Local Areas and Fear of Criminal Victimisation: Applying Multilevel Models to the British Crime Survey

IAN BRUNTON-SMITH

December 2008

Thesis submitted for the Degree of Doctor of Philosophy

Department of Sociology

University of Surrey

ABSTRACT

Fear of crime is now a central area of criminological debate and a key element of Government crime policy. Yet despite some 40 years of sustained enquiry a number of questions around the fear of crime still remain. One such question is the impact that local neighbourhood context plays in the formation of individual fears, and how these environmental influences relate to the differences in fear that have regularly been observed between different population groups. This thesis draws together the dominant individual and ecological explanations that have been put forward to explain variations in fear of crime into an integrated multilevel framework, providing a robust empirical test of the contention that neighbourhoods matter.

Linking information from the UK census directly to three years of British Crime Survey data, this thesis demonstrates empirical support for the impact of the neighbourhood level of social disorganisation on fear of crime, an effect which is shown to be felt more acutely by vulnerable groups in society. This also identifies an important link between individual ethnicity and the neighbourhood level of ethnic diversity, with Black residents being less fearful in neighbourhoods characterised by higher diversity, whilst White people report higher fear in these neighbourhoods. Using a measure of the local crime rate collected at a considerably smaller spatial scale than previous studies, it also identifies a direct link between the crime profile of the local area and levels of fear. Moreover, this relationship is found to be directly linked to the personal crime histories of residents, with recent victims of crime more aware of the local crime problem than non-victims.

Finally, this thesis introduces the competing influence of interviewers to provide us with further information about the contextual influences on fear. Interviewer variability has no direct effect on the neighbourhood effects previously identified, but shows us that the bulk of the remaining contextual influence is better attributed to differences between interviewers. Further to this, the study shows that older and more experienced interviewers generally elicit lower levels of fear from respondents. There is also an important link between individual and interviewer ethnicity, with Asian and Black respondents interviewed by someone from the same ethnicity reporting significantly lower levels of fear, reversing the traditional image of ethnic minorities as more fearful in society.

ACKNOWLEDGEMENTS

A special thanks to my supervisor Professor Patrick Sturgis for all your comments on earlier drafts of this thesis, your thoughts have been both challenging and informative. Your encouragement has been invaluable and I could not have got this far without your advice and support. Beyond the thesis you have also been instrumental in helping me to advance my academic career, and I look forward to collaborating with you in the future.

I would also like to thank Professor Roger Tarling for all your time and contributions. You have been a great source of advice and have given me a great deal of encouragement to pursue a lectureship in Criminology. Thanks also for introducing me to the Crime Surveys team at the Home Office, which gave me essential insights into analysis of the British Crime Survey.

I also owe a huge debt of gratitude to all of the staff in the Crime Surveys division of the Home Office for all of your time and support over the last three years. You were always willing to help with any analysis issues that I came across, and made me feel like part of the team. Special thanks to Alison Walker and John Flatley for granting me access to the geodemographic and interviewer identifiers, without which this thesis could not have been completed. Thanks also to Krista Janssen and Jon Allen for looking after me during my frequent visits.

Thanks to my Mum, Linda, for teaching me maths and for supporting me through the early days of this thesis. I would also like to thank you for encouraging me to follow a career in Academia, all that hard work has certainly been worth it.

Finally I would like to say a big thank you to Cheryl, who has been so understanding over the last three years and given me all the time I needed to complete my research. You have made it so much easier for me to finish my thesis on time, I could not have done it without you.

TABLE OF CONTENTS

CHAPTER 3: EXPLAINING ECOLOGICAL VARIATIONS IN FEAR OF CRIME

CHAPTER 4: INTRODUCING A LOCAL AREA FOCUS TO NATIONAL ASSESSMENTS OF FEAR OF CRIME

LIST OF TABLES

LIST OF FIGURES

LIST OF ACRONYMS

BCS	British Crime Survey
BME	Black and Minority Ethnic
BVPI	Best Value Performance Indicator
CAPI	Computer Assisted Personal Interview
CATI	Computer Assisted Telephone Interview
CDRP	Crime and Disorder Reduction Partnerships
DIC	Deviance Information Criterion
ICC	Intra Class Correlation
IGLS	Iterative Generalised Least Squares
IV	Instrumental Variable
LSOA	Lower layer Super Output Area
MAUP	Modifiable Areal Unit Problem
MCMC	Markov Chain Monte Carlo
MSOA	Middle layer Super Output Area
NCVS	National Crime and Victimisation Survey
ONS	Office for National Statistics
PCA	Principal Components Analysis
PCLEAJ	Presidents Commission on Law Enforcement and the Administration of Justice
PFA	Police Force Area
PSU	Primary Sampling Unit
SEM	Structural Equation Modelling
SOA	Super Output Area
USOA	Upper layer Super Output Area
VIF	Variance Inflation Factor
VPC	Variance Partition Coefficient

FOREWORD

Over the last 40 years, the fear of crime has come to be viewed as a significant social problem, receiving considerable attention from academics, politicians, and the public alike. So much so, that it has now become a central element of the political agenda, viewed as an important barometer of public opinion, and functioning as an official measure of police performance (Farrall & Gadd, 2004a). Fear of crime also plays a central role within political discourse about crime, with pledges to reduce fears regularly appearing within government rhetoric. Gordon Brown recently highlighted public fears as a central focus for the government, stating in his monthly press conference that "too many people, young and old, do not feel safe in the streets, and sometimes even in their homes" (Brown, 2008). This was accompanied by the announcement of a new series of measures intended to tackle the problem of knife crime; the latest source of public anxieties about crime. Brown's words closely resembled those of Tony Blair in his address at the Brighton annual conference in 1997, shortly after Labour came into power, where he highlighted "the threat to civil liberties of women afraid to go out, and pensioners afraid to stay at home, because of crime and the fear of crime" (Blair, 1997). This continued emphasis on public anxieties clearly demonstrates the sustained focus on tackling fear of crime from the Labour government.

In tandem with this strong political focus on fear of crime, academic attention has also increasingly been levelled at the problem of fear. Initially centring on the apparent irrationality of people's fears when considered in relation to their objective risks of crime, with the most fearful groups also identified as the least at risk, research into fear of crime has rapidly become a dominant source of criminological debate. This has led to the production of more than 3,500 articles examining various aspects of the fear of crime, from the identification of fearful groups and discussions of the social processes promoting fear, through to assessments of the implications of fear for society (Vanderveen, 2006).

Early treatments of the fear of crime identified various risk factors associated with higher than average levels of fear, and described these in relation to objective risks. This was primarily focused on the seemingly contradictory finding that fear was highest amongst women and the elderly, despite both groups facing comparatively low risks of victimisation. Although featuring heavily in early research, this simplistic dichotomy between objective risks and fear of crime has since been questioned from a range of perspectives. Some researchers have questioned how we define fear

(Farrall et al., 1997; Ferraro & LaGrange, 1987; Jackson, 2005), or highlighted deficiencies in official risk measures (Stanko, 1995), whilst others have presented more detailed models that incorporate other important individual and contextual differences (Fitzgerald & Hale, 1996; Hough, 1995; Skogan, 1990). Researchers have also questioned the aggregate focus of many of these early assessments, presenting locally specific pictures of the extent of fear of crime that more closely match the risks of crime that people experience on a day to day basis (Jones et al., 1986; Sparks et al., 1977; Young, 1988). Finally some researchers have directly questioned the notion that fear of crime is irrational, pointing to the positive impacts of fear in the form of risk avoidance strategies, encouraging people to actively lower their own risks of victimisation (Fattah & Sacco, 1989).

From these beginnings, research into fear of crime has rapidly expanded to incorporate a range of potential causes and consequences, looking both at individual differences and the wider social context in which fear is experienced on a day to day basis. As a result of this increasingly broad approach, notions of fear of crime have evolved from the early appraisals that viewed fear as inextricably linked to the problem of crime, to a picture of fear of crime as a problem in its own right that represents more than simply a response to changing levels of crime. These have then fed back into political discourse about fear of crime, prompting the introduction of a number of initiatives to reduce the problem of fear and raise public confidence in the criminal justice system.

Consequences of fear

High levels of fear of crime have been associated with a range of negative consequences for individuals and society, although the empirical evidence remains equivocal. Researchers have pointed to potential psychological costs, linking fear to higher levels of depression and feelings of anxiety, along with general rises in mental distress (Adams & Serpe, 2000). Fear has also been linked to feelings of social alienation, with higher levels of interpersonal distrust leading people to withdraw from community life (Garofalo, 1981). This in turn may reduce the forms of social support available to individuals, further exacerbating fear. It can also lead to various forms of target hardening, as people take protective measures to limit their risks of crime (Hale, 1996).

Researchers have also examined the links between high levels of fear and increased health problems including high blood pressure and social stress (Ellaway & McIntyre, 1998; Stafford et al., 2007), along with a tendency for people to perceive themselves to be in poorer health (Chandola, 2001; Jones & Duncan, 1995). In more general terms, levels of fear are also correlated with measures of quality of life, with higher fear of crime linked with lower reported life satisfaction (Illner, 1998; Jackson, 2006). This reduced wellbeing further demonstrates that fear of crime may be a real problem for people, affecting their general outlook on life and impacting on a range of social outcomes.

Turning to the broader social implications of fear of crime, a number of important consequences have been suggested throughout the literature. Increased interpersonal distrust and the constraints that this places on people's daily lives (including target hardening and a withdrawal from community life) have been associated with the atomization of local communities, reducing the informal controls that are available to communities to prevent crime (Skogan, 1986). This fracturing of local communities may then lead to reduced social cohesion and a breakdown in the sense of local attachment, which can result in some public places becoming 'no go areas', along with a clear segregation of social space (Box et al., 1988).

Fear of crime has also been linked to increasingly punitive public sentiments, reducing the appeal of liberal penal policies (Hough et al., 1988). This has important implications for policing and sentencing, with more severe sentencing practices supported as the public calls for increased policing of deviant behaviour. This can also undermine the legitimacy of the Criminal Justice System, with people viewing the courts as too soft on crime (Johnston, 2001). Additionally, Hale (1996) suggests that fear of crime can result in the displacement of crime onto more disadvantaged communities, as better off communities are able to take more protective measures to alleviate fear and move away from fear inducing neighbourhoods. This then leads to an increasing divide between advantaged and disadvantaged communities in society, with better off residents selecting themselves into safer neighbourhoods.

In addition to these direct consequences of fear of crime, the role of fear as a police performance indicator means it is essential that the individual and social correlates of fear are clearly understood. Fear has featured as a Best Value Performance Indicator (BVPI) for a number of years, and has now been incorporated within the new National Indicator Set used to assess the success of Crime and Disorder Reduction Partnership (CDRP) initiatives. It has also formed a central element of crime and justice policy since the Crime and Disorder Act of 1998. It is thus clear that fear of crime is an extremely important area of criminological study, with identified variations in fear having serious implications for the direction of the crime reduction strategies that are implemented by the government.

The gap in existing knowledge

Despite the importance of fear of crime as an area of criminological study, and a mass of available data outlining its consequences and correlates, there is still a clear gap in existing knowledge. Simplifying the matter somewhat, two largely divergent bodies of research can be identified over the last 40 years of debate. One has focused primarily on individual differences in fear, identifying a range of risk factors that have been grouped under the headings of vulnerability, victimisation experience, perceived risk, and media effects. The other has presented a more sociologically driven perspective on variations in fear of crime, using ecological differences in fear as the basis for more general explanations that point to the influence of community dynamics and neighbourhood level social processes as the instrumental cause of fear of crime. This has drawn from social disorganisation theory (originally explicated in the work of Shaw & McKay (1942)) to provide more detailed community level explanations for differences in fear, as well as highlighting the importance of signs of low level disorder and the impact of the local crime rate.

Although presented as two distinct approaches to understanding fear of crime, there have been attempts, at least theoretically, to link wider social processes back to individual differences in fear of crime. Amongst other things, these suggest that vulnerable groups are more likely to make judgements about their risk of crime in relation to environmental cues drawn from the local neighbourhood, and similarly are more likely to be influenced by the breakdown of informal social controls that are associated with disorganised communities (Killias, 1990). However, there has been a general lack of empirical evidence in support of an integrated explanation for variations in fear, with data limitations and a lack of methodological sophistication leading researchers to focus either on individual or ecological variations, at the expense of the other. This is not to say that analyses focusing on individual differences in fear have failed to include contextual data, but when it has been included it is typically treated as individual level data, leading to erroneous conclusions about the magnitude of estimated area effects. Similarly, analyses focusing on ecological differences are rarely able to supplement this with information about individual variability, and thus are missing important individual level processes that contribute to fear of crime.

As a result, a more accurate treatment of fear of crime that assesses individual differences within the social context in which they are experienced is required. Research has gone some way to achieving this goal, with locally focused surveys assessing fear of crime within its social context. However, despite telling us much about local variations in fear of crime, the scope of these studies has necessarily been limited, with analyses based on a few case study areas (see for example Kinsey

(1984); Hanmer & Saunders (1984); and Jones, et al., (1986)). To this end, this thesis adopts multilevel modelling techniques to provide a robust analysis of the general contention that local social context matters to fear of crime. It then goes on to provide a detailed assessment of the link between individual and contextual influences on fear of crime within the national scope of the British Crime Survey (BCS). Using a multilevel modelling approach enables individual and contextual data to be analysed simultaneously at the correct level of influence, allowing micro and macro models to be assessed within a single integrated framework (Goldstein, 2003).

The current thesis

This thesis presents a robust empirical test of the contribution of neighbourhood differences to variations in fear of crime, whilst simultaneously conditioning on individual differences based on notions of vulnerability, victimisation experience, and the impact of the media. Additionally, the impact of wider differences between CDRP is also incorporated to provide a more policy oriented assessment of differences in fear. Using contextual data taken from the UK census and the Office for National Statistics (ONS), it then goes on to test the link between social disorganisation and fear of crime. In addition to the impact of social disorganisation, the effects of low level disorder and recorded crime are examined, providing the first clear evidence of the relative contribution of these contextual explanations when incorporated alongside individual differences in fear. Having assessed individual and contextual theories within the same integrated modelling framework, the thesis goes on to ask how the micro and macro models are linked, providing empirical evidence of the extent that more vulnerable groups are differentially affected by the local social context in which they live their daily lives.

By attaching geo-coded data to the BCS, this thesis represents the first multilevel assessment of the individual and contextual influences on fear of crime using UK data. Capitalising on the clustered BCS sample structure, geographic data about the local neighbourhood of each respondent is incorporated alongside individual demographic information to place individuals directly within their local context. This geographic data has been collected about a significantly larger number of local areas than previous multilevel assessments of fear, enabling a more detailed analysis of the contextual influences on fear to be conducted. Additionally, a wide range of contextual information has been gathered about each local neighbourhood, allowing a more nuanced assessment of the link between contextual and individual differences in fear of crime. As such, this thesis views the national picture of fear of crime provided by the BCS through the lens of local neighbourhood studies.

This thesis is restricted in its empirical scope to the UK context, with all data taken from the BCS and the UK census. The use of a nationally representative sample of England and Wales means that it has been possible to examine the contextual influences on fear of crime from a considerably broader perspective than the majority of multilevel studies of fear, which have typically been restricted to data from a single city. Additionally, all previous multilevel assessments of fear of crime have been based on US data, making this a particularly important study as it enables an empirical assessment of the relevance of these contextual theories to the UK context.

Throughout this thesis I refer to the fear of crime, which is treated as an emotional response to the threat, or potential threat of crime. One of the early limitations with fear of crime research was a lack of clarity over what was being studied, and how to define fear of crime (Jackson et al., 2006). Reflecting the use of the BCS, where a sequence of questions asking about levels of worry about various crime types are used as measures of fear, in this thesis fear of crime is used interchangeably with worry about crime to refer to people's general feelings of anxiety about crime (for a more detailed discussion of this issue, see sections 1.3 And 4.6).

Outline

In chapter 1 I outline the origins of the fear of crime debate, describing the increasing attention it has received over the last 40 years both politically and academically. This begins in the US where the close links to the advent of victimisation surveys are highlighted, following the shift in the focus of criminology away from offenders and towards the victims of crime. Moving to the UK context, the increasing focus given to fear of crime throughout the 80s and 90s is explained in relation to the increasing politicisation of crime, and the shift in government rhetoric towards fear of crime being treated as a problem in its own right, as opposed to simply a response to changing levels of crime.

The lack of conceptual clarity in defining and measuring fear of crime is then discussed, alongside a critical assessment of the impact that this uncertainty has had on the findings from research. This begins with an examination of the 'global' measures of fear that dominated much early research, before turning attention to some of the alternative measurement strategies that have been put forward in response to criticisms levelled at these early measures. Chapter 1 finishes with a detailed discussion of some of the principle findings from existing research about who are the most fearful of crime. Drawing on the range of empirical studies that have been conducted over the last 40 years, various risk factors are identified that have been associated with higher levels of fear. These cover individual differences between different population groups including the higher levels of fear frequently reported amongst women and previous victims of crime, as well as broader differences in fear related to ecological characteristics of the local area such as the level of crime and the distinction between rural and urban areas.

