercept	18.89806	10.06022	0.06095	17.2171	10.3372	0.06085
Ethnicity	1.99262	2.56903	0.02881	1.4301	2.1199	0.02871
Model Intercept	18.2415	10.0669	0.06103	16.88691	10.34660	0.06082
Composite	2.4132	2.2590	0.02891	1.10540	2.01926	0.02869
Model Intercept	18.7127	10.0578	0.0609	17.2597	10.3406	0.06081
Intersectional	-2.0892	3.8305	0.02876	-1.2085	2.7767	0.02867
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

Residential crime harm – full intersect – IDW interpolated layer

	Frontiers only			Frontiers and all boundaries		
	coefficient	**Std error**	**R^2 / Adjusted R^2**	**coefficient**	**Std error**	**R^2 / Adjusted R^2**
Model Intercept	40380	1497	0.001001	24715	3329	0.005657
Religious frontier	7469*	3066	0.0008321	3517	3150	0.005321
Model Intercept	39064	1548	0.002336	24715	3328	0.006314
Country of Birth	10732***	2882	0.002167	6787*	2988	0.005978
Model Intercept	37643	1527	0.005426	24715	3324	0.008634
Ethnicity	16677***	2934	0.005258	13232***	3033	0.008299
Model Intercept	36360	1755	0.004109	24715	3326	0.006953
Composite	12971***	2624	0.00394	8497**	2837	0.006617
Model Intercept	41760	1381	0.0001359	24715.4	3329.0	0.005449
Intersectional	3834	4274	-3.295e-05	310.5	4308.7	0.005113
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

	Frontiers, boundaries and fixed effects at 100m			Frontiers, boundaries and fixed effects at 200m		
	coefficient	**Std error**	**R^2 / Adjusted R^2**	**coefficient**	**Std error**	**R^2 / Adjusted R^2**
Model Intercept	46234.1	15766.9	0.133	41606.1	16694.3	0.133
Religious frontier	-5957.9	3649.1	0.1034	-4486.5	3549.9	0.1034
Model Intercept	45232.7	15771.4	0.1327	40847.1	16671.7	0.1329
Country of Birth	-1398.3	3407.2	0.103	-3291.9	3375.9	0.1033
Model Intercept	44858.8	15750.5	0.1326	39231.44	16590.66	0.1328
Ethnicity	-394.3	3427.4	0.103	-84.15	3242.81	0.1031
Model Intercept	45199.2	15781.7	0.1326	39567.68	16623.91	0.1328
Composite	-1000.5	3244.5	0.103	-979.82	3080.22	0.1031
Model Intercept	45522.7	15745.6	0.1333	40072.59	16606.65	0.133
Intersectional	-9929.6*	4709.2	0.1036	-4295.61	3926.65	0.1033
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

Residential crime harm – centroid intersect – IDW interpolated layer

	Frontiers only			Frontiers and all boundaries		
	coefficient	**Std error**	**R^2 / Adjusted R^2**	**coefficient**	**Std error**	**R^2 / Adjusted R^2**
Model Intercept	42387	1416	2.941e-05	35661	2285	0.002397
Religious frontier	-1541	3692	-0.0001394	-5718	3852	0.00206
Model Intercept	41041	1445	0.0005581	35661	2285	0.002113
Country of Birth	6166.	3390	0.0003893	2590	3586	0.001776
Model Intercept	40271	1430	0.00177	35661	2284	0.002898
Ethnicity	11369**	3508	0.001601	8398*	3690	0.002561
Model Intercept	40293	1557	0.0008213	35661	2285	0.002113
Composite	6319*	2864	0.0006526	2312	3208	0.001776
Model Intercept	42437	1347	0.0001225	35661	2285	0.002391
Intersectional	-4775	5606	-4.633e-05	-8372	5685	0.002054
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

	Frontiers, boundaries and fixed effects at 100m			Frontiers, boundaries and fixed effects at 200m		
	coefficient	**Std error**	**R^2 / Adjusted R^2**	**coefficient**	**Std error**	**R^2 / Adjusted R^2**
Model Intercept	48888.1	15531.9	0.135	44000.7	16009.8	0.1332
Religious frontier	-16445.2***	4168.1	0.1054	-6070.5 .	3546.5	0.1035
Model Intercept	47625.6	15555.9	0.1328	4.311e+04	1.601e+04	0.1329
Country of Birth	-3968.8	3848.7	0.1031	-3.231e+03	3.345e+03	0.1032
Model Intercept	46601.0	15548.1	0.1328	42124.7	15975.8	0.1328
Ethnicity	-4424.1	3970.5	0.1031	681.2	3276.3	0.1031
Model Intercept	48395.6	15555.3	0.1332	43633.86	15983.43	0.1335
Composite	-7067.1 *	3490.7	0.1036	-6876.18*	3119.36	0.1038
Model Intercept	46966.8	15534.0	0.1339	43210.3	15971.7	0.1338
Intersectional	-17335.9**	5916.1	0.1043	-10963.5*	4288.8	0.1041
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

Residential crime harm – full intersect – Sum of Residential buildings

	Frontiers only			Frontiers and all boundaries		
	coefficient	**Std error**	**R^2 / Adjusted R^2**	**coefficient**	**Std error**	**R^2 / Adjusted R^2**
Model Intercept	1899.0	125.9	0.001268	1600.7	280.5	0.001507
Religious frontier	707.0**	257.8	0.001099	631.7*	265.4	0.00117
Model Intercept	1927.5	130.3	0.0006764	1600.7	280.6	0.0009681
Country of Birth	485.6*	242.5	0.0005077	395.8	252.0	0.0006307
Model Intercept	1889.8	128.7	0.001189	1600.7	280.5	0.001416
Ethnicity	656.5**	247.2	0.001021	579.5*	256.0	0.001079
Model Intercept	1737.6	147.7	0.00188	1600.7	280.4	0.001936
Composite	737.9***	220.9	0.001712	685.3**	239.1	0.001599
Model Intercept	2005.9	116.1	0.0004563	1600.7	280.6	0.0008809
Intersectional	590.9	359.3	0.0002876	507.1	363.1	0.0005434
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