Chapter 2 then extends this discussion by providing a more detailed examination of the different individual level perspectives that have been used to explain these identified variations in levels of fear. This explores notions of differential fear based on vulnerability, victimisation experience, and the impact of the media. These are described as largely atheoretical explanations for variations in fear, primarily accounting for observed differences in fear rather than presenting a detailed model that situates people within their social context. Additionally, despite featuring most frequently in assessments of fear of crime, the evidence in support of these individual level theories is somewhat inconsistent, prompting a shift in focus towards the importance of ecological variations.

Chapter 3 then goes on to introduce more theoretically driven explanations for fear of crime that have been motivated by the range of observed variations in fear across area types. This ecological focus is framed around the importance of social disorganisation, where variations in fear are explained in relation to the levels of economic disadvantage, ethnic heterogeneity, and residential mobility in the local neighbourhood. Several extensions to social disorganisation are also outlined, highlighting the importance of the prevalence of signs of disorder within the neighbourhood, and the suggested influence of subcultural diversity. These ecological theories are all premised on a belief that the fear of crime is partially driven by community level forces that operate independently of the people that live within them. These are presented as complementary explanations that have broadened the scope of fear of crime beyond individual differences, to incorporate details about the social context in which they are experienced.

However, the chapter concludes by arguing that despite developing a set of theoretical explanations that have helped to explain broader differences in fear between local areas, there is still a lack of empirical evidence that successfully links these ecological explanations back to individual differences in fear. Instead, research either focuses on individual differences, with area variations erroneously incorporated within the individual model, or takes a more contextual approach that fails to incorporate important individual variations in fear. As a result, there is a need for a detailed empirical investigation of fear that bridges the gap between explanations that account for individual differences, and those that have provided us with more contextually focused explanations.

Chapters 4 to 6 then provide a detailed empirical assessment of fear of crime that incorporates individual and local neighbourhood variations within an integrated multilevel modelling framework. This is based on data from three years of the BCS, a nationally representative victimisation survey conducted annually in England and Wales since 1981 (every two years prior to 1997), which is supplemented with neighbourhood level data taken from the 2001 UK census and the ONS. This is the first multilevel assessment of fear of crime within the UK context and builds on a series of analyses conducted within the United States (Robinson et al., 2003; Snell, 2001; Wilcox-Rountree et al., 2003; Wilcox-Rountree & Land, 1996a; Wilcox-Rountree & Land, 2000; Wyant, 2008). It is also the most extensive and detailed multilevel study of fear conducted to date, utilising a wide range of data on a significantly larger number of local neighbourhoods than previous assessments.

Chapter 4 begins with a review of existing approaches to the incorporation of contextual data to explain differences in fear of crime, highlighting the problems of data aggregation and disaggregation that limit the utility of existing studies. This is followed by a detailed account of the multilevel alternative, which offers a fully integrated modelling framework for incorporating individual and contextual explanations within a single analysis. This includes a critical assessment of the few existing studies that have adopted a multilevel approach to fear of crime data, where the absence of a clear UK example is highlighted.

Chapter 4 continues with a discussion of the importance of carefully defining neighbourhoods, comparing existing boundaries with the newly introduced census boundary data that is incorporated in this analysis. These neighbourhood boundaries are more spatially stable than many of the boundaries commonly used in contextual analyses, with data available at a smaller spatial scale to ensure that local variations in fear of crime are accurately captured. This is followed by an introduction to the individual data from the BCS, including a discussion of how fear of crime is operationalised. Finally, chapter 4 provides an initial assessment of the extent that variations in fear of crime can be attributed to neighbourhood context; both in isolation, and when examined alongside individual differences in fear. This forms the essential first step in a fully integrated assessment of the impact of neighbourhood contextual effects on individual fear of crime.

Chapter 5 extends this initial exploration of the influence of local context on fear of crime with the construction of a full ecological model to characterise differences between local areas. This enables a test of the central tenets of social disorganisation as well as the effect of the presence of signs of disorder and the recorded level of crime in the neighbourhood, whilst simultaneously controlling for individual differences in fear. The construction of the ecological model is based on a factorial ecology approach, used to identify distinct dimensions of neighbourhood differences from a set of neighbourhood characteristics taken from the UK census. These dimensions of neighbourhood difference describe each areas socio-economic structure, the degree of population mobility, and the level of urbanisation, along with the age and housing profile. In addition to these dimensions of neighbourhood difference, measures are included that capture the degree of ethnic diversity, the presence of objective disorder, and the local crime rate.

In chapter 6, the ecological model is fully integrated within the individual level fear of crime model, providing the first national level assessment of how local context affects individual's fear of crime. This begins with a test of the extent that individual level differences are consistent across local neighbourhoods, examining whether contextual differences influence the levels of fear of specific residents. This is an important advance over many existing studies, placing individuals directly within their local context to assess how individual differences vary across neighbourhoods. Chapter 6 then goes on to link these individual variations across neighbourhoods back to the ecological models that were first introduced in chapter 5, helping to get a handle on why some of the observed individual differences have an important neighbourhood component. This provides a formal empirical test, at a national scale, of the integrated explanations for differences in fear that have been offered by contextual theories.

In an attempt to offer an alternative explanation for the remaining contextual influences on fear of crime, chapter 7 extends the focus of this thesis to incorporate the impact of interviewer variability. This presents an answer to a longstanding methodological question that has featured heavily in survey methodology, outlining how contextual variation is split between area and interviewer effects. The impact of interviewer variance on survey estimates has traditionally been difficult to separate from the influence of sampling effects in face to face surveys, with interviewers typically assigned to a single area meaning that the two sources of variance are usually confounded. This has meant that researchers have focused on only one of these two sources of variance, ignoring the potential influence of the other, making a clear assessment of the relative importance of interviewers and areas difficult to ascertain. To help tease apart these influences, the ecological fear of crime models first outlined in chapter 5 are extended to include the competing influence of interviewer variations. This is made possible because of the broad scope of the BCS sample design, with interviewers regularly covering more than one local area, and areas often covered by more than one interviewer. As a result, using a cross classified multilevel modelling approach the influences of the two sources of variance are separated, providing a clear account of the relative importance of neighbourhood and interviewer differences to variations in fear of crime. The analysis is then further extended with the inclusion of details about each interviewer, enabling an assessment of the extent that interviewer variations in fear of crime can be successfully predicted with interviewer characteristics.

Finally, chapter 8 draws together the principle findings from this analysis of the individual and contextual determinants of fear of crime, examining how successful the models have been at integrating these contextual explanations for variations in fear. The ability to analyse individual fear of crime within its social context, whilst retaining the national focus of the BCS is a clear advantage of this type of approach, therefore the chapter also considers the policy implications of this broader assessment of the fear of crime. This includes a discussion of the implications of an integrated fear of crime model for future fear of crime analyses, as well as the implications of this measurement strategy for subsequent BCS reports.

The chapter then goes on to consider what impact the shift in focus towards interviewer effects advocated in chapter 7 might have for the contextual theories that have been put forward to account for differences in fear. These models demonstrated that fear of crime was more influenced by interviewers, and that area variations made a relatively small contribution to variations in levels of fear. This has clear implications for the way that BCS data is collected in the future, highlighting a cost of the BCS re-designs in 2001 that has not fully been discussed in previous examinations of the changes to the BCS methodology.

The thesis concludes with an outline of some of the key limitations with the current analysis, along with some suggestions for future work. This includes a discussion of the lack of available administrative data about CDRP, and a consideration of the potential benefit that might be gained from collecting data at the household level to incorporate another potentially influential source of contextual variation on fear. It also suggests a need to significantly extend the scope of the assessment of interviewer effects to incorporate a range of different question types, and additional interviewer data such as whether the interview was a reissue.

CHAPTER 1: THE ORIGINS OF FEAR OF CRIME AND EARLY RESEARCH FINDINGS

1.1 Introduction

Fear of crime has come to be viewed as a significant social problem that has generated considerable attention from academics, politicians and the public alike, despite having a relatively short history. Too much fear has been linked with a range of negative consequences, including health problems (Ellaway & McIntyre, 1998) and a reduction in people's quality of life (Jackson, 2006). High levels of fear have also been linked with more punitive attitudes from the general public, which has potentially serious implications for policing and sentencing policies (Hough et al., 1988). Additionally, it has been suggested that high levels of fear can lead to the atomization of local communities, resulting in the breakdown of important social structures within local neighbourhoods (Skogan, 1986).

In this chapter I begin by outlining the historical context of the fear of crime debate, describing the increasing attention that fear of crime has received and situating it within its social and political context. This includes a discussion of the differing ways that fear has been defined and measured since it was first introduced to survey research, along with an assessment of the impact that this has had on subsequent research. I then outline some of the principle findings about who are the most fearful groups in society, drawing on the wealth of existing research that has examined variations in fear.

In chapter 2, I go on to critically assess the theories that were first introduced to explain these observed differences in levels of fear of crime amongst different population groups. I pay particular attention to notions of vulnerability and victimisation experience, which have been the dominant explanations for individual differences in fear throughout existing literature. As a result of the close link between fear of crime and government survey research, I will argue that these early explanations for differing levels of fear have been largely atheoretical. As such, they have primarily been designed to describe the range of observed differences in fear, rather than to provide a detailed model of fear of crime that situates people within their local social context.

In chapter 3 I will then introduce a series of more theoretically driven explanations for differences in fear of crime that have been motivated by the range of observed variations in fear across different area types. These explanations have primarily drawn on social disorganisation theory and notions of neighbourhood disorder, suggesting that fear of crime is partially driven by community level forces that operate independently of the people that live in them. However, whilst these theories have provided considerably more detail about the origins of fear of crime, they have largely failed to successfully situate people within their local context. Consequently, I suggest that there is still a need for an empirical examination of fear of crime that bridges the gap between explanations focusing on individual differences in fear, and those that provide more contextually driven explanations.

1.2 The origins of fear of crime

The empirical study of fear of crime has a fairly short history, which Lee (2007) traces back to three American studies commissioned in 1965 as part of the 'Presidents Commission on Law Enforcement and the Administration of Justice' (PCLEAJ) (Biderman et al., 1967; Ennis, 1967; Reiss Jr, 1967). These studies were themselves preceded by a number of public opinion polls conducted throughout the early 1960s asking people about the problems that most concerned them in society, with crime regularly cited as an important issue (McIntyre, 1967). Whilst not directly labelled at this time as fear of crime, public anxieties about the extent of crime have a much longer history, with accounts of public concerns identified as far back as 1780 (Emsley, 1987). This awareness of the problem of crime has been tied directly to the development of Criminology as an academic discipline, along with the growing reliance on statistical evidence to facilitate the enumeration and mapping of crime throughout the 19th Century (for more detailed accounts of these precursors to the modern interest in fear of crime, see Lee (2007); and Beirne (1993)).

Despite this more extensive historical context, it is not until America in the 1960s that fear of crime as a concept fully began to emerge, resulting from what Lee (2007) describes as a coming together of a range of cultural, political, social and academic elements. America in the 1960s was experiencing rising levels of recorded crime, accompanied by a new government focus on Law and Order that had made crime, and public reactions to crime, a central political issue (Jackson et al., 2006). This was also a time characterised by broader public concerns, exemplified by public reactions to a series of riots in inner city ghettos that signalled a heightened public awareness about the extent of disorder (Stanko, 2000). The US had also been witnessing a steady increase in the collection of statistical data about the population, with an expanding number of public opinion surveys used as barometers of public attitudes, and crime figures featuring heavily in the media (McIntyre, 1967). This was a time, then, when crime, and public reactions to it, was becoming an increasingly important part of the public and political agenda.

Also influential to the emergence of fear of crime research was the rising profile of victimology, reflecting a more general shift in the focus of Criminology away from offenders and towards the victims of crime (Pointing & Maguire, 1988). This increased attention levelled at the victims of crime has been described as a direct response to the growing criticisms aimed at recorded crime figures for providing inaccurate estimates of the extent of crime. Critics argued that official crime figures were presenting an inadequate picture of the extent of crime, pointing to potential disparities between the number of crimes experienced by the public, and the number that were actually reported (Zedner, 1996). Limitations with police recording practices were also highlighted, with critics of official figures arguing that many of the crimes reported to the police were never actually officially recorded, and hence failed to be included in official figures. This growing concern that official figures were under-representing the true extent of crime came to be known as the 'dark figure' of crime, prompting the development of alternative methods to count crime (Maguire, 2007; Skogan, 1978).

As a response to the deficiencies identified in official recorded crime figures, three studies were conducted as part of the PCLEAJ to provide a clearer picture of the levels of crime. The three organisations that were selected to conduct these studies represented public opinion researchers (The National Opinion Research Center), the Government (The Bureau of Social Science Research), and Academia (The University of Michigan), chosen to present an unbiased account of the crime problem (Lee, 2001). Drawing on victimology, and the recent growth in public opinion research, these three studies approached the estimation of the extent of crime from the perspective of the victims of these crimes, developing surveys that included a series of questions asking people about their experiences. By focusing on the victims of crime, the rationale was that these surveys would provide estimates that were not influenced by public reporting habits, or the recording procedures of the police, giving the first clear evidence about the extent of the dark figure of crime (Mayhew & Hough, 1988). As such they represented the birth of the victimisation survey in the US, providing a template for the National Crime Survey, later renamed as the National Crime and Victimisation Survey (NCVS) and prompting the widespread adoption of victimisation surveys throughout the world (Lee, 2007).

Importantly, reflecting the role of public opinion research in their development, these surveys also included a range of more attitudinal questions alongside those dealing with behavioural experiences of crime. Amongst these were the first examples of questions intended to capture people's levels of anxiety about crime, providing initial evidence about the extent that people were fearful in their daily lives (Jackson et al., 2006). The Commission reported high levels of public anxiety about crime, which they found was not closely linked to the risks of victimisation. Therefore, those identified as amongst the least at risk of crime reported the highest levels of fear, whilst those at most risk reported relatively lower fear. This included higher levels of fear amongst women, and greater fear about violent crime despite this being a relatively rare occurrence (Jackson et al., 2006). These findings were the first clear evidence that people's anxieties about crime may be distinct from their risks of crime, with levels of fear that did not appear to match the reality of experiences. This finding would quickly become synonymous with fear of crime research, fuelling 40 years of academic debate to try and explain this apparently paradoxical relationship.

Jackson et al., (2006) provide us with an interesting appraisal of these early studies, demonstrating a clear focus within them on the social context in which the data were collected, and in particular a series of race riots that were occurring in urban ghettos. Rather than representing fear as a problem in its own right, they argue that in these early studies it was clearly positioned as a response to the social problems of the day, reflecting more general concerns about moral and social order and the more racialised concerns of White America. They go on to suggest that this conceptualisation of fear as an expression of wider concerns was quickly lost. Instead the headline findings were drawn on by the media and within the political sphere to justify the increasing attention on issues of law and order. As a result, the focus of the emerging discourse was shifted to the extent of people's fears about crime, and why these fears didn't match people's risks of victimisation (Lee, 2007).

As attention focused on the seeming irrationality of reported levels of fear, a large body of research began to emerge that attempted to examine who were the most fearful of crime and why (Hale, 1996). This resulted in what Lee (2007: 76) terms a 'fear of crime feedback loop', whereby studies were increasingly conducted that reported the extent of public fears. These were then used by the government to justify increasingly strong law and order policies, legitimising fear of crime as a problem in its own right. This in turn increased the public awareness of the extent of the problem of crime, and consequently their anxieties increased, which then fed back into the fear of crime surveys that were being conducted. The problem of the fear of crime, then, rapidly became a dominant feature of American discourse about crime.

Despite the rapid increase in attention given to the fear of crime in America, it was not until the 1970s that the concept fully migrated to the UK, preceded by a few earlier media reports situating fear of crime as a problem experienced by the American public (Jackson et al., 2006). By the early 1970s the UK had also begun to adopt a more victim centred approach to Criminology, and was increasingly prioritising crime, and public concerns about crime, in the political agenda (Pointing & Maguire, 1988). More money was therefore being spent on 'law and order' initiatives and the Criminal Justice System, with tough crime policies used by the Conservative government as a successful way to win votes (Lee, 1999). The increasing importance of crime in the political agenda was accompanied by the introduction of victimisation surveys in the UK to better measure levels of crime (Mayhew & Hough, 1988). This was intended to provide a more accurate picture of the extent of crime following the model established in America.

The first example of this was the commissioning of a small scale survey conducted by Sparks et al., (1977) entitled 'surveying victims', which also provided initial evidence of the extent of people's anxieties about crime. The findings from this study painted a picture similar to the American account of fear, with levels of fear that appeared largely unrelated to people's objective risk. This 'pilot' study then fed into the development of the BCS, a national victimisation survey that was to be conducted every two years[1] to provide a steady flow of data about the extent of crime and people's anxieties, complementing recorded crime figures (Mayhew & Hough, 1988). It was the BCS that would become the principle source of information on levels of fear of crime in England and Wales, with a number of reports produced throughout the 1980s that would inform subsequent debate (Maxfield, 1984; 1987).

Drawing on data from in-depth interviews with leading academics and Home Office researchers, Jackson et al., (2006) suggest that along with the role of the BCS in providing an estimate of the dark figure of crime, one of its primary purposes was to downplay the problem of crime. This was done by demonstrating that people's risks of becoming a victim were very low, and that most victimisation was not serious in nature. This focus on downplaying the risks of crime was also evident in the early government responses to data on people's levels of fear, which were aimed at re-educating the public about their low risks. These presented an optimistic picture of people's risks of crime, using national aggregates to produce estimates that highlighted how low overall risks were. For example,

[1] This changed to annually in 1997

the average person would be a victim of burglary once every 40 years and a robbery every 5 centuries (Hough & Mayhew, 1983).

By the early 1990s fear of crime had become an increasingly important element of government published crime statistics. This was accompanied by a clear shift in emphasis away from the re-education of the public about their risks of crime, to an acceptance of fear of crime as a problem in its own right (Jackson et al., 2006). The change in focus was partly a response to criticisms of early reports for downplaying risks by relying on an overly simplistic aggregate picture that failed to incorporate people's lived experiences (Young, 1988). An emphasis on reducing levels of fear was also being increasingly used as a political tool to win votes, with a number of policies introduced that were aimed directly at minimising fears rather than dealing with fear indirectly through a reduction in crime. This included the establishment of community led 'reassurance policing' strategies, whose remit went beyond simply the reduction of crime to include a focus on reducing fears by raising public confidence in the police and making policing more visible within the community (Millie & Herrington, 2005). It also led to fear of crime being used as a Home Office BVPI to monitor police performance, acting as a barometer of public confidence in the police (Farrall & Gadd, 2004a). Fear of crime, then, had become a central element of government crime policy, making it increasingly important to be able to successfully identify what it is about individuals and their local environments that make them more or less fearful.

In tandem with this increasing political focus on the fear of crime, there has been a rapidly increasing level of academic attention given to understanding fear since its introduction, with 200 articles identified in an early review by Hale, compared with more than 3,500 articles on the subject just 10 years later (Hale, 1996; Vanderveen, 2006). Like official reports on fear, many early studies were primarily focused on the 'irrationality' of individual fear. These generally used relationships with demographic characteristics to generate theories based on the importance of feelings of vulnerability and the impact of experiences of victimisation. Later critics began to question the early focus on the irrational nature of fear, arguing that it was in fact a rational response to real levels of risk that were inadequately captured by official statistics measured at a national scale (Hollway & Jefferson, 1997).

Attention has also been given to the individual and social consequences of fear, linking feelings of fear to changes of behaviour such as a withdrawal from community life, the avoidance of specific local areas, and an increased reliance on security measures (Hale, 1996). At a societal level, fear has been linked to the atomization of communities, where reduced social cohesion and a breakdown in the sense of local attachment weaken informal social controls (Skogan, 1986). This in turn limits the ability of the community to deal with crime and low level disorder in the neighbourhood (Covington & Taylor, 1991). High levels of fear of crime have also been linked with changes in population composition and increasing inequality (itself often linked with higher crime), as a consequence of increased social migration away from areas associated with higher levels of fear (Jackson et al., 2006). Additionally, increasing fear has been used to account for changing public sentiment towards the criminal justice system, undermining its' authority, and leading to calls for a more punitive society (Hough et al., 1988). It is therefore clear that fear of crime was, and continues to be, an important area of social enquiry and political debate.

1.3 Defining and operationalising fear of crime

In a recent review of existing fear of crime literature, Vanderveen (2006) concludes that a great deal of conceptual confusion over what is meant by the fear of crime still exists, with many related terms being used interchangeably to define and measure fear. The "lack of specificity in defining and measuring fear of crime" continues to be one of the major criticisms levelled at fear of crime literature (Ferraro, 1995: 21), and one which Hale argues has been "one of the principal reasons for conflicting findings concerning the fear of crime" (1996: 80). Before examining who is fearful and why, it is therefore informative to provide some account of how the concept has been defined and operationalised within existing studies.

1.3.1 The difficulties of defining fear

Vanderveen (2006) notes that in much existing research, very little attention is paid to accurately defining fear, with questions treated as measures of fear that might actually represent quite different concepts. As a result she argues that fear of crime has become an 'umbrella concept', that has variously been linked with feeling unsafe, a feeling of angst or anxiety, panic, perceived risk of becoming a victim, perceptions of disorder, insecurity with modern living, and as more cognitive judgements about the extent of crime. Additionally, Farrall and Ditton (1999) highlight the confusion between fearful responses to crime, and other emotional responses like anger, and anxiety. This has led to considerable uncertainty about what fear of crime actually is, and consequently whether different studies have been identifying and measuring the same thing.

Despite this confusion, there have been some important examples of more detailed conceptual treatments of fear of crime within the existing literature. Ferraro and LaGrange's (1987) critical assessment of existing measures has been particularly influential in advancing a working definition of fear of crime, drawing on earlier work by Garofalo and Laub (1978) that had begun to question the absence of a clear and theoretically guided definition (see also Dubow et al., (1979); and Warr (1984)). This began with the production of a conceptual framework for defining various perceptions about crime, which they use to summarise the differing ways that fear of crime has been described and operationalised in existing studies (reproduced here as table 1.1).

Table 1.1: A Conceptual Framework for Defining Perceptions about Crime

	Type of Perception		
Level of Reference	*Cognitive* Judgements	Values	*Affective* Emotions
General	Risk to others; crime or safety assessments	Concern about crime to others	Fear for others victimisation
Example	*Do you think that people in this neighbourhood are safe in their homes at night?*	*Choose the single most serious domestic problem that you would like to see the Government do something about*	*I worry a great deal about the safety of my loved ones from crime and criminals*
Personal	Risk to self; safety of self	Concern about crime to self; Personal intolerance	Fear for self-victimisation
Example	*How safe do you feel being alone in your neighbourhood at night?*	*Are you personally concerned about becoming a victim of crime?*	*How afraid are you of becoming a victim of mugging?*

Source: Ferraro and LaGrange (1987)

This framework distinguishes between three broad types of crime perception that have been used to define and measure fear of crime in the existing literature, ranging from cognitive to affective assessments. Based on this classification, many studies of fear of crime have relied on more cognitive definitions of fear that deal with the likelihood of becoming a victim of crime, what Ferraro and LaGrange (1987) argue should more accurately be described as risk perceptions. In contrast, other studies have used a more value oriented definition, which they describe as a general concern about the levels of crime in society. Finally, other studies have adopted what they refer to as an 'affective' definition of fear, which focuses more specifically on emotional reactions to crime such as fear and worry. Their conceptual framework also highlights the importance of the level of reference that perceptions of crime have been defined at. They demonstrate a distinction between conceptualisations of fear that are related closely to individual reactions to crime, and treatments that provide more general definitions related to broader perceptions about society.

Drawing on work in social psychology, Ferraro and LaGrange (1987) argue that just one of these dimensions of crime perception is a real reflection of fear of crime; the affective dimension that focuses on individuals' emotional reactions. More specifically, they define fear as an "individual's emotional response of dread or anxiety to crime or symbols that a person associates with crime"

(Ferraro, 1995: 4). They go on to argue that many treatments of fear of crime have actually been working with related, but conceptually distinct concepts that might better be described as predictors of fear. This failure to distinguish between fear, risk, and beliefs about the extent of crime is a key criticism that limits the validity of early research findings, at least as they relate to variations in fear. In contrast, their affective definition draws out the more "emotive" elements of fear that have been described in psychology, with the various physiological changes associated with increased fear marking it out as fundamentally different from more cognitive judgements of risk and concern (Ferraro, 1995: 24). From this perspective, the role of perceived risk is to influence peoples' levels of fear, rather than being a dimension of fear itself.

Jackson (2005) provides further evidence in support of Ferraro and LaGrange's (1987) arguments that risk, fear and concern about crime should be considered as distinct, although closely related concepts. By applying confirmatory factor analysis techniques to data measuring levels of fear, perceptions of risk, and beliefs about the extent of crime, Jackson demonstrates significantly better model fit when these concepts are defined separately, rather than being treated as indicators of the same concept. He goes on to demonstrate how people's levels of fear are, in part, influenced by perceptions of risk and beliefs about the extent of crime, articulating more explicitly how the three concepts relate to one another. Perceived risk, then, is integral to our understanding of fear of crime, being influential in determining the level of fear that people report.

Figgie (1980) introduces another important distinction in relation to definitions of fear of crime, highlighting a conceptual difference between what he refers to as 'formless' and 'concrete' fears. Here, the term 'formless' fear is used to describe more general fears related to the threat of crime, whereas 'concrete' fears are defined as reactions to specific types of crime. This extension has been productively used to demonstrate clear differences between reactions to violent crimes and responses to crimes that are property-related. Taking this distinction further, some researchers have argued for a broader appraisal of fear of crime, relating it to more general anxieties that are not crime related. As a result, they suggest that fear should be treated as both an emotional reaction to the threat of becoming a victim of crime, described as the 'experiential' dimension of fear, and as a more generalised emotional reaction to concerns about wider society, the 'expressive' dimension of fear (Farrall et al., 2006; Hollway & Jefferson, 1997).

There is also an emerging discourse, notably in the work of Farrall et al., (1997), which argues for the inclusion of a temporal element in definitions of fear of crime (see also Farrall et al., (2006); and

Jackson, (2004)). This is used to distinguish between less temporally specific, general summaries of worry about becoming the victim of crime; what Hough (2004) refers to as a mental state, from more specific emotional responses to particular incidents that are short-lived and transitory in nature; what can be thought of as mental events. In support of this dichotomy Farrall et al., (2006) provide evidence of two distinct types of 'fearer'; the 'anxious', who are generally worried about crime but who have not actually been fearful of crime on any specific occasion; and the 'worried', who actually recall experiencing specific incidents of fear about victimisation in their daily lives.

However, whilst it may be true that there is a distinction between general anxieties and specific reactions to fearful episodes, the utility of this distinction is still in question. Hough (2004) counters the calls made by Farrall and colleagues (see for example Farrall (2004)) for a focus on fear as an emotional reaction to specific episodes by questioning whether specific fearful events have any real meaning for people beyond an immediate physiological reaction, or whether they will have any lasting impact on people's daily lives. In contrast, he argues that the more general anxieties which may be difficult to pinpoint in time and space, but nevertheless contribute to people's overall sense of wellbeing, can provide us with an important "perspective about crime and people's experience of it" (Hough, 2004: 175). Whilst much debate still remains, these studies have made a significant contribution to our understanding of fear by identifying different dimensions of fear, with episodic and generalised fears both having potentially important implications.

1.3.2 Measuring fear of crime

Reflecting the lack of conceptual clarity surrounding its definition, a range of different survey items have variously been used as indicators of fear with less attention given to the adequacy of the measures employed (Farrall & Gadd, 2004a). Yet there is now a growing body of evidence that many of the items used to measure fear of crime may be methodologically flawed in various ways (see inter alia Farrall et al., (1997); Ferraro & LaGrange (1987); and Garofalo & Laub (1978)). Looking back to the original victimisation studies conducted as part of the PCLEAJ in America, Jackson (2007) identifies a range of questions that were used as measures of different aspects of fear of crime. These covered people's beliefs about the likelihood of being victimised, people's opinions of their neighbours and the neighbourhood, and their perceptions of the extent of crime in the area. They therefore treat fear of crime as a multidimensional concept, with various indicators enabling a complex understanding of the phenomenon.

Despite the impressively thorough measurement strategy employed in the original studies, much of this detail was quickly lost as simplified measures were developed. As a result, the most commonly used measures of fear of crime are considerably less sophisticated, asking variants of the question *'how safe do you (or would you) feel walking alone in this area after dark'* (Hale, 1996). This is often referred to as a 'global' measure of fear because it does not relate to specific crimes, instead picking up more diffuse, generalised anxieties (Hale, 1996). The wording of this question has remained largely unaltered since it was originally used in the 1960s, with its variants featuring heavily in early government and media reports because of the relatively straightforward enumeration of the extent of fears that it offered. However in response to some early criticism by Garofalo and Laub (1978), highlighting that the absence of the word 'fear' from the question made it unclear whether it was actually measuring fear, more recent studies have asked a variant that directly asks about feelings of fear.

This 'global' question has also faced the most widespread criticism, with a number of studies questioning its utility as a measure of fear of crime, or arguing that the choice of wording likely leads to an overestimation of fear (Ditton & Farrall, 2007; Farrall et al., 1997; 1999; Fattah, 1993; Ferraro & LaGrange, 1987). In addition to the lack of a direct reference to fear in many examples of this question (including the measure still incorporated in the BCS), it makes no reference to crime (Ferraro & LaGrange, 1987: 76). This has led some to question whether it is actually measuring a reaction to crime at all, or rather capturing reactions to other problems within the area such as fear of the dark, or a fear of strangers (Garofalo & Laub, 1978). Even when asked in the context of a crime survey, or with an opening statement about crime in general (as is the case in the NCVS and BCS), these questions lack specificity to particular crime types. This has led many to claim that at best these items can be used to assess "a formless fear of some vague threat to one's security", and not fear of specific crimes (Figgie, 1980).

These measures have also been criticised for asking about something that many population groups are unlikely to do very frequently, often mixing 'actual' and 'hypothetical' responses with the inclusion of the statement 'would you' (Farrall et al., 1997). This is typically done in order to maximise response rates, ensuring that the question can be answered by people even if they don't normally go out after dark. However, this can also lead to significant overestimation of fear of crime from those who base their responses on a hypothetical assessment, with the focus on the elderly as the most fearful in early research often attributed to this problem. Since the elderly are the least likely to go out after dark, they are the most likely to base their assessments on how safe they think they *would* feel, leading to possible overestimation of their fears (Hale, 1996). This deficiency has been partially addressed by some researchers with the inclusion of additional questions asking about fear during the day and whilst in the house at night, enabling a more detailed appraisal of levels of fear (Vanderveen, 2006). This has helped to address the problem of a reliance on hypothetical answers from many respondents, but the extent that people are really relating the question to the potential threat of victimisation and not some other situations still remains unclear.

The lack of reference to a specific spatial location has also regularly been cited as a problem with this question structure, with respondents potentially referring to a diverse range of area types when answering (Farrall & Ditton, 1999). This makes it unclear whether the question is measuring the same thing amongst different people. Additionally, Farrall and Ditton (1999) have argued that the failure to refer to a specific time frame makes it likely that people are drawing on different reference periods when estimating their levels of fear. Drawing on qualitative interviews they demonstrate that people refer to a range of different time frames when answering this type of question. Whilst some people base their estimates on how they are feeling at the time of the interview, others might be referring to experiences that happened over the last year, or one memorable victimisation experience that may have happened many years prior to the interview. This lack of temporal specificity has become more of a problem as fear of crime has become more widely used as a police performance indicator, meaning that it is not possible to accurately judge the impact of the implementation of specific initiatives (Farrall & Gadd, 2004a). Finally, Ferraro and LaGrange (1987) argue that the earlier variants of this question referring to feelings of safety are really a reflection of people's perceived risk of victimisation, and not their level of fear. Returning to their conceptual framework (table 1.1), they identify this item as a cognitive judgement that should not be treated as a measure of fear, but rather as a precursor to fear. Consequently they suggest that much early research has really confused the problem of fear with the problem of risk (Ferraro & LaGrange, 1987).

In response to the limitations levelled at these early 'global' measures, a series of more detailed questions were developed that made direct reference to specific crimes, and dealt more directly with fear as an emotional response to criminal events. These questions require respondents to summarize the intensity of their levels of fear about a range of different crimes. The questions typically take the form *'How afraid are you about…'* and are designed to be examined individually, or as combined scales relating to specific crime types. They are referred to as measures of 'concrete' fear (Figgie, 1980), with the distinction between fear of personal crime and fear of property crime regularly featuring in empirical assessments of these items (Vanderveen, 2006). As such, they represent a significant improvement over earlier measures, directly tapping into emotional responses to crime and allowing for different levels of fear to different types of crime (Jackson, 2005). They are, then, the principle alternative to 'global' measures in fear of crime research, measuring what Ferraro refers to as "expressions of imagined fear" (Ferraro, 1995: 25). In the UK, these questions have been adapted to refer to 'worry' about crime, which Hough (2004) argues may be a more suitable way to think about fear of crime in the UK context. This has led to a growing shift towards treating these questions specifically as measures of anxiety, a particular emotional response to crime that can be considered as one aspect of fear (Williams et al., 2000). This is what Hough (2004) refers to as a general emotional state, contrasted with the more intense emotional reaction to specific events that is generally more transitory in nature.

Recently these questions have also begun to face criticisms of their own, with Farrall et al., (1997) providing the most detailed critique of these measures and identifying several important limitations which they suggest may result in the overestimation of fear. Using data from a series of in-depth interviews, they argue that a reliance on 'closed' questions about people's overall levels of fear is misrepresenting peoples' real reactions to the threat of crime. In their work, they suggest that this masks considerable complexity in people's responses, demonstrating that anger and concern are more common when thinking about the likelihood of victimisation (Farrall et al., 1997). Drawing on Moser and Kalton's (1971) critiques of the question wording used in surveys, they also argue that the use of the word 'how' promotes a belief that some level of fear is normal, contributing to the overestimation of levels of fear. This problem is further exacerbated by the inclusion of introductory statements like "most of us worry at some time or other about being the victim of crime".

Jackson (2005) provides a further critique of existing measures, arguing that emotions are most often transitory and difficult to summarise. Drawing on work by Kahneman et al., (1982), he casts doubt on people's ability to provide accurate summaries of their overall levels of fear, suggesting that in providing these summaries people are likely to be referring to specific spikes of fear that are particularly memorable but also generally uncommon. This results in estimates of fear which may not reflect day to day feelings. Finally, Farrall et al., (1997; 2004b) and Jackson (2005) argue that these questions are missing an important temporal dimension of fear, making it impossible to distinguish fear as a general 'mental state' from the more intense, but transitory emotional reactions to specific events. They argue that simply by focusing on summary levels of the intensity of fear, an incomplete, and exaggerated, picture of the levels of fear of crime is being propagated. They also suggest that people draw on very different time-frames when thinking about their levels of fear, so standard questions about the intensity of fear will have different meanings for different people.