	Frontiers, boundaries and fixed effects at 100m			Frontiers, boundaries and fixed effects at 200m		
	coefficient	Std error	R^2 / Adjusted R^2	coefficient	Std error	R^2 / Adjusted R^2
Model Intercept	2120.85	1379.59	0.06131	2196.494	1460.697	0.06138
Religious frontier	125.76	319.30	0.02919	242.979	310.606	0.02926
Model Intercept	2076.569	1379.586	0.06144	2379.594	1458.696	0.0613
Country of Birth	292.553	298.042	0.02933	-111.209	295.378	0.02918
Model Intercept	2170.56	1377.72	0.06147	2329.756	1451.245	0.06161
Ethnicity	320.19	299.80	0.02936	406.433	283.660	0.0295
Model Intercept	1999.00	1380.25	0.06175	2164.76	1454.04	0.06177
Composite	478.58.	283.76	0.02965	468.43.	269.42	0.02967
Model Intercept	2143.018	1377.957	0.0613	2319.2047	1453.0550	0.06128
Intersectional	98.220	412.120	0.02918	29.8698	343.5759	0.02916
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1						

Residential crime volume – centroid intersect – Sum of Residential buildings

	Frontiers only			Frontiers and all boundaries		
	coefficient	Std error	R^2 / Adjusted R^2	coefficient	Std error	R^2 / Adjusted R^2
Model Intercept	1986.9	119.0	0.0005283	1861.8	192.3	0.0006441
Religious frontier	549.2 .	310.4	0.0003596	471.5	324.2	0.0003066
Model Intercept	2029.8	121.5	9.001e-05	1861.80	192.31	0.0003045
Country of Birth	208.2	285.2	-7.881e-05	96.55	301.86	-3.31e-05
Model Intercept	1967.4	120.4	0.0007032	1861.8	192.3	0.000787
Ethnicity	602.6*	295.2	0.0005345	534.6 .	310.6	0.0004495
Model Intercept	1912.6	130.9	0.0008004	1861.80	192.26	0.0008224
Composite	524.6*	240.8	0.0006317	480.67 .	269.90	0.000485
Model Intercept	2057.2	113.3	2.46e-05	1861.80	192.31	0.0002915
Intersectional	179.9	471.4	-0.0001442	76.17	478.53	-4.609e-05
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1						

	Frontiers, boundaries and fixed effects at 100m			Frontiers, boundaries and fixed effects at 200m		
	coefficient	Std error	R^2 / Adjusted R^2	coefficient	Std error	R^2 / Adjusted R^2
Model Intercept	2165.09	1360.49	0.0614	2109.964	1401.001	0.06129
Religious frontier	-228.84	365.09	0.02929	5.611	310.352	0.02917
Model Intercept	2156.03	1360.91	0.06136	2082.325	1400.668	0.06131
Country of Birth	-109.49	336.70	0.02924	92.363	292.676	0.02919
Model Intercept	2164.136	1360.184	0.06144	2129.58	1397.53	0.06149
Ethnicity	278.286	347.344	0.02933	313.57	286.60	0.02937
Model Intercept	2.119e+03	1.361e+03	0.06136	2078.340	1398.892	0.06134
Composite	1.005e+02	3.055e+02	0.02924	148.339	273.011	0.02922
Model Intercept	2138.07	1359.83	0.06142	2125.077	1398.092	0.06131
Intersectional	-374.76	517.89	0.02931	-130.107	375.423	0.02919
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1						

Appendix 7: Complete negative binominal results chapter 5

	All Crime Volume										
Negative Binomial											
	Null	**Social frontier only (within 100m)**					**Plus other borders (within 100m)**				
Model	**1**	**2a**	**2b**	**2c**	**2d**	**2e**	**3a**	**3b**	**3c**	**3d**	**3e**
Intercept	1.8863	1.7769	1.8165	1.7701	1.6542	1.8686	0.8769	0.8769	0.8769	0.8769	0.8769
Non-UK born frontier		0.3893***					0.0578				
Std. error		0.4408					0.0455				
Religious frontier			0.3120***					-0.0004			
Std. error			0.4761					0.0481			
Non-white frontier				0.4213***					0.0960*		
Std. error				0.0445					0.0458		
Composite frontier					0.5435***					0.1486***	
Std. error					0.0391					0.0433	
Intersectional frontier						0.1651**					-0.1102.
Std. error						0.0635					0.0621
LSOA boundary	X	X	X	X	X	X	✓	✓	✓	✓	✓
LSOA Fixed Effects	X	X	X	X	X	X	X	X	X	X	X
AIC	58931	58851	58887	58838	58736	58926	58168	58170	58165	58158	58167
Signif. codes: ‘***’ 0.001, ‘**’ 0.01, ‘*’ 0.05, ‘.’ 0.1											

	All Crime Volume									
Negative Binomial										
	Plus other borders (within 100m) and LSOA fixed effects					**Plus other borders (within 200m) and LSOA fixed effects**				
Model	**4a**	**4b**	**4c**	**4d**	**4e**	**5a**	**5b**	**5c**	**5d**	**5e**
Intercept	1.3847	1.4040	1.3586	1.3747	1.3759	0.8900	0.9024	0.8544	0.8644	0.8731
Non-UK born frontier	-0.0442					-0.07281 .				
Std. error	0.0449					0.04384				
Religious frontier		-0.1212*					-0.0864 .			
Std. error		0.0494					0.0482			
Non-white frontier			-0.1026 *					-0.0129		
Std. error			0.0449					0.0423		
Composite frontier				-0.0015					-0.0155	
Std. error				0.0434					0.0455	
Intersectional frontier					-0.2104 ***					-0.1676 **
Std. error					0.0606					0.0523
LSOA boundary	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
LSOA Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
AIC	55677	55672	55673	55677	55667	55569	55568	55571	55571	55561
Signif. codes: ‘***’ 0.001, ‘**’ 0.01, ‘*’ 0.05, ‘.’ 0.1										