Consequently, Farrall and Ditton (1999) have proposed a new set of questions to measure fear of crime. These are specifically intended as a complement to existing questions, designed to extend understanding of the fear of crime by more carefully examining the nature of worry. This places a greater emphasis on the frequency with which people worry about becoming the victim of a crime, asking respondents *'have you felt fearful of becoming the victim of ...?'*, and if yes, *'how many times have you felt fearful in the last month?'*. They argue that incorporating these additional questions makes it possible to distinguish between general anxieties about crime and more specific reactions to particular events, with lower estimates of fear evident when using the frequency of fear items. These questions are still in development, and have yet to be widely implemented in surveys, although they were included in a subsample of the BCS in 2003/04. They represent the beginnings of a more detailed and complex strategy for measuring fear of crime that distinguishes general anxieties about crime from specific fearful reactions to particular criminal events.

A very different measurement strategy is outlined by Skogan (1987) in his appraisal of the different definitions of fear. He indicates that some researchers have advocated the use of behavioural questions as a measure of fear, using various items such as whether people would avoid particular areas based on the possibility of becoming a victim. The use of these behavioural questions is premised on the belief that what people do is a better indicator of their fear than what people say (Gomme, 1986). However, these measures have been criticised for not actually measuring behaviour, instead measuring how people *say* they behave (Fattah & Sacco, 1989). Additionally critics have argued that these should more accurately be viewed as consequences of fear, rather than as indicators of fear (Hale, 1996).

1.3.3 A more positive outlook on the measurement of fear

As this review has shown, the measurement of fear of crime has been a much debated subject, and there is still much disagreement over the adequacy of existing measures. It has now been generally accepted that the 'global' safety items are unsuitable as measures of fear of crime, but there is less agreement when considering measures that have been designed more specifically to deal with anxieties about particular crimes. Recently researchers have begun to argue that these measures are also inadequate, leading to overestimates of the extent of fear and failing to distinguish the emotional state of anxiety from more discrete fearful reactions to particular events. Whilst it is acknowledged that these fearful events may be qualitatively different from more generally held anxieties, Hough (2004) suggests that the principle focus of fear of crime research should still be on the intensity of general anxieties about crime. Pointing to the inherent difficulties in quantifying the frequency of discrete fearful reactions, and the distinct lack of clarity over what qualifies as a fearful event, he argues that focusing on mental states of worry provided by intensity measures is a more profitable approach. Further to this, he highlights the more meaningful nature of general summaries of worry provided by intensity questions, when compared with the conceptual 'murkiness' attached to the counting of specific instances of fear.

Hough (2004) also questions the suggestion that intensity measures lead to the overestimation of fear, suggesting that this reflects a misunderstanding over the intentions of these 'likert scale' based questions. Rather than acting as 'yardsticks' of fear, these questions are designed to provide us with useful information about relative levels of fear amongst different population groups, along with details about changes in fear over time. As such they are not intended to accurately quantify how many people are 'very fearful' of crime, despite the prevailing media and political rhetoric that often presents fear in this manner. In contrast to the negative view of current fear of crime measures, Hough (2004) therefore provides a more positive perspective on existing measures, highlighting their inherent use in measuring mental states. Kahneman and Krueger (2006) have also begun to look more favourably on these types of intensity measure, demonstrating strong correlations between summary measures of overall life satisfaction and important outcomes including self reported health, smiling frequency, and income, which they present as evidence of the validity of subjective summary measures. As such, subjective intensity measures can present us with a useful, albeit imperfect way to characterise levels of anxiety and other public attitudes.

1.4 Who are the most fearful of crime in society?

The close link between fear of crime and victimisation surveys has had a direct impact on the direction of subsequent research, with the majority of early studies focusing their attention on the identification of differences in reported levels of fear between population subgroups (Hale, 1996). This included observed differences in fear based on gender, age, ethnicity, social class and victimisation experience. The focus on the identification of fearful subgroups was largely driven by early Home Office reports of the extent and nature of crime, and public responses to crime, that have accompanied victim survey results.

1.4.1 Gender and age

Early Home Office reports on fear of crime primarily focused their attention on the apparently contradictory findings that fear was highest amongst women and elderly people, despite them having the lowest estimated risks of becoming a victim of crime. Conversely, younger people and men reported lower levels of fear, despite facing comparatively greater risks of victimisation (Hale, 1996). This result was widely reported in early research, and can be clearly seen in table 1.2 below, an example reproduced from Hough and Mayhew (1983). This details the reported levels of safety for men and women by age group along with their rates of victimisation, based on data from the first wave of the BCS. In line with other studies, this identifies women and the elderly as the most fearful, yet also identifies them as the least likely to be the victim of street crime. These seemingly anomalous findings came to be known as the fear-risk paradox (Sacco, 1990), prompting widespread investigation to explain the apparent 'irrationality' of women's and older people's fear of crime.

Table 1.2: Fears for Personal Safety after Dark and 'Risks of Street Crime'

	% feeling 'very unsafe'	% victims of 'street crime'
Men		
16-30	1	8
31-60	2	2
61+	9	1
Women		
16-30	15	3
31-60	17	1
61+	34	1
Unweighted N	*10,905*	*10,905*

Question: How safe do you feel walking alone in this area after dark?
Source: 1982 British Crime Survey

The relationship between gender and fear of crime is the most consistently demonstrated in existing literature, with higher levels of fear amongst women regularly identified as the strongest predictor of variations in fear (Vanderveen, 2006). Women have been identified as more fearful than men irrespective of the specific measures used, however the gender gap has generally been found to be largest when considering fear of personal crimes. This has led some researchers to focus on the influence of fear of sexual assault, which Ferraro (1996) argues is the driving force behind women's fear of all types of crime. Looking across a range of different crime types, Ferraro demonstrates a strong influence of fear of rape on women's fear of all other victimisations net of individual differences and perceptions of risk. He also shows that when fear of rape has been controlled for, the gender difference in fear of burglary and robbery is removed, and when looking at fear of assault men become more fearful. This led him to suggest that in many instances women's fear of crime is predominantly a reflection of an underlying fear of being sexually assaulted.

Feminist researchers have been instrumental in extending our understanding of why women report higher levels of fear than men, questioning the early claims that women's fear is irrational. The work of Stanko (1988) has been particularly influential, arguing that women's higher fear might actually be an accurate reflection of their increased risk of becoming the victim of crime, with the apparent paradox resulting from the inadequacy of official measures of risk (see also Stanko (1995)). In this feminist critique of early research, she argues that the low objective risks of crime that are associated with women do not reflect their true risks because the main offences that women are disproportionately the victim of (namely domestic violence and sexual assault) are also the most difficult to measure. Consequently they are the most likely to go unreported in official figures, meaning that women's risks are routinely underestimated (Sacco, 1990). Developing this argument, Lupton and Tulloch (1999) highlight the influence of low level disorder on women's fears, with women subjected to considerably higher levels of harassment and threatening behaviour in their daily lives than can be captured by official statistics.

It has been well documented that women are disproportionately the victims of sexual assault (see for example Nicholas et al., (2005)) and important advances have been made in the successful counting of these offences, with recent victimisation surveys incorporating a self completion element to minimise the burden on female respondents. However, Stanko (1988) argues that even with the rising sophistication of victimisation surveys we are still failing to accurately capture women's true experiences of victimisation. In particular, she suggests that the prevalence of domestic violence is difficult to capture in surveys because it occurs in the home, with partners often present during interviews. Similarly, the stigma associated with sexual assault means many women are still reluctant to report it. The difficulty in measuring these offences, and their resulting underestimation, has led them to be described as 'hidden crimes'. Stanko (1995) also emphasises the importance of the nature of the crimes that are experienced by women, arguing that the potential consequences of domestic violence and sexual assault are considerably more serious than the potential consequences of many of the crimes experienced by men.

The relationship between age and fear has featured nearly as frequently in research as the relationship with gender. Many early studies reported that fear was highest amongst older people, with older women identified as the most fearful group (see for example, Box et al., (1988); Clarke &

Lewis, (1982); Clemente & Kleiman, (1977); Lawton & Yaffe, (1980); and Warr (1984)). This was in stark contrast to their lower levels of risk, prompting media accounts of the elderly being confined to their own homes for fear of their own safety, and a general consensus that old people are the most fearful of crime (Chaddee & Ditton, 2003). Despite appearing to be a robust relationship, a number of researchers have now begun to challenge these early findings, arguing that the 'simplistic' notion that the elderly are more fearful should be questioned (see for example Chaddee & Ditton (2003); Ferraro & LaGrange (1992); and LaGrange & Ferraro (1987)).

In a comprehensive review of all of the studies that have examined the relationship between age and fear, Chaddee and Ditton., (2003) actually note a considerable degree of inconsistency about the link between fear and age. Whilst a number of studies have identified higher fear amongst older people (see for example Box et al., (1988); Ortega & Myles, (1987); and Skogan & Maxfield, (1981)), they find that a similar proportion of studies do not identify such a relationship (for example Ferraro & LaGrange, (1992); Gomme, (1986); McCoy, (1996); Pain, (1995); and Tulloch, (2000)). They go on to provide a series of explanations for these inconclusive findings, arguing that the oft repeated image of the elderly as fearful prisoners in their own homes more accurately reflects common misconceptions promulgated by the media. Chaddee and Ditton (2003) point first to the measurement instruments used to characterise fear of crime, highlighting a tendency for researchers to identify a positive relationship when global measures are adopted, whilst crime specific measures generally produce a negative relationship, or no relationship at all. This suggests that although general anxieties may be higher amongst older people, these anxieties are not translated in to higher levels of worry about specific crimes (Hough, 1985).

The higher general anxieties amongst older people can be partially explained by the inclusion of 'hypothetical' response options in global measures of fear of crime, with the elderly the least likely to go out and hence the most likely to be basing their assessments on something that they rarely do (Ferraro, 1995; Hale, 1996). When further probed about why they would not go out after dark, it is telling that most elderly people do not report their fear of crime, instead referring to other explanations like fear of the dark (LaGrange & Ferraro, 1987). This would suggest that older people are not naturally more afraid of crime; rather they experience more general anxieties about being alone after dark in their neighbourhoods.

Chaddee and Ditton (2003) also suggest that the early reliance on simple bivariate relationships between age and fear led many early studies to erroneously identify the elderly as more fearful.

When studies correctly incorporated social context and direct victimisation experience, the relationship with age disappeared, indicating that it was really a reflection of other important differences between population groups. They then point to the range of different conceptualisations of 'the elderly' as a group throughout the literature, with no careful delineation of from what age someone should be defined as elderly, and different results identified depending on the choice of age used. Similarly, gerontologists have criticised the simplistic treatment of the elderly as a single group in many fear of crime studies, claiming that many erroneous findings likely result from the failure to accurately capture important variations amongst older people (Lupton & Tulloch, 1999; Pain, 1997). Other studies have suggested that it may be more accurate to examine non-linear relationships between age and fear, with Moore and Shepherd (2007) finding higher levels of fear amongst the middle-ages (see also LaGrange & Ferraro (1987), and Ferraro (1995)).

In contrast to the wealth of research on older people's fears, empirical evidence on the extent and nature of young people's fear of crime has been considerably less prominent, in part reflecting the restriction of most social surveys to people over the age of 16. Some recent studies have begun to engage with this population, providing initial evidence about the fears of young people (see for example, Alvarez & Bachman, (1997); Hutchinson-Wallace & May, (2005); May & Dunaway, (2000); Nayak, (2003); and Schreck & Miller, (2003)). Using small scale surveys, these studies have demonstrated many similarities with existing research on adult populations, with fear higher amongst young women and those from ethnic minorities, as well as those that have been victimised. Additionally, young people's level of attachment to their parents has been identified by May et al., (2002), and Hutchinson-Wallace and May (2005) as another important influence on levels of fear. However, young people remain an under-researched population regarding fear of crime.

1.4.2 Ethnicity and social class

Empirical research has also regularly identified higher levels of fear amongst ethnic minorities (see Allen, (2006); Fitzgerald & Hale, (1996); Skogan & Maxfield (1981); and Taylor & Hale (1986)). Using two waves of BCS data, Fitzgerald and Hale (1996) demonstrate higher worry about all crimes amongst Afro-Caribbean and Asian groups, with those living in inner city areas being the most fearful. When they look at 'global' measures of fear the picture is somewhat less clear, with Afro-Caribbean's feeling no less safe walking in the area after dark but more unsafe in their own home, whereas all Asian groups feel more unsafe than White people (Fitzgerald & Hale, 1996). In a more recent BCS study, Allen (2006) also reports higher worry amongst all Black and Minority Ethnic (BME) groups, particularly when thinking about personal crime and burglary.

Differences in fear based on socio-economic status have also been frequently featured throughout the literature, with many studies reporting higher fear amongst people from low socio-economic status groups (see for example Allen, (2006); Hough, (1995); Pantazis, (2000); and Will & McGrath, (1995)). Pantazis (2000) demonstrates higher levels of 'global' fear amongst people with lower incomes, with clear drops in fear amongst those with higher income. This downward trend in fear amongst those with higher incomes is evident across gender and age groups, and remains when controlling for differences in area type. Similarly, using BCS data Hough (1995) demonstrates higher fear amongst those in semi-skilled and manual work than those in skilled manual and non-manual jobs.

Krannich et al., (1989) argue that these differences based on ethnicity and socio-economic status have close ties to wider ecological characteristics, explaining the higher levels of fear amongst BME groups as a function of the ethnic composition of the area. Similarly, Taylor and Hale (1986) highlight the fact that BME groups and people from lower socio-economic groups tend to live in areas with higher levels of crime, deprivation and local disorder, suggesting that their higher levels of fear reflect these environmental differences. However, even when ecological characteristics have been controlled, the available evidence still identifies higher fear amongst BME groups and people in lower socio-economic groups, indicating that there are other potentially important explanations for this higher fear (Fitzgerald & Hale, 1996; Pantazis, 2000).

1.4.3 Previous victimisation

Along with some clear differences in levels of fear based on demographic characteristics, a number of studies have identified higher levels of fear amongst people who have reported being previously victimised (Allen, 2006; Quann & Hung, 2002; Skogan, 1987). Importantly, in contrast to the fear-risk paradox that was identified when considering overall levels of risk and fear, this finding suggests that fear is, at least in part, a rational response to past experiences of crime. This rational dimension of fear is most apparent when particular crime types are examined, with differences in general levels of anxiety between victims and non-victims often considerably smaller. Sundeen and Matthieu (1976) were the first to demonstrate that the effect of particular crime types is often related to the type of crime specific fear that is being examined. This finding has subsequently been replicated in a number of studies (see for example Miethe & Lee (1984); and Skogan (1987)). In a similar vein, Ferraro (1995) demonstrated that experiences of some crimes are particularly prone to result in higher levels of fear, highlighting the dominant influence of sexual assault on women's fears. It seems clear from the available evidence, then, that it is the nature of the crime experienced that is important, rather than simply the fact that someone has been victimised.

Despite the face validity of this relationship, in summarising the results from previous studies, Hale (1996) and Vanderveen (2006) both note a surprising degree of inconsistency over the existence of a direct link between experiences of victimisation and higher levels of fear. Whilst some research has demonstrated a clear influence of previous victimisation experience (for example Skogan (1987); Quann & Hung (2002); and Weinrath & Gartrell (1996)), other studies find no clear relationship (see for example Baker (1983); and Ferraro (1995)). Several explanations for this apparent inconsistency in results have since been raised, which have helped to clarify the original claims about the nature of the relationship.

Unsurprisingly, part of this inconsistency in the effect of victimisation experience reflects the measurement instruments that have been used to characterise fear of crime, with many studies failing to find differences between victims and non-victims when relying on global measures (Hale, 1996). Similarly, the type of victimisation that is experienced can be influential, with Wilcox-Rountree and Land (1996b) demonstrating higher fear amongst victims of personal crime, but no differences when examining victims of property crime. Miethe and Lee (1984) point to the relatively low numbers of victims that are typically identified in crime surveys, arguing that this leads researchers to use broad definitions of victimisation. This often means that to maximise the useable number of victims in a sample, researchers must group together more serious offences with those that are relatively minor and hence unlikely to have any influence on fear. This makes it possible that the effects of serious victimisation experience on fear may be being masked by trivial offences that are more frequently reported, but which have no lasting effect on fear. Similarly, Hale (1996) argues that the reference period used when measuring previous experience should not be overlooked. He suggests that the influence of victimisation experience will often be transitory, so the 12 month reference period often relied on in victimisation surveys may lead to low estimates of victimisation because of a preponderance of crimes that occurred a relatively long time before the interview.

Skogan (1987) takes a different perspective, suggesting that existing studies may be producing unclear pictures of the effect of direct victimisation on fear by failing to accurately identify the small group of individuals that suffer repeat victimisation. Skogan argues that these are the most likely group to be significantly affected by victimisation and hence report higher levels of fear. However, the broad focus of national victimisation surveys makes it difficult to identify those who suffer from multiple victimisations, with only a small number of victims generally identified who have experienced multiple victimisations, and their experiences routinely capped at 5 offences to avoid overestimating national crime figures (Lynn & Elliot, 2000). As a result, there is comparatively little evidence about the fear histories of multiple victims, and how they differ from victims of only one offence.