	All Crime Harm										
Negative Binomial											
	Null	**Social frontier only (within 100m)**					**Plus other borders (within 100m)**				
Model	**1**	**2a**	**2b**	**2c**	**2d**	**2e**	**3a**	**3b**	**3c**	**3d**	**3e**
Intercept	6.1889	6.0456	6.0933	6.0365	5.9096	6.1608	4.9982	4.9982	4.9982	5.5182	4.9982
Non-UK born frontier **Std. error**		0.4914 *** 0.0679					0.1335 . 0.0719				
Religious frontier **Std. error**			0.4115 *** 0.0733					0.0743 0.0761			
Non-white frontier **Std. error**				0.5309 *** 0.0687					0.1795 * 0.0724		
Composite frontier **Std. error**					0.6369 *** 0.0604					0.2251 ** 0.0690	
Intersectional frontier **Std. error**						0.2527 ** 0.0976					-0.0449 0.0980
LSOA boundary	X	X	X	X	X	X	✓	✓	✓	✓	✓
LSOA Fixed Effects	X	X	X	X	X	X	X	X	X	X	X
AIC	105061	105007	105029	104998	104948	105056	104641	104644	104638	104790	104644
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1											

	All Crime Harm									
Negative Binomial										
	Plus other borders (within 100m) and LSOA fixed effects					**Plus other borders (within 200m) and LSOA fixed effects**				
Model	**4a**	**4b**	**4c**	**4d**	**4e**	**5a**	**5b**	**5c**	**5d**	**5e**
Intercept	5.9132	5.9474	5.9126	5.9182	5.9429	5.2956	5.2929	5.3259	5.2868	5.3351
Non-UK born frontier **Std. error**	0.0341 0.0774					0.0524 0.0755				
Religious frontier **Std. error**		-0.1370 0.0854					0.0510 0.0834			
Non-white frontier **Std. error**			-0.1872 * 0.0773					0.0129 0.0728		
Composite frontier **Std. error**				0.0127 0.0746					0.0625 0.0780	
Intersectional frontier **Std. error**					-0.2714 ** 0.1048					-0.0497 0.0907
LSOA boundary	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
LSOA Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
AIC	103396	103394	103391	103396	103390	103355	103355	103355	103355	103355
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1										

	Outside Crime Volume										
Negative Binomial											
	Null	**Social frontier only (within 100m)**					**Plus other borders (within 100m)**				
Model	**1**	**2a**	**2b**	**2c**	**2d**	**2e**	**3a**	**3b**	**3c**	**3d**	**3e**
Intercept	1.1087	1.0146	1.0369	0.9857	0.8868	1.0890	0.1587	0.1587	0.1587	0.1587	0.1587
Non-UK born frontier		0.3406***					0.0180				
Std. error		0.0447					0.0462				
Religious frontier			0.3198***					0.0186			
Std. error			0.0482					0.0489			
Non-white frontier				0.4424***					0.1307**		
Std. error				0.0451					0.0465		
Composite frontier					0.5225***					0.1421**	
Std. error					0.0397					0.0440	
Intersectional frontier						0.1824**					-0.0836
Std. error						0.0643					0.0630
LSOA boundary	X	X	X	X	X	X	✓	✓	✓	✓	✓
LSOA Fixed Effects	X	X	X	X	X	X	X	X	X	X	X
AIC	46402	46344	46358	46303	46229	46396	45749	45749	45741	45739	45747
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1											

	Outside Crime Volume									
Negative Binomial										
	Plus other borders (within 100m) and LSOA fixed effects					**Plus other borders (within 200m) and LSOA fixed effects**				
Model	**4a**	**4b**	**4c**	**4d**	**4e**	**5a**	**5b**	**5c**	**5d**	**5e**
Intercept	0.7178	0.7322	0.6883	0.7055	0.7027	0.1982	0.2180	0.1681	0.1730	0.1807
Non-UK born frontier	-0.0442					-0.0669				
Std. error	0.0465					0.0455				
Religious frontier		-0.0962.					-0.0987*			
Std. error		0.0508					0.0497			
Non-white frontier			-0.0974*					-0.0029		
Std. error			0.0464					0.0438		
Composite frontier				0.0057					-0.0082	
Std. error				0.0449					0.0473	
Intersectional frontier					-0.1861***					-0.1737**
Std. error					0.0625					0.0540
LSOA boundary	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
LSOA Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
AIC	43598	43596	43595	43599	43591	43496	43494	43498	43498	43488
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1										

	Outside Crime Harm										
Negative Binomial											
	Null	**Social frontier only (within 100m)**					**Plus other borders (within 100m)**				
Model	**1**	**2a**	**2b**	**2c**	**2d**	**2e**	**3a**	**3b**	**3c**	**3d**	**3e**
Intercept	5.2025	5.0590	5.0966	5.0376	4.9298	5.1592	3.9687	3.9687	3.9687	3.9687	3.9687
Non-UK born frontier **Std. error**		0.4919*** 0.0744					0.1272 0.0787				
Religious frontier **Std. error**			0.4489*** 0.0802					0.1070 0.0833			
Non-white frontier **Std. error**				0.5669*** 0.0751					0.2106** 0.0793		
Composite frontier **Std. error**					0.6241*** 0.0662					0.1831* 0.0750	
Intersectional frontier **Std. error**						0.3683*** 0.1068					0.0675 0.1073
LSOA boundary	X	X	X	X	X	X	✓	✓	✓	✓	✓
LSOA Fixed Effects	X	X	X	X	X	X	X	X	X	X	X
AIC	79532	79487	79500	79472	79442	79521	79162	79163	79158	79159	79164
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1											