In contrast to these methodological explanations for the lack of an effect of victimisation experience, Agnew (1985) has attempted to explain the lack of a difference in fear between victims and non-victims by adopting Sykes and Matza's (1957) notion of "techniques of neutralisation", which people use to deal with the effects of victimisation. Agnew argues that in a similar manner to offenders downplaying their culpability to offences, victims of crime will generally tend to downplay their experiences, and hence their levels of fear will be relatively unaffected by the influence of direct victimisation. This might be by shifting the blame for their victimisation on to others, rationalising that it was their own fault, or by holding on to a belief in a just world where the perpetrator will be punished for their crimes. Additionally, he argues that victims might appeal to higher values, justifying their own victimisation as a result of protecting someone else (Agnew, 1985). However, this focus on techniques of neutralisation has been difficult to empirically verify, and is also likely to be crime and victim specific.

1.4.4 Indirect experience

Higher levels of fear have also been demonstrated amongst people that report personally knowing others who have been victimised, and amongst people who believe that the level of crime in the surrounding area is high (Ferraro, 1995; Hough, 1995; Skogan & Maxfield, 1981; Vanderveen, 2006; Wilcox-Rountree & Land, 1996b). To explain this, researchers have suggested that personal contact with those that have experienced victimisation, along with a general awareness of the levels of crime in the locality gained from neighbours, serve to increase the salience of the problem of crime for individuals (Hale, 1996). This in turn results in higher average reported levels of fear from people that have come into contact with victims, or who live in areas where crime is regularly experienced (Taylor & Hale, 1986).

Variations in fear have also been identified on the basis of media consumption, with television and newspapers both highlighted as important sources of differences in fear of crime. Looking first at television viewing, Gerbner and Gross (1976) demonstrate that frequent television viewers are more likely to perceive themselves to be at higher risk of crime than those that do not watch much television. Focusing more directly on the types of program watched, Chiricos et al., (1997) report higher levels of fear amongst viewers of programs containing portrayals of criminal victimisation, noting particularly high levels of fear amongst those that are regular viewers of the local news. However, links between television viewing and variations in fear of crime have been notoriously difficult to replicate, with many studies failing to find a relationship between television and fear (for full reviews of current evidence see Ditton et al., (2004); and Reiner, (2007)).

Turning to newspaper readership, higher fear of crime is evident amongst readers of tabloid newspapers and local newspapers, when compared to readers of broadsheets, and those that do not regularly read a newspaper (Lane & Meeker, 2003a; Liska & Baccaglini, 1990; Williams & Dickinson, 1993). However, like the proposed relationships with television viewing, findings that link newspaper readership to fear of crime have been inconsistent. Therefore, a number of studies have failed to identify variations in fear as a function of newspaper readership, or demonstrated that when other important characteristics are controlled for, this relationship disappears (Chiricos et al., 1997; Gomme, 1986; Sacco, 1982).

1.4.5 Ecological differences

Along with the differences in fear that have been identified on the basis on individual characteristics, studies have also demonstrated notable variations in fear based on residential location. For example, the latest BCS reports that 10% of residents in the South West have high levels of worry about violent crime, compared with 28% of residents in London (Nicholas et al., 2007). Such variations in fear based on residential location have been used to emphasise the importance of contextual factors when examining fear of crime, with a number of objective ecological indicators linked with differences in fear.

Looking at past evidence, there is surprisingly little empirical support for a link between fear of crime and the extent of crime within the local area, paralleling the inconsistencies evident when examining victimisation histories at the individual level (Hale, 1996; Vanderveen, 2006). This failure to consistently identify a relationship is likely to partly reflect the inadequacies of available crime measures, with many studies relying on data at broad spatial scales that have little relevance to the lived experiences of residents of particular local areas. Additionally, many studies rely on simplistic measures of recorded crime that fail to accurately capture the range of crimes that people experience.

In contrast, studies have demonstrated significantly higher levels of fear in inner-city areas when compared with more urban and rural areas (Allen, 2006; Beylea & Zingraff, 1988). Similarly research evidence has linked higher levels of fear with increasing community size (Lebowitz, 1975; Wilcox-Rountree & Land, 1996b), and population density (Bankston et al., 1987). Other studies have demonstrated higher levels of fear from people living in neighbourhoods with more ethnically diverse populations (Kershaw & Tseloni, 2005), and with higher levels of population turnover (Krannich et al., 1985). Related to the impact of residential mobility, Krannich et al., (1989), and Taylor and Covington (1993) demonstrate the importance of the degree of neighbourhood change, with neighbourhoods experiencing rapid community change also associated with higher levels of fear than more stable neighbourhoods. Covington and Taylor (1991), found higher levels of fear from people living in lower status neighbourhoods, even when controlling for other important variables including victimisation experience and basic demographics (see also Miethe & Mcdowall (1993); and Hale et al., (1994)). Studies have also identified higher levels of fear in areas characterised by a greater prevalence of low level disorders (see inter alia, Allen, (2006); Ferraro, (1995); and Taylor, (2001)), although there is still considerable debate over how best to measure disorder within the area (a full discussion of this issue can be found in chapter 3).

As well as identifying differences in fear across area types, studies have reported reductions in the size of some individual differences in fear when these contextual differences have been incorporated. This provides important evidence of the central role that local context can play in helping to understand differences in levels of fear (Hale, 1996). For example, Fitzgerald and Hale (1996) noted large reductions in the gap between White and non-White people when the effect of living in an inner city area was controlled. This was attributed to the higher concentration of BME groups living in inner city locations, which were also identified as higher crime rate areas.

Similar to individual differences in fear, in reviewing the evidence that has been collected about the ecological influences on fear, Hale (1996) notes considerable variability across studies, with many studies failing to find any differences based on environmental characteristics. Some of this variability across studies can be attributed to the type of fear of crime measures used. For example, there is evidence to suggest that the higher levels of fear from urban residents partially reflects the use of 'global' questions relating to general feelings of safety out in the neighbourhood (Beylea & Zingraff, 1988). In contrast, differences in fear of specific offenses have been found to be less reliably informed by whether the areas is identified as urban or rural (Bankston et al., 1987).

Area based differences in levels of fear also form the basis for 'left realist' critiques of early Home Office accounts of the extent and nature of crime (Young, 1996). Left realists argue that the national picture afforded by victimisation surveys is inadequate, with the apparent irrationality of fear a direct product of taking a national perspective. Using local surveys to capture small scale variations in levels of crime and fear, left realists point to a closer link between fear and risks of victimisation than is suggested by national assessments. Drawing on these findings, left realists have been instrumental in arguing against the national focus of victimisation surveys, and for a more nuanced local picture where important variations are not masked by broad aggregations (Young, 1988). They suggest that this local focus can provide a more context specific picture of the extent and nature of crime and fear, more realistically treating people within their neighbourhood context (see for example Kinsey (1984); Hanmer & Saunders (1984); and Jones et al., (1986)).

1.6 Summary

Perhaps unsurprisingly given the large number of studies that have examined fear of crime, a range of 'fearful' groups have been identified throughout the literature, and a number of ecological influences on fear have been highlighted. However, reflecting the turbulent history of the measurement of fear of crime, evidence in support of these variations is somewhat inconsistent. This has meant that some of those identified as more fearful using one measurement strategy have not been found to be more fearful when using another operationalisation of fear, or when other potentially important factors have been controlled for. Despite these apparent inconsistencies, researchers have put forward a number of explanations for observed differences in fear, moving the fear of crime debate beyond attempts to identify fearful groups to a more integrated theoretical framework to help understand why these groups are more fearful.

In chapters 2 and 3, I will provide a critical assessment of the range of explanations that have been put forward to account for these variations in fear. This will begin with an examination of those theories that have focused specifically on observed variations in fear between different types of people, including notions of vulnerability and victimisation experience. I will argue that the evidence in support of these explanations is inconsistent, and that these approaches have failed to successfully incorporate the wider social context in which fear is experienced. In chapter 3 I will then introduce those explanations which focus on the role of broader ecological differences and community structures that may be instrumental for inhibiting or increasing fear amongst their residents. This is framed around explanations that draw on social disorganisation theory, and those that have looked at the impact of the presence of neighbourhood disorder. I will argue that these neighbourhood level theories have provided us with a set of explanations that recognise the importance of the broader context of fear. However, there is still a need for assessments of fear that effectively connect these broader sociologically driven explanations for variations in fear to the differences that have been observed at the individual level, and how the two spheres of influence interact.

CHAPTER 2: EXPLAINING INDIVIDUAL VARIATIONS IN FEAR OF CRIME

2.1 Introduction

In chapter 1 I outlined the historical context of the fear of crime debate, linking it directly to the advent of victimisation surveys in America. This was followed by an examination of the various ways that fear of crime has been conceptualised and operationalised throughout the literature, and the impact that this has had on the results from empirical studies. Chapter 1 concluded with a discussion of the main findings from existing research, looking at the types of people and groups that have been identified as the most fearful, and the types of area that are associated with higher levels of fear amongst their residents.

Prompted by some of the notable variations in fear across different population groups that were identified in early Home Office reports on fear of crime, researchers soon began to provide more general explanations for the higher levels of fear amongst particular groups. In this chapter I examine the dominant individual level explanations that have been put forward to account for these observed variations, focusing on notions of vulnerability, victimisation experience, and the fear inducing effect of the media. I argue that these early explanations for variations in fear gave relatively little attention to developing a broader theoretical framework, with the ecological context in which these fears were experienced largely absent.

In chapter 3, I then go on to consider the extended scope offered by the more theoretically driven explanations that were developed to help explain area based differences in fear. Looking specifically at social disorganisation theory and the impact of disorder, I highlight the role of neighbourhood processes in promoting and inhibiting fear. These have been instrumental in extending our understanding, and have provided explanations that attempt to link individual differences in fear to the ecological context in which people live their daily lives. However, despite offering an integrated theoretical framework to explain differences in fear, there is currently an absence of empirical evidence that connects individual differences to contextual variations within a single analysis. Instead, most research adopts either an individual or contextual focus, with the theoretical links between the two implied rather than empirically verified.

2.2 Vulnerability

The notion that fear is highest amongst groups that can also be described as the most vulnerable is one of the most often repeated explanations for the variations in fear identified in survey research. This was initially linked to the higher levels of fear amongst women and elderly people, providing a plausible reason for their 'irrational' fears when considered in relation to their lower objective risks of crime (Skogan & Maxfield, 1981). Its central tenets have since formed the basis for many accounts of differences in fear, including variations based on health (Adams & Serpe, 2000), socio-economic status (Pantazis, 2000) and ethnicity (Taylor & Hale, 1986). There are also clear links between vulnerability and victimisation experience which have been emphasised throughout existing literature.

The concept of vulnerability was first clearly outlined in Skogan and Maxfield's (1981) seminal study of fear of crime in Chicago, Philadelphia and San Francisco. Amongst other things, in this work they argued that the higher fear amongst women and older people reflected their increased physical vulnerability, whilst the higher fear amongst ethnic minorities and poorer people was a result of their increased social vulnerability. The concept of vulnerability was later extended by Killias (1990), who further distinguished between social and situational aspects of vulnerability (see also Killias & Clerici, (2000)). Killias (1990) also highlighted three intervening 'dimensions of threat' that he argued resulted in higher levels of fear from those identified as more vulnerable; exposure to non-negligible risk; the seriousness of the anticipated consequences of victimisation; and people's feelings of a lack of control over the likelihood of victimisation and its outcomes.

Physical

Drawing on the extended framework provided by Killias (1990), physical vulnerability relates specifically to people's ability to resist crimes, and to effectively recover their health following an incident of victimisation. Therefore, those identified as more physically vulnerable will be less able to resist physical attack, and will consequently judge the consequences of victimisation to be more serious. They may also be less able to effectively escape from potential dangers, further increasing the potential threat of crime and raising levels of fear. Physical vulnerability may also lead people to believe that they are at greater risk from crime, which in turn results in more fear.

Physical vulnerability has primarily been used to explain the higher levels of fear amongst women and older people, with physical differences leading both groups to perceive the consequences of being the victim of crime as more serious (Box et al., 1988). This is typically associated with people's recognition of their own lack of effective defence from physical victimisation, prompting a belief that the harms of victimisation will be greater (Hale, 1996). Focusing specifically on the use of vulnerability to explain women's higher fear, Ferraro (1995) highlights the importance of the threat of sexual assault, which he argues typifies women's feelings of increased physical vulnerability. This is primarily associated with feelings of a lack of control over their own risks of victimisation, resulting in judgements that the consequences of victimisation will be more serious. Since it was first introduced, the impact of feelings of powerlessness associated with the 'shadow of sexual assault' has remained a prominent feature in explanations that use vulnerability to account for women's higher fear.

Feminist researchers have expanded on notions of women being more physically vulnerable by focusing on the range of crimes that they are disproportionately the victim of, but which regularly go unreported. Stanko (1995) emphasises the importance of the nature of these crimes, arguing that the potential consequences of domestic violence and sexual assault are considerably more serious than the potential consequences of many of the crimes experienced by men. They are also likely to have more long-lasting and compounding effects, with the occurrence of domestic violence having important implications for women's feelings of safety whilst at home. Therefore, in contrast to the traditional focus on the irrationality of women's fears, feminist researchers have argued that women's higher levels of fear are really a rational response to their higher risks which are not adequately captured by statistical counts of crime (Scott, 2003).

Some researchers have attempted to use more direct measures of physical vulnerability to test the proposition that physical differences promote fear of crime. In a study using data from the 1994 BCS, Hough (1995) demonstrates a relationship between three measures of vulnerability (self assessed health, physical size, and ability to defend oneself from attack) and anxiety about personal crime, controlling for demographic differences and measures of victimisation experience. Similarly, Killias and Clerici (2000) find a significant relationship between interviewer assessments of people's physical vulnerability and global measures of fear of crime using a sample of Swiss nationals. Adams and Serpe (2000) also identify a relationship between physical vulnerability and fear, with higher levels of fear amongst people of poor health, net of other personal differences (for other direct tests of vulnerability see Allen (2006); and Chandola (2001)).

Social

In contrast to physical vulnerability, social vulnerability is generally used to reflect how an individuals' location within society differentially affects their exposure to the likelihood of victimisation, as well as their capacity to absorb the costs of crime (Hough, 1995). Groups identified as more socially vulnerable are believed to have fewer social resources to recover from victimisation, with restricted networks of social support making the consequences of crime more severe. Social vulnerability also reflects the financial resources that are available to people, with more economically disadvantaged people feeling less able to control their likelihood of victimisation because they cannot afford effective protection measures (Killias & Clerici, 2000).

Social vulnerability has frequently been used to explain the higher levels of fear of household crime that have been identified amongst people from lower socio-economic status groups (Hough, 1995; Pantazis, 2000). People from lower socio-economic status groups are identified as less equipped to deal with the financial implications of victimisation. This reflects their reduced resources to successfully recover from property crime, making the consequences of being victimised more serious (Will & Mcgrath, 1995). Socio-economic status has also been linked to fear of physical victimisation, with people from lower status groups often unable to take time off work to fully recover from a criminal event, and hence perceiving the financial implications of being the victim of violence as more serious (Pantazis, 2000). Additionally, those who are less financially secure may feel less able to effectively protect themselves from the risks of victimisation, with fewer resources available to buy protective measures against crime such as burglar alarms and security locks.

Research has also drawn on notions of social vulnerability to account for the higher fear amongst BME groups, with reduced social ties reflecting their segregated position within society (Taylor & Hale, 1986). However, it has generally been more common for research to turn to contextual explanations for variations in fear based on BME status. Older people have also been identified as more socially vulnerable, with researchers arguing that older people are more likely to be socially isolated, promoting higher levels of fear (Mawby, 1988). Additionally, LaGrange and Ferraro (1987) argue that elderly people may have less extensive social support networks, making the consequences of criminal victimisation significantly more serious, and further restricting their ability to recover effectively.

Pantazis (2000) urges caution over claims that social networks are weaker, and hence more fear inducing, amongst disadvantaged groups. Instead, she suggests that whilst the social networks may be different, this should not automatically imply that they are weaker. She goes on to argue that people from more disadvantaged groups will typically have more geographically concentrated networks of family and friends, whereas more advantaged groups will usually have broader and more geographically dispersed networks. As a result, fear may actually be lower amongst more disadvantaged groups, as they have stronger local networks to aid recovery.

Situational

Finally, drawing on contextual explanations for differences in fear, Killias (1990) introduces a situational aspect to vulnerability, which he uses to explain some of the area based variations in fear identified in early studies. Situational vulnerability describes how characteristics of the local physical environment are linked to peoples' risks of crime, and act as cues to the extent of crime (Fisher & Nasar, 1995). For example, people living in inner city areas that have higher crime rates are identified as more vulnerable to the risks of crime, which in turn promotes higher fear. Along with the effect of the local crime rate, situational aspects of vulnerability have included the levels of graffiti and other low level problems in the local area which increase people's perceived risks of crime and hence their fear. These physical signs of risk are more typically labelled as signs of disorder, and feature heavily in more contextual explanations for variations in fear. As such, it is suggested that more vulnerable groups will likely be more susceptible to the influence of the local environment, judging their risks of crime to be greater. Importantly, this situational aspect of vulnerability often interacts with social vulnerability, with those groups identified as the most socially vulnerable often also living in the most vulnerable areas (Fisher & Nasar, 1995; Skogan & Maxfield, 1981).

2.2.1 Questioning notions of vulnerability

Despite a large body of research that has drawn on notions of vulnerability, there are several limitations with this explanation for variations in fear. Firstly, most research has relied on proxy demographic characteristics to represent vulnerability, rather than using direct indicators of its physical, and social aspects. This has resulted in a fairly simplistic notion of vulnerability that fails to accurately capture differences within demographic groups. For example, studies will often use gender and age to represent physically vulnerable groups, with no distinctions made between different types of women or older people which may make them more or less physically vulnerable than others. This also means that it is often not possible to demonstrate that differences in fear are the result of vulnerability, as opposed to a reflection of other differences between demographic groups. Some studies, such as Hough (1995), and Killias and Clerici (2000) have included direct measures of physical vulnerability; including the level of physical strength, the presence of limiting illnesses or self assessed self-defence capabilities. Whilst these studies are generally supportive of the influence of physical vulnerability, the inclusion of these measures does not fully account for the observed demographic differences, demonstrating that there is more to the higher fear amongst some population groups than the effect of increased physical vulnerability.

Similarly, whilst many studies have labelled BME groups and socio-economically disadvantaged groups as more socially vulnerable, and hence more fearful of crime, far fewer studies have incorporated direct measures of social vulnerability. Strong networks of support may lower levels of fear by reducing the perceived consequences of victimisation for residents, a finding that confirms the claims of social vulnerability. However, strong local networks have also been linked to higher fear, providing people with additional information about the extent of crime in the local area and raising its salience, a finding often referred to as indirect victimisation (Vanderveen, 2006). This implies that it is the nature of the contacts between residents, and the social context in which they are experienced, that are as important as the strength of these local contacts in influencing levels of fear.

A further problem with using vulnerability as an explanation for higher fear amongst certain population groups is the high degree of inconsistency across studies when identifying who are more fearful. Reviewing the accumulated evidence, Hale (1996) and Vanderveen (2006) demonstrate that many of the relationships indentified in early research have since been questioned, including the higher fear amongst older people and BME groups. These inconsistencies have partly been explained by the evolving measures used to characterise fear, with 'global' safety measures gradually being replaced by more crime specific measures that appear to be less closely related to vulnerability. This suggests that whilst vulnerability may be a suitable explanation for differences in general levels of safety or perceived risk, it is less influential in determining people's anxiety and fear about being the victim of particular crimes.

2.3 Differential socialisation

An alternative explanation for the higher levels of fear amongst women is given by those highlighting the importance of differential socialisation (Sacco, 1990). This draws on a large body of literature that has argued that gender differences are largely the product of socialisation processes, with children 'learning' their gender roles from an early age (see for example Oakley, (1974)). Relating these socialisation processes to fear of crime, it is suggested that from an early age boys learn to be risk takers and to behave fearlessly, tough and aggressive. In contrast girls learn to be passive, constrain their behaviour, and as a result generally perceive their risks of crime to be higher and hence are more fearful. These gendered roles are then carried on into adulthood where they contribute to the large differences in fear regularly observed between men and women. In a recent study of fear amongst children, Goodey (1997) presents evidence of these socialisation processes in action, highlighting marked differences in fear between boys and girls that she argues directly reflect boy's emerging masculinity and their dominant position in society.

A related socialisation perspective was outlined in a recent study by Sutton and Farrall (2005), where they emphasise the importance of socially desirable responding practices. Using a 'lie scale' (Crowne & Marlowe, 1960), designed to capture the extent that people strategically manipulate their responses to survey questions to appear in a more favourable light, they demonstrate that men are more likely to select socially desirable responses and are also likely to report lower levels of fear (Sutton & Farrall, 2005). In contrast, they find no link between scores on the lie scale and fear of crime amongst women. They argue that this link between desirable responding practices and lower levels of fear amongst men reflects a tendency for men to downplay their fears as a result of increased social pressures to conform to their gender role as fearless males.

However, despite presenting a plausible model to account for the differences in fear that appear to be evident from an early age, the processes of differential socialisation are difficult to empirically verify. Psychological research has been conducted that attempts to examine these learning processes in more detail, yet this has failed to adequately identify whether socialisation processes cause children of different sexes to behave differently, or whether the different behaviours of boys and girls result in different socialisation practices from adults (Maccoby, 2000). In an attempt to better examine the causal direction of socialisation processes, some studies have adopted experimental designs that examine how adults interact with children that are dressed up in gender ambiguous clothing. Reviewing the findings from these studies, Stern and Hildebrandt-Karraker (1989) report generally weak and inconsistent findings from study to study. Consequently it remains unclear the extent that socialisation processes operate in relation to differing levels of fear.

2.4 Victimisation experience

Another important focus for researchers has been the higher levels of fear amongst previous victims of crime. Victimisation experience has been identified as the primary source of information about crime amongst victims, leading them to believe there is more crime in the local area and that their own risks of subsequent victimisation are higher (Skogan & Maxfield, 1981). This also informs victims of the consequences of victimisation, further increasing their fear. Research generally finds stronger impacts of previous experience of personal victimisation, with experience of property crime often demonstrating no significant relationship with fear (Hale, 1996). Stronger effects are also found when considering reactions to specific types of crime, suggesting that people connect their past experiences directly to their perceived risks of being similarly victimised again.

By focusing on the effect of victimisation on people's perceptions of the seriousness of the consequences of crime, and the impact on people's perceived risks of future victimisation, the links between victimisation experience and vulnerability are clearly apparent. Previous victimisation experience can act as a signal to people of their own inability to effectively protect themselves from the threat of crime, and foster a belief that their risks of future victimisation are higher (Killias, 1990). This might also reflect the influence of a heightened awareness of the seriousness of future victimisation given previous experiences. Victims of crime may therefore feel more vulnerable to future victimisation, and hence report higher levels of fear. Directly testing this proposition, Winkel (1998) showed that whilst direct victimisation does indeed raise people's perceived risks about future victimisation, it can actually serve to lower people's concerns about the consequences of crime. As a result, he argues that the two effects of victimisation cancel one another out, reducing the link between victimisation and fear.

Despite the apparently straightforward link between victimisation and fear of crime, current evidence remains inconsistent, with many studies failing to find a direct relationship, or finding only a small correlation (see for example Baker (1983); and Ferraro (1995)). This lack of consistency has been linked to the ways that victimisation experience is measured in survey research, with studies typically grouping together a range of offences to form a measure of victimisation, potentially masking the effects of serious victimisation with the inclusion of less serious offences. The varying lengths of time between experiences of victimisation and survey interviews might also result in inconsistencies across studies, with Skogan (1987) suggesting that whilst the impact of victimisation on fear can be strong, it can also be relatively short lived.

The BCS estimates that approximately 22% of the population are victims of crime each year, with serious victimisation considerably rarer (Kershaw et al., 2008). This means that the majority of the population will likely draw on other sources of knowledge about the extent and nature of crime to inform their fears. Researchers therefore also highlight the influence of second hand knowledge about the extent of crime gained through personal conversations with others that have been victims of crime in the neighbourhood. This vicarious victimisation is considerably more widespread than direct experiences of crime, with research demonstrating that a large proportion of people know others who have been victimised (Vanderveen, 2006).

Skogan and Maxfield (1981) provide a detailed assessment of the concept of indirect victimisation experience, identifying two important factors that interact to determine the extent that personal communication promotes higher fear; the extent of crime in the area, and the strength of local personal networks that transfer knowledge between residents. When crime is more widespread within an area, people are more likely to talk with one another about the extent of crime, increasing their awareness of their own potential risks. Similarly, they found that stronger personal networks of communication made it easier for information about crime to pass between local residents, raising the salience of crime as a problem. They also demonstrated a tendency for people to remember hearing about victims that share similar characteristics to themselves, what they refer to as a 'social proximity' effect (Skogan & Maxfield, 1981: 178).

As with many other correlates of fear of crime, there is mixed evidence in support of indirect victimisation as an explanation for variations in fear. Some studies have demonstrated a significant relationship, showing higher levels of fear amongst people who know others who have been victimised (Arnold, 1991; Box et al., 1988). In contrast, other studies fail to identify a direct relationship with fear once other correlates have been controlled (Ferraro, 1996; Tyler, 1980). This again reflects the different measurement strategies that have been adopted, with global measures more likely to be correlated with indirect victimisation (Hale, 1996).

2.5 The media effect

Another potential source of indirect knowledge about crime that has regularly been linked with variations in fear is the effect of the media (Gunter, 1987). The influence of the media has frequently been cited in fear of crime research, mirroring the high levels of attention that have been levelled at media effects within other areas of criminology. There has been a longstanding concern that the media is a significant cause of crime within criminology, stemming from a series of content analyses that demonstrated a disproportionate focus on crime within various media outlets, and a disproportionate focus on crimes of a serious and violent nature (Marsh, 1991). Researchers have argued that this over-emphasis on crime in the media is partly responsible for criminal behaviour, with a number of studies referring to 'copycat' crimes as a demonstration of the influence of media representations of crime (Howitt, 1998; Surette, 1998). Other researchers have suggested that the media leads to crime by eroding the social controls that prompt people to restrict their deviant behaviour (Reiner, 2007). The media has since been linked with variations in fear of crime, acting as an important source of knowledge for people about the extent and nature of crime, and raising the salience of crime as a problem by presenting an exaggerated picture.

The effect of the media has featured in a range of analyses using a variety of methodological approaches including content analysis (Ericson, 1991; Graber, 1980; Marsh, 1991; Reiner et al., 2000; Williams & Dickinson, 1993), studies of television viewing habits (Chiricos et al., 1997; Eschholz et al., 2003; Gerbner & Gross, 1976) and the use of survey research (Allen, 2006; Garofalo, 1981; Lowry et al., 2003). Attention has largely been dominated by the potential fear inducing effect of television viewing, with both factual and non-factual crime related programs linked with higher levels of fear by acting as a surrogate for direct knowledge and experience of crime (Chiricos et al., 1997). This is premised on the disproportionate attention that is given to crime in the media, in particular more serious violent offences and potential crime waves, which is believed to lead people to overestimate their risks of victimisation (Liska & Baccaglini, 1990).

Most notable amongst research examining the impact of TV viewing on fear of crime is the work of Gerbner and Gross (1976) who conducted an extensive assessment of this relationship over a range of studies. Based on this research, they developed 'cultivation' theory, which argues that television is instrumental in shaping and misshaping audiences' ideas about the world. In a sequence of studies including content analyses and survey research, they demonstrated that frequent instances of violence on television prompted regular viewers to believe that the extent of crime was more widespread, and that their risks of being a victim of violent crime were higher. Despite receiving considerable academic attention, critics have since challenged this appraisal of the influence of TV viewing for being too simplistic, arguing that current evidence is generally inconclusive and that "across the board consequences of television viewing were unrealistic" (Chiricos et al., (1997: 345), see also Ditton et al., (2004)). Instead they suggest that the observed relationship between media viewing and fear is contingent on "characteristics of the message, of the audience, and of the dependent variable used to measure fear" (344). As a result of these criticisms, the original cultivation theory was later extended to incorporate the notion of 'resonance', which suggests that the fear generating effects of cultivation are most pronounced amongst those whose social experiences are most similar to those being portrayed (Gerbner et al., 1980).

Similarly, the type of programs that people are exposed to have been identified as an important factor in determining levels of fear. For example, Eschholz et al., (2003) demonstrate significantly higher levels of fear amongst people watching crime drama, reality and tabloid programs, net of individual differences in fear. Research has also highlighted a strong impact of more local news media, with significant rises in levels of fear linked to the increased immediacy of events in local media (Chiricos et al., 1997). This has strong parallels with the ideas of resonance proposed by Gerbner et al., (1980), with events that occur in closer proximity to people having increased relevance and consequently a bigger influence on fear.

Research has also examined the influence of newspaper readership, linking the differing reporting styles that characterise particular types of print media with different reported levels of fear amongst their readers. These studies demonstrate the influence of 'selective journalism', with disproportionate focus given to crime stories in newspapers and particular salience given to serious crimes, which are defined as particularly newsworthy (Williams & Dickinson, 1993). They also argue that different types of newspaper are more or less likely to misrepresent the extent of crime, using this as a means to demonstrate the influence that the media has on people's levels of fear. For example, Williams and Dickinson (1993) demonstrated significantly higher fear amongst tabloid readers when compared to broadsheet readers, which they argue reflects the wildly different reporting styles of these two types of paper. Using content analysis, they identify an average of 3.1% of the total newspaper space from the Guardian devoted to crime stories, compared with an average of 30.4% of the space in the Sun newspaper. They argue that this overemphasis on crime in tabloid newspapers raises the salience of crime as a significant problem for its readers, leading to higher levels of fear of crime.

It is not just the proportion of newspaper space devoted to crime stories that has been identified as an important influence on levels of fear, with Reiner (1996) also highlighting the importance of the differential reporting styles of tabloid and broadsheet newspapers. Therefore, whilst tabloid newspapers generally focus on more sensational stories, selecting offenders to reinforce crime stereotypes, broadsheets present a more objective picture of crime. Additionally, Reiner presents a more detailed assessment of the factors that are most likely to make a particular crime story fear inducing, highlighting the importance of the level of violence, realism, just resolution, and proximity of the victim to the reader. Other researchers focus more directly on the importance of the content of specific news stories, with Winkel and Vrij (1990) highlighting the importance of the degree of similarity between the area in which the crime occurred and the residents own local neighbourhood, identifying higher levels of fear when people closely identify with the area.

However, despite a range of studies focusing on different media effects, evidence in support of a direct influence of the media on fear has generally been lacking, with inconsistent results reported across studies (Ditton et al., 2004). In contrast to the popular representation of the media as a negative influence, some research points to positive effects of the media with accounts of crime in other areas against unfamiliar victims reassuring people of their low risk of crime, what Heath (1984) attributes to feeling safe by comparison. Other studies have failed to find an effect of the media at all, with apparent relationships disappearing when other differences between people are accounted for. This lack of consistency across studies is also true in research examining the influence of the media on levels of crime, leading to the general conclusion that if the media are influential, the impact is likely to be weak, potentially short-lived, and specific to particular people (Reiner, 2007).

Selection bias also seriously hinders the claims made by proponents of the influence of the media promoting fear. This highlights the inherent difficulty in attributing a causal effect of the media on levels of fear, with studies failing to demonstrate that it is the media that is making people more fearful. In reality, it is equally plausible that fearful people are more likely to actively seek out particular types of television program, or read particular types of paper, leading to the appearance that the media causes fear. Therefore, in spite of a large amount of attention levelled at the influence of the media on levels of fear, current evidence is inconsistent.

2.6 Summary

This chapter has outlined the central individual level explanations for variations in fear of crime. This has primarily centred on notions of vulnerability, victimisation experience and the media. Whilst these explanations have all received some measure of empirical support, they do not adequately move beyond observed empirical regularities to provide a more sociologically oriented explanation for differences in fear of crime. In chapter 3 I will extend the scope of the literature review to look at ecological variations in fear of crime, outlining the explanations for fear of crime that emphasise the importance of local community dynamics and the networks of integration within local communities. This will focus on two dominant explanations for ecological variations in fear of crime that have been evident throughout the literature; social disorganisation and the disorder perspective. In addition to these two perspectives, I will also briefly outline the notions of defensible space and subcultural diversity.

CHAPTER 3: EXPLAINING ECOLOGICAL VARIATIONS IN FEAR OF CRIME

3.1 Introduction

The majority of early studies of fear of crime focused their attention on identifying which types of people were the most fearful of crime, identifying differences based on socio-demographic variables, the impact of direct and indirect victimisation experience, and the contribution of the media. Explanations for these variations in fear were primarily atheoretical, with the concepts of vulnerability and victimisation experience introduced to account for the observed differences in fear. Whilst this has proved to be a beneficial mechanism to explain why some groups are more fearful than others, researchers have since looked beyond these empirical regularities to present more theoretically driven models that link fear with the wider context of social life (Hale et al., 1994; Hollway & Jefferson, 1997). These complement individual explanations by incorporating the wider social environment in which people live their daily lives, focusing on much broader processes relating to societal breakdown, the atomization of local communities and the loss of social integration.

Taking broader, ecological variations in fear as its starting point, this chapter outlines these more theoretically driven explanations that focus on the importance of the local social context. By emphasising the importance of local community dynamics, and the networks of integration within local neighbourhoods, fear is presented as something more than simply a response to crime or people's perceptions about their risks of crime, with processes also occurring at the community level. This increased focus on explaining fear in relation to broader sociological processes mirrored the increasing attention given to the influence of areas on individual outcomes in social research more generally (Lupton, 2003), and more empirically driven assessments of regional and neighbourhood variations in victimisation rates (see for example Osborn et al., (1992); and Wilcox-Rountee & Land (2000)).

Like individual explanations for variations in fear, early ecological approaches focused on the impact of differing crime levels, attempting to link variations in fear directly to variations in people's objective risks of crime based on residential location. Therefore, the higher levels of fear in inner-city areas and more socially disadvantaged neighbourhoods were attributed to the higher levels of crime in these areas (Lee, 1982; Liska et al., 1982). This was particularly influenced by left realist examinations of fear based on local victimisation surveys, which argued that when examined at the local level, reported levels of fear more closely matched people's risks of crime (Young, 1988).