	Outside Crime Harm									
Negative Binomial										
	Plus other borders (within 100m) and LSOA fixed effects					**Plus other borders (within 200m) and LSOA fixed effects**				
Model	**4a**	**4b**	**4c**	**4d**	**4e**	**5a**	**5b**	**5c**	**5d**	**5e**
Intercept	4.2657	4.3375	4.2017	4.2663	4.2589	3.9194	3.9902	3.9814	3.7902	3.9967
Non-UK born frontier **Std. error**	0.0436 0.0843					0.2209** 0.0824				
Religious frontier **Std. error**		-0.1611 . 0.0.093					-0.0301 0.0910			
Non-white frontier **Std. error**			-0.3153*** 0.0842					0.0599 0.0794		
Composite frontier **Std. error**				0.0155 0.0812					0.2932*** 0.0851	
Intersectional frontier **Std. error**					-0.3147* 0.1141					-0.2288* 0.0989
LSOA boundary	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
LSOA Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
AIC	77963	77961	77953	77963	77958	77956	77961	77961	77952	77957
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1										

	All Crime Volume – CENTROID INTERSECT										
Negative Binomial											
	Null	**Social frontier only (within 100m)**					**Plus other borders (within 100m)**				
Model	**1**	**2a**	**2b**	**2c**	**2d**	**2e**	**3a**	**3b**	**3c**	**3d**	**3e**
Intercept		1.8355	1.8612	1.8265	1.7741	1.8851	1.3686	1.3686	1.3686	1.36855	1.3686
Non-UK born frontier **Std. error**		0.2911*** 0.0525					-0.0806 0.0557				
Religious frontier **Std. error**			0.1854** 0.0575					-0.1763 ** 0.0597			
Non-white frontier **Std. error**				0.3497*** 0.0534					-0.0117 0.0564		
Composite frontier **Std. error**					0.4007 0.0442					-0.0178 0.0506	
Intersectional frontier **Std. error**						0.0208 0.0814					-0.3080*** 0.0813
LSOA boundary	X	X	X	X	X	X	✓	✓	✓	✓	✓
LSOA Fixed Effects	X	X	X	X	X	X	X	X	X	X	X
AIC		58900	58922	58887	58846	58933	58489	58482	58491	58491	58477
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1											

	All Crime Volume – CENTROID INTERSECT									
Negative Binomial										
	Plus other borders (within 100m) and LSOA fixed effects					**Plus other borders (within 200m) and LSOA fixed effects**				
Model	**4a**	**4b**	**4c**	**4d**	**4e**	**5a**	**5b**	**5c**	**5d**	**5e**
Intercept	1.5447	1.5580	1.5123	1.5510	1.5179	1.3325	1.3460	1.3050	1.3232	1.3203
Non-UK born frontier **Std. error**	-0.0929 . 0.0511					-0.0776 . 0.0438				
Religious frontier **Std. error**		-0.2459 *** 0.05611					-0.1281 ** 0.0480			
Non-white frontier **Std. error**			-0.1210* 0.0520					-0.03582 0.04305		
Composite frontier **Std. error**				-0.0918 . 0.0473					-0.0325 0.0436	
Intersectional frontier **Std. error**					-0.3143*** 0.0742					-0.2282*** 0.0560
LSOA boundary	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
LSOA Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
AIC	55696	55682	55694	55696	55683	55678	55674	55680	55680	55666
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1										

	All Crime Harm – CENTROID INTERSECT										
Negative Binomial											
	Null	**Social frontier only (within 100m)**					**Plus other borders (within 100m)**				
Model	**1**	**2a**	**2b**	**2c**	**2d**	**2e**	**3a**	**3b**	**3c**	**3d**	**3e**
Intercept		6.1220	6.1539	6.1128	6.0572	6.18402	5.6245	5.6245	5.6245	5.6245	5.6245
Non-UK born frontier **Std. error**		0.3712*** 0.0808					-0.0160 0.0872				
Religious frontier **Std. error**			0.2515** 0.0884					-0.1273 0.0934			
Non-white frontier **Std. error**				0.4301*** 0.0823					0.0531 0.0884		
Composite frontier **Std. error**					0.4605*** 0.0682					0.0239 0.0793	
Intersectional frontier **Std. error**						0.0812 0.1249					-0.264* 0.1270
LSOA boundary	X	X	X	X	X	X	✓	✓	✓	✓	✓
LSOA Fixed Effects	X	X	X	X	X	X	X	X	X	X	X
AIC		105040	105055	105033	105014	105063	104849	104847	104848	104849	104845
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1											

	All Crime Harm – CENTROID INTERSECT									
Negative Binomial										
	Plus other borders (within 100m) and LSOA fixed effects					**Plus other borders (within 200m) and LSOA fixed effects**				
Model	**4a**	**4b**	**4c**	**4d**	**4e**	**5a**	**5b**	**5c**	**5d**	**5e**
Intercept	6.0987	6.1392	6.0728	6.1151	6.08436	5.7692	5.8068	5.7748	5.7782	5.8156
Non-UK born frontier **Std. error**	-0.0143 0.0882					0.0180 0.0754				
Religious frontier **Std. error**		-0.2728** 0.0970					-0.0970 0.0830			
Non-white frontier **Std. error**			-0.2008* 0.0897					-0.0760 0.0741		
Composite frontier **Std. error**				-0.0825 0.0815					-0.0023 0.0748	
Intersectional frontier **Std. error**					-0.3129* 0.1279					-0.2359* 0.0968
LSOA boundary	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
LSOA Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
AIC	103402	103395	103398	103401	103397	103405	103404	103404	103405	103400
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1										