However, despite demonstrating markedly different crime profiles at the local level when compared against national figures, direct evidence in support of a link to fear is still limited (Hale, 1996; Vanderveen, 2006). Comparatively few studies have been able to identify a consistent relationship when other ecological characteristics have been incorporated. Instead, when using large scale surveys that allow comparisons between different areas in both levels of fear and levels of crime, research has found that "the patterning of fear across areas does not match the patterning of crime levels" (Taylor & Hale, 1986: 153). This inconsistent relationship is likely to partially reflect data limitations when comparing local areas, with studies still relying on officially recorded crime figures at a broad spatial scale that masks potentially important local differences, but also suggests other important ecological effects are influencing fear.

This failure to identify a relationship with official levels of reported crime has led researchers to look further afield for explanations for area level variations in fear. Hollway and Jefferson (1997) argue that the inconsistent relationship with crime suggests that 'fear of crime' represents something more than simply a 'fear' of 'crime', reflecting the effect of reactions to physical cues from the local environment that the area is in decline, and more general anxieties that are not directly related to crime. To characterise this broader interpretation of fear, studies began to link fear with reactions to the deterioration of the local environment, feelings of a worsening of community life, peoples' sense of isolation, and feelings of a lack of local economic and political power (Donnelly, 1988).

These studies explicitly acknowledge that fear and anxiety about crime are, in part, a product of the context in which they are experienced, with this embedded context a central component of how individuals make sense of their risk of crime (Jackson, 2005). This 'ecological tradition' therefore treats people within spatial proximity to one another as an "interdependent system, in which individual people are influenced by the characteristics of the neighbourhood in which they live" (Elffers, 2003: 351). As a result of this increased focus on the importance of context, researchers began to extend their examinations beyond simple descriptions of the variations across areas, building more detailed and theoretically driven models to explain why these variations occur (Ackah, 2000). This wider meaning of fear of crime is plausible given the paucity of evidence directly linking it to crime, placing fears within a broader theoretical framework whereby a direct response to the threat of crime is only one possible outcome (Taylor & Hale, 1986).

3.2 Social disorganisation

Looking beyond individual differences to explain variations in fear of crime across areas, a number of studies have drawn on elements of the social disorganisation theory of Shaw and McKay (1942; 1969). Social disorganisation is described by Bursik (1988) as the "inability of local communities to realise the common values of their residents or solve commonly experienced problems" (521). As such, it relates to those aspects of local communities that serve to inhibit them from maintaining effective social controls against deviant and disorderly behaviour. Although it was originally used as an explanation for differences in crime and delinquency between different residential locations, researchers have also productively expanded on the central tenets of the theory to incorporate the fear of crime (Kanan & Pruitt, 2002).

A focus on social disorganisation developed out of the early urban sociology work of the Chicago school that had begun to emerge in the 1920s and 30s. These studies emphasised the importance of the physical and social environment in shaping human behaviour and social outcomes, examining the impact of urbanisation and social mobility on a range of individual outcomes. The theory was later formalised in the work of Shaw and McKay (1942), based on their 20 year study of the spatial distribution of delinquency across urban areas in Chicago. Using census reports, juvenile court records and housing data, Shaw and McKay linked local delinquency rates to measures of population change, substandard housing, and economic and racial segregation. Not surprisingly, they identified the highest rates of delinquency in areas of low socio-economic status. Importantly, however, they also demonstrated considerable consistency in these neighbourhood problems across time, despite complete changes in the populations occupying those areas (Snell, 2001). As a result, rather than viewing delinquency as a direct result of a lack of economic resources, they suggested that this occurred in conjunction with the impact of residential change and high levels of heterogeneity, limiting the ability of community's to control their residents .

Shaw and McKay (1942) present three structural dimensions that they argued influence the degree of informal social control open to a community, and consequently its level of delinquency; the socio-economic status of the area; the level of residential mobility; and the degree of ethnic heterogeneity. They suggested that rapid population changes within low socio-economic status neighbourhoods led to a breakdown of formal social organisational traditions, limiting the ability of local communities to informally control the behaviour of their residents and outsiders, and prompting increased delinquency. This obstruction of informal social controls was primarily reflected through restrictions on residents' abilities to develop strong friendship networks within their community, reduced participation in local organisations, and a limited set of social resources available to supervise teenage peer groups.

Neighbourhoods with low socio-economic status were identified as more likely to experience higher levels of residential mobility, disrupting the community's network of social relations as people struggled to form friendship ties with neighbours. Skogan (1986) argues that these locally based social networks were instrumental to a community's capacity for informal social control by making them better able to recognise strangers and more apt to engage in guardianship activities against potentially disruptive behaviour. A reduction in the availability of community ties was thus an important source of reduced informal control over residents. Low socio-economic status neighbourhoods were also likely to have fewer available economic resources, reducing the informal organisations available to residents, which in turn limited their opportunities for active participation in the neighbourhood. This further restricted their ability to control disorderly behaviour (Shaw & McKay, 1942). Additionally, in a more recent assessment of social disorganisation, Sampson and Groves (1989) describe membership of the local community as the embodiment of local solidarity, therefore when participation is low, the capacity for a community to defend its' local interests is weakened.

Shaw and McKay (1942) argued that higher levels of ethnic heterogeneity were another important cause of social disorganisation, impeding successful communication amongst residents and obstructing the formation of common goals and values. This further limits the informal social controls available to the community by reducing consensus over what constitutes disorderly behaviour (Sampson & Groves, 1989). Consequently this leads to the fragmentation of social order as segmented population groups are formed, promoting distrust amongst neighbours and an unwillingness to intervene to prevent deviant activities, further reducing the levels of informal control and leading to higher crime rates (Suttles, 1968).

Social disorganisation had a considerable influence on early ecological research in criminology, with a number of studies produced in the 50s and 60s that drew heavily on this thesis. However, by the 1970s their theory had become considerably less prominent (Bursik, 1988). It was not until the influential study of Sampson and Groves (1989) that the theory of social disorganisation was revived in Criminology, following their formal test of the full disorganisation model. Like the original study by Shaw and McKay, their research took neighbourhoods as the unit of analysis, and demonstrated relationships between heterogeneity, mobility, neighbourhood economic status, and the levels of neighbourhood disorganisation (Sampson & Groves, 1989). Their study went a step further than previous assessments by introducing direct measures of the neighbourhood level of organisational participation, friendship networks, and unsupervised teen groups, which they demonstrated mediated the relationship between the structural measures of disorganisation and the rate of criminal victimisation. This was presented as clear support for social disorganisation theory, showing that the structural characteristics of the neighbourhood influenced crime through the central components of disorganisation.

Sampson and Groves (1989) were also instrumental in extending the single city focus of the original study to allow for comparisons on a national scale. This was achieved by introducing the influence of urbanicity, which they argued was also closely related to the level of community disorganisation. They reasoned that inner city and urban neighbourhoods have a reduced capacity for social control when compared to their rural counterparts, based on the lower ratio of known to unknown neighbours. This leads them to have weaker social networks, making residents more likely to feel socially isolated, and consequently more fearful. Along with the influence of urbanisation, they also argued for the inclusion of a measure of family disruption, characterising the extent of single parent families within the neighbourhood. They suggested that this directly reflects the amount of supervision that parents can offer, with less active supervision resulting in more problems with low level disorder from teen groups. In addition to viewing them as important sources of supervision for their own children, Sampson and Groves (1989) identified parents as important agents of informal social control of other youth within the neighbourhood, further limiting the level of deviant behaviour.

Unlike the original three structural dimensions posited by Shaw and McKay (1942), these additional structural measures were not found to be closely related to the indicators of social disorganisation. Instead they exhibited direct relationships with crime. As a result, they might be better described as important neighbourhood controls that operate on crime independently of social disorganisation. Since Sampson and Groves' (1989) seminal test of social disorganisation theory, their central findings have been replicated on two independent datasets by Veysey and Messner (1999) and Lowenkamp et al., (2003), providing further support for the claims of social disorganisation.

Although it was originally introduced to explain variations in levels of crime across areas, researchers have also drawn on social disorganisation theory to explain neighbourhood differences in fear of crime. There are two dominant ways that social disorganisation has been linked to levels of fear in existing research. The first views fear as a direct response to the levels of crime in the neighbourhood, thus implying a similar relationship between the structural determinants of disorganisation and fear through reduced mechanisms of formal and informal social control (Bursik, 1988). This relationship has since been extended by viewing fear as both a reaction to higher levels of crime in more disorganised neighbourhoods, and as another dimension of disorganisation that may lead people to withdraw from community life, further increasing the extent of crime as informal social controls are weakened (Carr, 2005; Woldoff, 2006). However, whilst this offers a straightforward mechanism to explain the link between structural dimensions of local areas and the levels of fear, it does not reconcile the inconsistent relationship between fear and recorded crime in existing research. Additionally, the lack of available longitudinal data means that it has not been possible to empirically test the existence of a feedback loop between crime and fear of crime.

The second approach focuses on the importance of feelings of isolation that are evident in areas with fewer social ties between residents. These feelings lead people to believe they would not receive help in a crisis, prompting a belief that the negative consequences of crime will be greater (Adams & Serpe, 2000; Wilkinson, 1984). This has clear links with individual notions of vulnerability and victimisation experience, with more vulnerable people being more likely to perceive the neighbourhood as less able to deal with crime and being more affected by restricted support networks. Additionally, they are also expected to judge the consequences of crime to be more serious, based on their own vulnerability and the structure of the community. However, despite being framed as an integrated perspective that incorporates individual vulnerability, empirical evidence in support of the direct interaction between disorganisation and vulnerability is largely absent from contextual treatments of fear of crime.

The lower levels of community involvement in more heterogeneous and unstable neighbourhoods might also imply that fewer people in the area are familiar, leading to higher levels of anxiety and further withdrawal from the local community (Krannich et al., 1989). In contrast, more socially integrated neighbourhoods are expected to have stronger networks of local support, alleviating the levels of fear from residents (Hale, 1996). This approach also highlights the important part that informal social control has on levels of fear, with residents in more disorganised neighbourhoods perceiving themselves to have less influence on the behaviour of others, leading to increased fear (Lewis & Salem, 1986; Taylor & Covington, 1993). It thus implies that social disorganisation can influence fear of crime largely independently from its impact on levels of crime.

Despite the popularity of social disorganisation as an explanation for neighbourhood level variations in crime and fear, several criticisms have been levelled at the original theory. Bursik (1988) argues that the strict focus on neighbourhood processes in the original theory abstracts them from important individual dynamics that may also be instrumental in explaining fear of crime. Therefore, the theory fails to successfully incorporate the knowledge that has been provided by individual level theories to explain how individual and neighbourhood processes interact to generate fear. Bursik and Grasmick (1993) further argue that the original theory is too narrowly focused on the interpersonal networks of social control between residents within communities, calling for an increased emphasis on the wider public sphere of control. Identifying neighbourhoods that experience high levels of delinquency, yet also display strong local networks of informal control, they highlight the potential importance of agencies external to the local community for maintaining order such as community policing, which operate in tandem with informal controls.

Other researchers have questioned the measurement of disorganisation as a construct that is distinct from its outcomes, suggesting that unsupervised teen groups may in fact better be classified as a less serious form of deviance, rather than an indicator of disorganisation (Veysey & Messner, 1999). Whilst this presents us with a clear tautology when considering variations in levels of crime, the implications for fear of crime are less severe, leading to the development of the disorder perspective (outlined below). Finally, Rosenbaum (1987) questions the implicit assumption that social organisation is a positive influence within communities, suggesting that formal and informal controls within the neighbourhood may actually increase levels of fear. Rosenbaum argues that social control mechanisms may actually result in a negative community environment, with increased informal surveillance increasing the pressures on individuals in the form of discrimination, and increasing individuals' suspicion of other residents, leading to higher levels of fear. This negative effect of formal control mechanisms was demonstrated in a study by Crawford (2003), where the increased presence of uniformed police within a neighbourhood was associated with higher levels of fear from residents.

As a result of some of these criticisms, researchers have extended the original social disorganisation theory set out by Shaw and McKay (1942). These perspectives adopt many of the central elements of social disorganisation theory, and rely on the same objective structural dimensions. They differentiate themselves from the main theory by placing varying emphasis on particular aspects of social disorganisation and expanding on its' central mechanisms.

3.2.1 Neighbourhood control

Bursik and Grasmick (1993) present a more elaborate form of social disorganisation in their neighbourhood control theory. This acknowledges the overlapping and conflicting sources of organisation in a given community to present a more complex conceptualisation of informal social controls (Jensen, 2005). Pointing to the existence of neighbourhoods that have extensive personal networks facilitating informal social controls, but which nevertheless have relatively high rates of crime, they argue for the need to incorporate the wider context of formal controls (Bursik & Grasmick, 1993). In particular they highlight the influence of external market forces instigating community changes that can have an influence on levels of crime in addition to the effects of informal local controls. To account for this, Bursik and Grasmick (1993) differentiate between three distinct sources of informal social control, which they argue are all influential in determining the extent that a community can informally restrict the deviant behaviour of residents and outsiders. These are referred to as the private, parochial and public levels of control.

Unlike the original treatment of social disorganisation theory outlined by Shaw and McKay (1942), Bursik and Grasmick (1993) distinguish between private and parochial forms of control. Primary ties between close family and friends form the private level of social control, with pervasive interpersonal ties amongst residents resulting in a higher degree of control. These family networks are identified as an important source of local informal control, intervening in the group activities of local youth that are often the precursors to more serious delinquent behaviour. In contrast, the parochial level of control refers to the supervisory capacities of a community that are the result of broader relationships amongst people, and membership of social institutions such as churches, schools and businesses (Jensen, 2005).

However, the principle extension to the original social disorganisation theory is the inclusion of the broader, public level of control, which more explicitly recognises the wider context in which informal social controls operate. Bursik and Grasmick (1993) relate this public level of control directly to a local neighbourhood's ability to obtain public goods and services that are allocated by agencies external to the community, which they argue are instrumental in limiting levels of crime and reducing fear. They suggest that a local community's ability to organise effectively against crime problems will be partially dependent on their ability to influence the public decision making agencies that are responsible for delivering these resources to the community (see also Carr, (2005)). For example, the level of community policing and the resources provided to implement local crime control initiatives are both controlled by agencies external to the neighbourhood, and these are identified as important sources of social control within the community (Herbert, 2005).

In a study of 66 Baltimore neighbourhoods, Snell (2001) provides an extensive test of this perspective, and its relationship to levels of fear. Incorporating the influence of agencies of public control within the traditional social disorganisation framework, he finds no support for the additional influence of public sources of control once other dimensions of social disorganisation have been included. However, this is based on a sample of only 66 neighbourhoods, and uses a limited operationalisation of public control that only measures the willingness of the police to intervene in a variety of local disturbances. Therefore, it is possible that with a more detailed set of measures, public sources of social control may be demonstrated to have an effect on residents' levels of fear.

3.2.2 Collective efficacy

Sampson et al., (1997) introduce a further evolution of social disorganisation theory, focusing on the part that 'collective efficacy' has to play in influencing levels of crime, and indirectly fear. Essentially, this can be thought of as the opposite to disorganisation, highlighting the positive control mechanisms available in organised communities. Here they argue for the important roles of the level of mutual trust and cohesion amongst residents within a community, which interact with a neighbourhood's capacity for informal social control. These are identified as group level influences that can positively impact on the ability of a community to realise its collective goals by increasing their willingness to intervene for the common good. This occurs by enhancing the capacity of a neighbourhood for mutual cooperation amongst residents (Sampson et al., 1999).

Collective efficacy was introduced as a neighbourhood level consequence of social capital (Putnam, 2000), highlighting the importance of levels of trust between residents for facilitating informal social control mechanisms. Therefore, whilst a community may have strong social networks facilitating the informal control of disorderly behaviour, without strong feelings of trust and cohesion amongst residents, they may be unwilling to confront people that are disrupting public spaces. This results in a reduced capacity to regulate disorderly behaviour. Similarly, lower levels of collective efficacy will limit residents' willingness to tackle low level physical signs of disorder within the community

(Sampson et al., 1997). Sampson and Groves therefore argue that more socially cohesive neighbourhoods are "fertile contexts for the realisation of informal social control" and that considerable variation in the extent of cohesion across communities is instrumental in explaining the variations evident in levels of crime and fear (919).

Collective efficacy is thus identified as another important mediator between the structural determinants of social disorganisation and levels of crime and fear. In their study of variations in levels of crime across 343 Chicago neighbourhoods, Sampson et al., (1997) find that collective efficacy does partially mediate the relationship between social composition and levels of violence. This is true even when controlling for friendship and kinship ties, organisational participation and neighbourhood services, providing strong initial support for their perspective. Looking specifically at fear of crime, Jackson (2004) uses SEM methodology to test a model where collective efficacy influences peoples' perceptions of both the extent of crime in the area, and their perceived risk of being victimised, which in turn feed into specific incidents of worry about crime. Jackson finds empirical support for this model, arguing that it provides strong initial evidence that fear of crime is partly a reflection of collective feelings of trust and social cohesion. However, this was based on a relatively small cross-sectional postal survey in a small area of London, suggesting the need for a more extensive test of the claims about the role of collective efficacy.