	OUT Crime Volume– CENTROID INTERSECT										
Negative Binomial											
	Null	**Social frontier only (within 100m)**					**Plus other borders (within 100m)**				
Model	**1**	**2a**	**2b**	**2c**	**2d**	**2e**	**3a**	**3b**	**3c**	**3d**	**3e**
Intercept		1.0594	1.0784	1.0381	0.98607	1.1051	0.6035	0.6035	0.6035	0.6035	0.6035
Non-UK born frontier **Std. error**		0.2836*** 0.0532					-0.0824 0.0563				
Religious frontier **Std. error**			0.2206*** 0.0582					-0.1327* 0.0604			
Non-white frontier **Std. error**				0.4037*** 0.0540					0.0547 0.0570		
Composite frontier **Std. error**					0.4328*** 0.0447					0.0303 0.0512	
Intersectional frontier **Std. error**						0.0610 0.0825					-0.2617** 0.0824
LSOA boundary	X	X	X	X	X	X	✓	✓	✓	✓	✓
LSOA Fixed Effects	X	X	X	X	X	X	X	X	X	X	X
AIC		46374	46389	46344	46306	46403	45995	45992	45996	45997	45988
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1											

	OUT Crime Volume – CENTROID INTERSECT									
Negative Binomial										
	Plus other borders (within 100m) and LSOA fixed effects					**Plus other borders (within 200m) and LSOA fixed effects**				
Model	**4a**	**4b**	**4c**	**4d**	**4e**	**5a**	**5b**	**5c**	**5d**	**5e**
Intercept	0.8858	0.8925	0.8613	0.8840	0.8669	0.7018	0.7122	0.6795	0.6875	0.6867
Non-UK born frontier **Std. error**	-0.07506 0.05284					-0.0668 0.0454				
Religious frontier **Std. error**		-0.2276*** 0.0578					-0.0959 . 0.0494			
Non-white frontier **Std. error**			-0.1063* 0.0536					-0.0243 0.0446		
Composite frontier **Std. error**				-0.0475 0.0489					-0.0082 0.0452	
Intersectional frontier **Std. error**					-0.3284*** 0.0767					-0.2007*** 0.0578
LSOA boundary	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
LSOA Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
AIC	43613	43601	43611	43614	43598	43608	43607	43610	43610	43600
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1										

	OUT Crime Harm – CENTROID INTERSECT										
Negative Binomial											
	Null	**Social frontier only (within 100m)**					**Plus other borders (within 100m)**				
Model	**1**	**2a**	**2b**	**2c**	**2d**	**2e**	**3a**	**3b**	**3c**	**3d**	**3e**
Intercept		5.1228	5.1495	5.1091	5.0454	5.18316	4.5829	4.5829	4.5829	4.5829	4.5829
Non-UK born frontier **Std. error**		0.4304*** 0.0884					0.0228 0.0953				
Religious frontier **Std. error**			0.3619*** 0.0967					-0.0333 0.1021			
Non-white frontier **Std. error**				0.5098*** 0.0900					0.1144 0.0966		
Composite frontier **Std. error**					0.5344*** 0.0745					0.0787 0.0867	
Intersectional frontier **Std. error**						0.2895* 0.1367					-0.0719 0.1389
LSOA boundary	X	X	X	X	X	X	✓	✓	✓	✓	✓
LSOA Fixed Effects	X	X	X	X	X	X	X	X	X	X	X
AIC		79508	79519	79498	79478	79529	79324	79324	79323	79323.69	79324
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1											

	OUT Crime Harm – CENTROID INTERSECT									
Negative Binomial										
	Plus other borders (within 100m) and LSOA fixed effects					**Plus other borders (within 200m) and LSOA fixed effects**				
Model	**4a**	**4b**	**4c**	**4d**	**4e**	**5a**	**5b**	**5c**	**5d**	**5e**
Intercept	4.7083	4.7534	4.6750	4.6913	4.6916	4.2248	4.3072	4.2237	4.2070	4.2589
Non-UK born frontier **Std. error**	0.0920 0.0961					0.0980 0.0822				
Religious frontier **Std. error**		-0.1857 . 0.1058					-0.1513 . 0.0904			
Non-white frontier **Std. error**			-0.2302 * 0.0977					-0.1192 0.0807		
Composite frontier **Std. error**				0.0531 0.0888					0.0706 0.0814	
Intersectional frontier **Std. error**					-0.2596 . 0.1394					-0.2629 * 0.1054
LSOA boundary	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
LSOA Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
AIC	77984	77982	77981	77984	77982	77970	77969	77969	77970	77966
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1										

	RES Crime - count - OFFSET - FULL INTERSECT										
Negative Binomial											
	Null	**Social frontier only (within 100m)**					**Plus other borders (within 100m)**				
Model	**1**	**2a**	**2b**	**2c**	**2d**	**2e**	**3a**	**3b**	**3c**	**3d**	**3e**
Intercept	-1.5516	-1.5960	-1.5917	-1.6172	-1.6343	-1.5764	-1.6690	-1.6689	-1.6693	-1.6690	-1.6689
Non-UK born frontier		0.1244***					0.1101***				
Std. error		0.0299					0.0308				
Religious frontier			0.1344***					0.1205***			
Std. error			0.0317					0.0324			
Non-white frontier				0.2002***					0.1902***		
Std. error				0.0303					0.0312		
Composite frontier					0.1600***					0.1503***	
Std. error					0.0275					0.0293	
Intersectional frontier						0.1702***					0.1567***
Std. error						0.0444					0.0447
LSOA boundary	X	X	X	X	X	X	✓	✓	✓	✓	✓
LSOA Fixed Effects	X	X	X	X	X	X	X	X	X	X	X
AIC	32150	32078	32077	32052	32062	32080	32076	32075	32052	32063	32076
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1											

	RES Crime - count - OFFSET - FULL INTERSECT									
Negative Binomial										
	Plus other borders (within 100m) and LSOA fixed effects					**Plus other borders (within 200m) and LSOA fixed effects**				
Model	**4a**	**4b**	**4c**	**4d**	**4e**	**5a**	**5b**	**5c**	**5d**	**5e**
Intercept	-1.8513	-1.8351	-1.8220	-1.8518	-1.8328	-1.7828	-1.7897	-1.7606	-1.7865	-1.7754
Non-UK born frontier	0.0766*					0.0329				
Std. error	0.0302					0.0302				
Religious frontier		0.0401					0.0449			
Std. error		0.0324					0.0316			
Non-white frontier			0.0642*					0.0453		
Std. error			0.0306					0.0292		
Composite frontier				0.0757**					0.0465	
Std. error				0.0290					0.0320	
Intersectional frontier					0.0792.					0.0548
Std. error					0.0417					0.0347
LSOA boundary	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
LSOA Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
AIC	30223	30228	30225	30223	30226	30227	30226	30226	30226	30226
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1										

	RES Crime - count - OFFSET - CENTROID INTERSECT										
Negative Binomial											
	Null	**Social frontier only (within 100m)**					**Plus other borders (within 100m)**				
Model	**1**	**2a**	**2b**	**2c**	**2d**	**2e**	**3a**	**3b**	**3c**	**3d**	**3e**
Intercept		-1.5667	-1.5706	-1.5820	-1.5933	-1.5587	-1.6001	-1.6001	-1.6002	-1.6002	-1.6001
Non-UK born frontier **Std. error**		0.0778 * 0.0350					0.0590 0.0368				
Religious frontier **Std. error**			0.1217 ** 0.0380					0.1062** 0.0395			
Non-white frontier **Std. error**				0.1668 *** 0.0360					0.1568 *** 0.0377		
Composite frontier **Std. error**					0.1319 *** 0.0295					0.1268*** 0.0328	
Intersectional frontier **Std. error**						0.1163 * 0.0585					0.0978 . 0.0592
LSOA boundary	X	X	X	X	X	X	✓	✓	✓	✓	✓
LSOA Fixed Effects	X	X	X	X	X	X	X	X	X	X	X
AIC		32147	32142	32130	32132	32148	32146	32142	32132	32134	32146
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1											

	RES Crime - count - OFFSET - CENTROID INTERSECT									
Negative Binomial										
	Plus other borders (within 100m) and LSOA fixed effects					**Plus other borders (within 200m) and LSOA fixed effects**				
Model	**4a**	**4b**	**4c**	**4d**	**4e**	**5a**	**5b**	**5c**	**5d**	**5e**
Intercept	-1.8373	-1.8291	-1.8271	-1.8372	-1.8300	-1.8329	-1.8231	-1.8162	-1.8301	-1.8218
Non-UK born frontier **Std. error**	0.03155 0.03403					0.0373 0.0296				
Religious frontier **Std. error**		-0.0132 0.0370					0.0186 0.0314			
Non-white frontier **Std. error**			0.0280 0.0352					0.0305 0.0292		
Composite frontier **Std. error**				0.0245 0.0309					0.0296 0.0294	
Intersectional frontier **Std. error**					0.0283 0.0526					0.0330 0.0378
LSOA boundary	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
LSOA Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
AIC	30282	30283	30283	30283	30283	30283	30284	30284	30284	30284
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1										

	RES Crime - Harm - OFFSET FULL INTERSECT										
Negative Binomial											
	Null	**Social frontier only (within 100m)**					**Plus other borders (within 100m)**				
Model	**1**	**2a**	**2b**	**2c**	**2d**	**2e**	**3a**	**3b**	**3c**	**3d**	**3e**
Intercept	3.0196	2.9489	2.9380	2.9335	2.8485	2.98988	2.7721	2.7721	2.7721	2.7721	2.77209
Non-UK born frontier **Std. error**		0.2260*** 0.0575					0.1825** 0.0597				
Religious frontier **Std. error**			0.3048*** 0.0611					0.2670*** 0.0628			
Non-white frontier **Std. error**				0.2863*** 0.0586					0.2474** 0.0609		
Composite frontier **Std. error**					0.3486*** 0.0523					0.3208*** 0.0566	
Intersectional frontier **Std. error**						0.2533** 0.0852					0.2137* 0.0860
LSOA boundary	X	X	X	X	X	X	✓	✓	✓	✓	✓
LSOA Fixed Effects	X	X	X	X	X	X	X	X	X	X	X
AIC	73231	73218	73207	73209	73189	73224	73211	73202	73204	73189	73214
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1											

	RES Crime - Harm - OFFSET FULL INTERSECT									
Negative Binomial										
	Plus other borders (within 100m) and LSOA fixed effects					**Plus other borders (within 200m) and LSOA fixed effects**				
Model	**4a**	**4b**	**4c**	**4d**	**4e**	**5a**	**5b**	**5c**	**5d**	**5e**
Intercept	3.0241	3.1065	3.1214	3.0712	3.1104	3.4397	3.4063	3.5078	3.4467	3.4601
Non-UK born frontier **Std. error**	0.2732*** 0.0666					0.1359* 0.0660				
Religious frontier **Std. error**		0.0680 0.0714					0.1444* 0.0694			
Non-white frontier **Std. error**			0.1422* 0.0670					0.1678** 0.0634		
Composite frontier **Std. error**				0.1928** 0.0634					0.1473* 0.0693	
Intersectional frontier **Std. error**					0.0773 0.0921					0.1478. 0.0768
LSOA boundary	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
LSOA Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
AIC	72506	72519	72516	72512	72519	72509	72508	72506	72508	72509
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1										

	RES Crime - Harm - OFFSET CENTROID INTERSECT										
Negative Binomial											
	Null	**Social frontier only (within 100m)**					**Plus other borders (within 100m)**				
Model	**1**	**2a**	**2b**	**2c**	**2d**	**2e**	**3a**	**3b**	**3c**	**3d**	**3e**
Intercept		3.0102	2.9888	2.9790	2.9506	3.0237	2.9244	2.92442	2.9244	2.9244	2.9244
Non-UK born frontier **Std. error**		0.0979 0.0674					0.0448 0.0713				
Religious frontier **Std. error**			0.2441*** 0.0733					0.2061** 0.0765			
Non-white frontier **Std. error**				0.2675*** 0.0697					0.2338** 0.0733		
Composite frontier **Std. error**					0.2427*** 0.0568					0.2206*** 0.0637	
Intersectional frontier **Std. error**						0.0837 0.1114					0.0347 0.1130
LSOA boundary	X	X	X	X	X	X	✓	✓	✓	✓	✓
LSOA Fixed Effects	X	X	X	X	X	X	X	X	X	X	X
AIC		73452	73443	73439	73436	73454	73449	73442	73439	73437	73449
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1											

	RES Crime - Harm - OFFSET CENTROID INTERSECT									
Negative Binomial										
	Plus other borders (within 100m) and LSOA fixed effects					**Plus other borders (within 200m) and LSOA fixed effects**				
Model	**4a**	**4b**	**4c**	**4d**	**4e**	**5a**	**5b**	**5c**	**5d**	**5e**
Intercept	3.0207	3.0533	3.0487	3.0154	3.0286	3.1339	3.1978	3.2260	3.1828	3.2288
Non-UK born frontier **Std. error**	0.1461 . 0.0750					0.1741** 0.0652				
Religious frontier **Std. error**		-0.1028 0.0813					0.0863 0.0691			
Non-white frontier **Std. error**			0.0871 0.0773					0.0894 0.0638		
Composite frontier **Std. error**				0.0647 0.0680					0.1055 0.0644	
Intersectional frontier **Std. error**					-0.1047 0.1153					0.0036 0.0836
LSOA boundary	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
LSOA Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
AIC	72734	72735	72736	72736	72736	72733	72737	72737	72736	72739
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1										

	Res Crime - count - OFFSET - IDW layer as offset										
Negative Binomial											
	Null	**Social frontier only (within 100m)**					**Plus other borders (within 100m)**				
Model	**1**	**2a**	**2b**	**2c**	**2d**	**2e**	**3a**	**3b**	**3c**	**3d**	**3e**
Intercept	1.4835	1.4368	1.4612	1.4170	1.3885	1.4820	0.9443	0.9443	0.9443	0.9443	0.9443
Non-UK born frontier		0.1530***					0.0519				
Std. error		0.0367					0.0376				
Religious frontier			0.0902*					-0.00636			
Std. error			0.0390					0.0397			
Non-white frontier				0.2261***					0.1310***		
Std. error				0.0373					0.0382		
Composite frontier					0.2010***					0.0726*	
Std. error					0.0335					0.0358	
Intersectional frontier						0.0139					-0.0682
Std. error						0.0545					0.0544
LSOA boundary	X	X	X	X	X	X	✓	✓	✓	✓	✓
LSOA Fixed Effects	X	X	X	X	X	X	X	X	X	X	X
AIC	34934	34918	34931	34899	34900	34936	34789	34791	34779	34787	34789
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1											

	Res Crime - count - OFFSET - IDW layer as offset									
Negative Binomial										
	Plus other borders (within 100m) and LSOA fixed effects					**Plus other borders (within 200m) and LSOA fixed effects**				
Model	**4a**	**4b**	**4c**	**4d**	**4e**	**5a**	**5b**	**5c**	**5d**	**5e**
Intercept	1.0164	1.0271	0.9971	1.0140	1.0162	0.9037	0.9161	0.8624	0.8926	0.8904
Non-UK born frontier	-0.0398					-0.0620 .				
Std. error	0.0372					0.0371				
Religious frontier		-0.1193**					-0.0844*			
Std. error		0.0399					0.0389			
Non-white frontier			-0.0818					-0.0684 .		
Std. error			0.0375					0.0358		
Composite frontier				-0.0317					-0.0462	
Std. error				0.0357					0.0393	
Intersectional frontier					-0.2002***					-0.1269**
Std. error					0.0513					0.0428
LSOA boundary	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
LSOA Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
AIC	32744	32736	32741	32744	32731	32740	32738	32739	32742	32734
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1										

	Res Crime - harm - OFFSET - IDW layer as offset										
Negative Binomial											
	Null	**Social frontier only (within 100m)**					**Plus other borders (within 100m)**				
Model	**1**	**2a**	**2b**	**2c**	**2d**	**2e**	**3a**	**3b**	**3c**	**3d**	**3e**
Intercept	6.0440	5.9677	6.0009	5.9307	5.89600	6.0345	5.5100	5.5100	5.5100	5.5100	5.5100
Non-UK born frontier **Std. error**		0.2427*** 0.0610					0.1465* 0.0632				
Religious frontier **Std. error**			0.1697** 0.0649					0.0764 0.0666			
Non-white frontier **Std. error**				0.3668*** 0.0621					0.2791 0.0641		
Composite frontier **Std. error**					0.3051*** 0.0555					0.1891** 0.0600	
Intersectional frontier **Std. error**						0.0879 0.0904					0.0068 0.0911
LSOA boundary	X	X	X	X	X	X	✓	✓	✓	✓	✓
LSOA Fixed Effects	X	X	X	X	X	X	X	X	X	X	X
AIC	74424	74410	74419	74389	74396	74425	74368	74372	74354	74364	74374
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1											

	Res Crime - harm - OFFSET - IDW layer as offset									
Negative Binomial										
	Plus other borders (within 100m) and LSOA fixed effects					**Plus other borders (within 200m) and LSOA fixed effects**				
Model	**4a**	**4b**	**4c**	**4d**	**4e**	**5a**	**5b**	**5c**	**5d**	**5e**
Intercept	5.9031	5.9942	5.9553	5.9412	5.9928	5.8293	5.8836	5.8714	5.8604	5.8726
Non-UK born frontier **Std. error**	0.1567 * 0.0700					0.0842 0.0694				
Religious frontier **Std. error**		-0.1450 . 0.0749					-0.0182 0.0729			
Non-white frontier **Std. error**			-0.0430 0.0704					-0.0086 0.0666		
Composite frontier **Std. error**				0.0523 0.0666					0.0283 0.0728	
Intersectional frontier **Std. error**					-0.2316 * 0.0967					-0.0028 0.0807
LSOA boundary	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
LSOA Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
AIC	73524	73525	73528	73527	73523	73531	73532	73532	73532	73532
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1										

	Res Crime - count - OFFSET - IDW layer as offset - CENTROID										
Negative Binomial											
	Null	**Social frontier only (within 100m)**					**Plus other borders (within 100m)**				
Model	**1**	**2a**	**2b**	**2c**	**2d**	**2e**	**3a**	**3b**	**3c**	**3d**	**3e**
Intercept		1.4690	1.4869	1.4570	1.4517	1.4897	1.2759	1.2758	1.2759	1.2759	1.2758
Non-UK born frontier		0.0771 .					-0.0331				
Std. error		0.0432					0.0454				
Religious frontier			-0.0238					-0.1352 **			
Std. error			0.0472					0.0489			
Non-white frontier				0.1497 ***					0.0486		
Std. error				0.0446					0.0467		
Composite frontier					0.1037 **					-0.0265	
Std. error					0.0365					0.0406	
Intersectional frontier						-0.1137					-0.2108 **
Std. error						0.0718					0.0725
LSOA boundary	X	X	X	X	X	X	✓	✓	✓	✓	✓
LSOA Fixed Effects	X	X	X	X	X	X	X	X	X	X	X
AIC		34933	34936	34924	34928	34933	34872	34865	34872	34872	34865
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1											

	Res Crime - count - OFFSET - IDW layer as offset - CENTROID									
Negative Binomial										
	Plus other borders (within 100m) and LSOA fixed effects					**Plus other borders (within 200m) and LSOA fixed effects**				
Model	**4a**	**4b**	**4c**	**4d**	**4e**	**5a**	**5b**	**5c**	**5d**	**5e**
Intercept	1.0527	1.0602	1.0210	1.0672	1.0281	0.9704	0.9718	0.9297	0.9744	0.9557
Non-UK born frontier	-0.0745 .					-0.0827 *				
Std. error	0.0422					0.0366				
Religious frontier		-0.2183 ***					-0.1425 ***			
Std. error		0.0456					0.0388			
Non-white frontier			-0.1153 **					-0.0996 **		
Std. error			0.0434					0.0360		
Composite frontier				-0.1154 **					-0.0910 *	
Std. error				0.0383					0.0364	
Intersectional frontier					-0.2554 ***					-0.2047 ***
Std. error					0.0648					0.0467
LSOA boundary	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
LSOA Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
AIC	32742	32723	32738	32736	32731	32737	32729	32734	32736	32724
Signif. codes: '***' 0.001, '**' 0.01, '*' 0.05, '.' 0.1										

	Res Crime - harm - OFFSET - IDW layer as offset - CENTROID										
Negative Binomial											
	Null	**Social frontier only (within 100m)**					**Plus other borders (within 100m)**				
Model	**1**	**2a**	**2b**	**2c**	**2d**	**2e**	**3a**	**3b**	**3c**	**3d**	**3e**
Intercept		6.0171	6.0494	5.9982	5.9987	6.0506	5.8766	5.8766	5.8766	5.8766	5.8766
Non-UK born frontier		0.1400					0.0564				
Std. error		0.0717					0.0759				
Religious frontier			-0.0370					-0.1310			
Std. error			0.0781					0.0815			
Non-white frontier				0.2487 ***					0.1775 *		
Std. error				0.0742					0.0781		
Composite frontier					0.1457 *					0.0509	
Std. error					0.0606					0.0679	
Intersectional frontier						-0.1194					-0.2007 .
Std. error						0.1186					0.1203
LSOA boundary	X	X	X	X	X	X	✓	✓	✓	✓	✓
LSOA Fixed Effects	X	X	X	X	X	X	X	X	X	X	X
AIC		74422	74426	74414	74420	74425	74411	74409	74407	74411	74409
Signif. codes: ‘***’ 0.001, ‘**’ 0.01, ‘*’ 0.05, ‘.’ 0.1											

	Res Crime - harm - OFFSET - IDW layer as offset - CENTROID									
Negative Binomial										
	Plus other borders (within 100m) and LSOA fixed effects					**Plus other borders (within 200m) and LSOA fixed effects**				
Model	**4a**	**4b**	**4c**	**4d**	**4e**	**5a**	**5b**	**5c**	**5d**	**5e**
Intercept	5.9739	6.0374	5.9661	6.0007	5.9698	5.8116	5.8956	5.8668	5.8717	5.9140
Non-UK born frontier	0.0891					0.0974				
Std. error	0.0790					0.0687				
Religious frontier		-0.3480 ***					-0.0957			
Std. error		0.0856					0.0729			
Non-white frontier			-0.1219					-0.0760		
Std. error			0.0815					0.0673		
Composite frontier				-0.0658					-0.0069	
Std. error				0.0717					0.0679	
Intersectional frontier					-0.3501 **					-0.2150 *
Std. error					0.1215					0.0881
LSOA boundary	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
LSOA Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
AIC	73520	73507	73519	73520	73514	73528	73528	73529	73530	73525
Signif. codes: ‘***’ 0.001, ‘**’ 0.01, ‘*’ 0.05, ‘.’ 0.1										