3.3 The disorder perspective

The other commonly used explanation for ecological variations in levels of fear is the impact of low level disorder. The disorder perspective is a direct descendant of social disorganisation that takes as its starting point social disorganisation's focus on the presence of unsupervised teen groups as a symbol of reduced neighbourhood social control. Despite featuring within the original treatments of fear of crime by Biderman et al., (1967), it was Hunter (1978) who was the first to explicitly formulate the disorder perspective (also regularly referred to as incivilities, or signs of crime). In his work, Hunter introduces a range of signs of low level disorder that are present in the local neighbourhood environment which he links to higher levels of fear of crime. These include signs of vandalism, abandoned buildings, graffiti, and unchecked litter. He argues that areas experiencing higher levels of social disorganisation will also exhibit more signs of disorder as they lack the social and economic resources to control disorderly behaviour and deal effectively with low level signs of physical deterioration (Kanan & Pruitt, 2002). This in turn promotes higher levels of fear, acting as an important symbol of the extent that the neighbourhood is in decline, and providing clear visual cues for residents that warn them of their potential risk (Ferraro, 1995).

Hunter (1978) further argues that fear of crime is fundamentally a fear of disorder, which he identifies as an important indicator to people of the extent of crime. He goes on to suggest that disorder is likely to have a stronger influence on people's fear than crime will. This is because disorder is often more visible within the local neighbourhood than crime, and will also be more prevalent as it captures a broad range of low level signs of deterioration. Lane and Meeker (2003b) expand on this argument, suggesting that disorder will also be more closely linked to fear because it acts as a symbol of "deeper, underlying problems in the area", in particular the lack of effective social control mechanisms available to the community (431).

The disorder perspective was quickly extended, with Wilson and Kelling's (1982) influential 'broken windows' thesis drawing heavily on the earlier work of Hunter (1978). Wilson and Kelling incorporate levels of crime within their disorder model, highlighting the important role that unrepaired physical signs of disorder play in eroding community trust and promoting further disorder. They argue that this erosion of community bonds will encourage additional disorderly behaviour amongst residents by providing 'cues' to potential offenders that disorder will be tolerated. At the same time, disorder discourages residents from intervening by fostering the belief that the local community is not well equipped to deal with deviance. For Wilson and Kelling then, physical signs of disorder are thought to lead to fear, which in turn promotes more disorderly and deviant behaviour. This theory has recently formed the basis of Innes' (2004) 'signal crimes perspective', in which he explores how signs of disorder within a local community come to be defined as potentially dangerous and hence indicators of potential risk that lead to fear.

The disorder perspective was further extended in the work of Skogan (1990), who called for a stronger distinction between sources of physical and social disorder. This separates the influence of physical signs of neighbourhood decay from the social expressions of a loss of community control that are represented by groups of unsupervised youth, unchecked drunken behaviour, noisy neighbours, and visible signs of drug use. These sources of social disorder have since been labelled as anti-social behaviour, and now feature alongside crime in official Home Office reports (see for example Nicholas et al,. (2007)). However, recent examinations of the impact of disorder have rarely been able to identify a clear distinction between the two sources of disorder in relation to levels of fear, suggesting that disorder may be better treated as a unidimensional influence (see for example Roh and Oliver, (2005)).

Researchers have also extended the disorder perspective by attempting to place it within the context of individual differences in fear. For example, McGarrell et al., (1997) suggest that individual differences in levels of fear are dependent on the levels of disorder identified within the local neighbourhood. In this study they demonstrate that in the absence of high levels of disorder, individual differences exert a strong influence on levels of fear, with sharp differences between victims and non-victims. In contrast, when people see more disorder within the local area, the effects of individual differences are muted. A similar finding is also demonstrated by Wilcox-Rountree and Land (1996b), who find that the effects of previous victimisation on fear of burglary are considerably weaker in neighbourhoods that do not report much disorder. Along with the link to victimisation experience, individual vulnerability also links to the impact of signs of disorder within the neighbourhood, with vulnerable people drawing more heavily on environmental cues to form judgements about the extent of crime and their own personal risks of crime (Killias, 1990; Vanderveen, 2006). However, despite featuring within theoretical treatments of disorder, this has yet to be empirically verified within an integrated assessment of the individual and contextual influences on fear.

Finally, Robinson et al., (2003) provide us with the only longitudinal evidence of the impact of disorder on fear, confirming its central propositions and providing the first evidence of a causal effect of disorder on fear. Using two waves of data they find that those who initially saw more disorder than their neighbours became increasingly dissatisfied with the neighbourhood, as did those seeing an increase in disorder. Importantly, they also find that individuals who see disorder increasing report significantly higher levels of fear.

The large majority of research examining the disorder perspective has focused on the relationship between perceived disorder and fear, using indicators that require respondents to rate 'how much of a problem' various social and physical signs of disorder are in their local neighbourhood (Vanderveen, 2006). These models argue that people witness disorder, and form opinions about how much of a problem it is, and how much it impacts on their daily lives. These internalised feelings about disorder in turn manifest themselves in higher levels of fear or safety. However, some researchers have questioned the utility of using such perception measures to assess the relationship between fear and disorder, arguing that they may present us with an inaccurate picture as a result of methodological limitations (Perkins & Taylor, 1996; Sampson & Raudenbush, 1999; Taylor, 2001; Tseloni, 2007).

These researchers question the assumptions implicit in treatments using perceived disorder that those who perceive disorder to be more of a problem in the local areas will consequently have higher levels of fear. They go on to argue that it is equally plausible that people who have higher levels of fear will be more likely to report signs of disorder as problematic. This highlights the parallel nature of fear of crime and perceptions of disorder being a problem in the local area, questioning the causal ordering implicit in many existing studies. Additionally, Taylor (2001) highlights the high degree of variability in perceptions of disorder amongst residents from the same neighbourhood as a demonstration that they may be unsuitable as measures of disorder.

Consequently, the use of more objective measures of low level disorder has been advocated. These rely on interviewer assessments of the local area to characterise the extent of disorder, helping to mitigate the problems inherent in earlier perception measures. The results from a series of studies that use these objective measures of disorder indicate a weaker and inconsistent relationship between disorder and fear (Perkins & Taylor, 1996; Taylor, 2001). This suggests that the impact of disorder may have been overemphasised in previous studies because of a reliance on perception measures. A similar focus on objective measures was adopted by Sampson and Raudenbush (1999) in their study of the relationship between disorder and levels of crime in Chicago neighbourhoods. Here they employed systematic social observation methods to accurately document the extent and nature of low level disorder across 23,000 street blocks in approximately 200 local neighbourhoods. This was done using recording equipment and trained observers to ensure all instances of disorder were accurately captured and coded. Using this data they demonstrated links between the structural characteristics of an area and the levels of disorder. However they went on to show that the link between disorder and experience of crime was largely spurious once individual differences had been incorporated (Sampson & Raudenbush, 1999). Despite suggesting that the relationship may not be as strong as previous proponents of the disorder perspective have claimed, currently there is only limited evidence that has linked objective disorder to levels of fear, with the collection of objective data on the extent of disorder often prohibitively expensive.

An extension to the disorder perspective is provided by the introduction of the importance of community concern. This was first outlined in the work of Garofalo and Laub (1978), and introduces the importance of residents' perceptions of community dynamics. It therefore broadens the disorder perspective by suggesting that signs of disorder in a neighbourhood lead to increasing concerns from residents that the community is deteriorating, and potentially unsafe. This increased concern about the state of the community may in turn lead residents to feel more vulnerable, leading to higher levels of fear. Therefore, this perspective argues that neighbourhood disorder is related to fear indirectly through its influence on residents levels of community concern (Taylor & Hale, 1986). This also allows for an indirect relationship between levels of crime and fear through community concern.

Proponents of the community concern model emphasise the importance of local social ties within the community, which they argue are critical in determining the extent that low level disorder results in feelings of concern (Covington & Taylor, 1991). This means that residents are more likely to translate observed disorder within the neighbourhood into increased concern that the community is in decline if they have weak social ties with their neighbours. In contrast, in neighbourhoods with strong social ties, the impact of low level disorder on community concern will be significantly dampened, and hence fears will be less affected.

Testing the community concern perspective, Lane and Meeker (2003b) find a positive relationship between concern and fear of gang crimes, with the extensions provided by the community concern model performing significantly better than the basic disorder model. However, there is still relatively little evidence in support of the community concern perspective, with many studies failing to find a direct relationship between levels of community concern and fear. For example, despite demonstrating a positive relationship between levels of disorder and feelings of concern that the neighbourhood is in decline, Taylor and Hale (1986), found no direct relationship between concern and levels of fear. Instead they find a direct relationship between disorder and fear, concluding that there is greater support for the disorder perspective. Consequently the influence of community concern has received relatively little attention as an explanation for variations in levels of fear (Hale, 1996).

3.4 Defensible space

An alternative model to explain variations in fear is presented by Newman and Franck, (1982) who use their concept of defensible space to demonstrate that fear of crime is affected by the built environment (originally introduced in Newman, (1978)). Highlighting the importance of accommodation type and the effect of property design, Newman and Franck (1982) argue that a community's capacity for social control is directly influenced by the physical design of the neighbourhood. Drawing on ideas of 'territoriality', they argue that the design of the local area can either foster increased opportunities for informal surveillance and a more proprietary attitude towards the immediate neighbourhood, or promote restrictions on informal social control with the creation of isolated 'out of sight' areas that are difficult to oversee. Critical to the sense of ownership that the local area engenders is how the space is marked out and bounded, with a clear demarcation between private and public areas encouraging local residents to have a stake in the local area; caring for it, policing it, and reporting strangers and others who have no apparent good purpose to be there (Rock, 2007).

A number of researchers have demonstrated direct links between the built environment and fear, with Newman and Franck (1982) demonstrating that fear was higher amongst residents of larger housing blocks. Similarly, Taylor et al., (1984) report that the presence of surveillance opportunities and physical barriers that restricted access to parts of the local area, were associated with lower levels of fear. Other physical elements of the built environment have also been linked with reductions in fear of crime, with the increased use of surveillance cameras (Gill & Spriggs, 2005) and improved street lighting (Vrij & Winkel, 1991) featuring in research (see also Schweitzer et al., (1999)). However, Merry (1981a) highlights areas that qualify as architecturally defensible, yet which nevertheless go undefended by local residents. She therefore argues that the social processes involved in whether residents informally protect their local environment are more important than physical attributes of the area.

3.5 Subcultural diversity

Researchers have also identified a direct link between neighbourhood ethnic heterogeneity and variations in fear of crime, arguing that the higher fear amongst people living in more diverse areas reflects the impact of subcultural diversity (Merry, 1981b). The subcultural diversity thesis can be viewed as a specific application of 'conflict' theory, which has primarily been used to explain lower levels of trust in more ethnically diverse neighbourhoods (Putnam, 2007). This characterises diversity on the basis of 'insider' and 'outsider' groups within an area, with insiders those that share the dominant ethnicity of the community, and outsiders identified as those that are of a different ethnicity. Conflict theory focuses on the importance of the presence of 'others' in reducing social solidarity. This leads to inter-group tensions and fosters out-group suspicions, resulting in higher levels of fear. These inter-group tensions have also been linked with a reduced likelihood of effective socialisation within a neighbourhood, making residents less likely to intervene to solve problems like low level disorder (Taylor & Covington, 1993).

Proponents of subcultural diversity argue that fear of crime will be higher amongst those living in close proximity to people from different cultural backgrounds, with the manners and behaviours of other groups identified as fear inspiring (Covington & Taylor, 1991). This effectively captures people's fear of strangers, with increasing social uncertainty amongst people who live in diverse neighbourhoods. This is also closely linked to levels of community involvement, with subcultural diversity promoting feelings of social isolation amongst those living in neighbourhoods with high proportions of residents from cultural backgrounds different to their own. In this way, subcultural diversity can also be linked with collective efficacy as an important restriction on community cohesion (Adams & Serpe, 2000; Lane & Meeker, 2003b).

A number of studies have identified a direct link between the ethnic composition of the neighbourhood and levels of fear (see for example the work of Covington & Taylor (1991); Taylor & Covington (1993); and Lane & Meeker (2003b)), arguing that this reflects fear of those who are different. In contrast to this emphasis on the structural composition of the neighbourhood, Chiricos et al., (1997; 2001) argue that it is people's perceptions of the level of ethnic diversity that is the driving force behind variations in levels of fear. Controlling for a range of demographic characteristics they demonstrate significantly higher levels of fear from people that perceive themselves to be living in more diverse neighbourhoods. Despite evidence in support of this thesis, research has yet to carefully examine whether the effects of higher levels of diversity are the same for all types of individual, with current research implying that subcultural diversity has a universal effect irrespective of individual differences.

In contrast to this negative impact of ethnic diversity, 'contact' theory suggests that ethnic diversity may have a positive effect on community relations. Proponents of contact theory argue that the presence of 'outsider' groups might actually result in higher levels of social solidarity, by fostering increased tolerance of those identified as 'outsiders' (Putnam, 2007). From this perspective, increased contact with those that are different actually serves to enhance the community bonds within the neighbourhood, strengthening the available informal social controls within the community to deal with low level disorder. However, this has received considerably less empirical support than conflict theory, with existing evidence restricted to the impact of diversity on levels of trust (Putnam, 2007).

3.6 Summary

Variations in fear of crime have been explained with reference to a number of different mechanisms throughout the literature, drawing both on differences between individuals, and the impact of wider contextual effects. Early explanations focused primarily on individual differences in fear, highlighting the importance of feelings of vulnerability, previous victimisation experience and the impact of the media. Despite providing a useful framework for describing individual differences in fear, these explanations have suffered from inconsistent findings throughout the literature, limiting their use as general theories for differences in fear.

More detail has been given to the fear of crime debate with the incorporation of more theoretically driven explanations that examine the ecological and community level influences on fear. These theories are largely complementary to the individual theories of fear of crime, with clear links to individual processes throughout. Primarily drawing from social disorganisation theory and the disorder perspective, researchers have tested complex theoretical models that detail how structural characteristics of local neighbourhoods impact on the ability of communities to control deviant behaviour and limit public anxieties. They have also highlighted the importance of environmental cues in the formation of individual fears, describing how individuals use the local environment in judgements of individual risk and the consequences of crime. As such, these models have examined fear of crime within the broader context of local area processes, extending our understanding beyond the identification of fearful population groups.

However, despite providing additional detail on the neighbourhood level processes that foster fear amongst their residents, and presenting theoretical models that link contextual influences back to individual differences in fear, there is currently only limited empirical evidence to support these linkages between individuals and the context in which they live their lives. As a result, it remains unclear the extent that ecological characteristics of the local neighbourhood are experienced universally by all types of people, or whether some groups really are more susceptible to ecological influences than others. In addition to this, many of the existing treatments of neighbourhood level effects are methodologically flawed, potentially leading to inaccurate inferences about the relative importance of area differences.

In chapter 4 I will outline the existing methods that have been adopted to assess the effect of local area differences on fear, arguing that assessments relying on aggregation and disaggregation techniques omit important individual level variations, or fail to adequately incorporate environmental characteristics. I will then introduce the multilevel framework, which enables researchers to incorporate area level analyses within assessments of individual level processes. Multilevel models also offer a flexible system for examining how individual processes vary across areas, and how different types of people experience area based influences differently. This makes it ideal for correctly combining individual assessments of fear with more theoretically driven models that argue for the importance of neighbourhood level processes. Chapter 4 then tests for the existence of contextual variations in fear of crime, net of individual differences, acting as a starting point for an integrated assessment of the individual and contextual influences on fear.

CHAPTER 4: INTRODUCING A LOCAL AREA FOCUS TO NATIONAL ASSESSMENTS OF FEAR OF CRIME

4.1 Introduction

In chapter 2 I critically assessed the theories that have been introduced to account for variations in fear of crime. I argued that early explanations were largely atheoretical, and limited to describing individual level differences. In chapter 3 I then introduced a series of more theoretically driven explanations that have been used to incorporate the importance of social context. Focusing primarily on social disorganisation and neighbourhood disorder, I argued that these have provided an alternative, more sociologically driven explanation for variations in fear. However, I also identified a tendency for these theories to be restricted to ecological variations, with only limited evidence linking these contextual explanations back to individual differences in fear.

The following three chapters provide a detailed assessment of the local neighbourhood influences on individuals' levels of fear of crime, using a nationally representative crime survey. By adopting a multilevel modelling strategy, individual differences in experiences of fear are modelled within the context of the local neighbourhoods in which people live. This helps to identify the extent that individual levels of fear of crime are shaped by the characteristics of the local neighbourhood.

In this chapter I outline the existing methodological approaches to the measurement of ecological influences on fear of crime, arguing that methods of aggregation and disaggregation fail to effectively incorporate individual and contextual data. I then introduce the multilevel modelling strategy that is adopted in this thesis to incorporate the structural dimensions of social disorganisation, explaining how this differs from the methods that have typically been used to incorporate the influence of context. I then present an initial application of these methods to the BCS, a nationally representative survey of people resident in England and Wales, to assess the extent that observable neighbourhood characteristics influence individual levels of fear. This begins with the specification of a full individual level fear of crime model, with covariates included that relate to notions of vulnerability, victimisation experience, and the impact of the media. This represents the first step in more efficiently incorporating local context within an individual level assessment of fear of crime, testing whether any significant local area effects on fear exist when known individual variations have been accounted for.

In chapters 5 and 6 I will then elaborate this simple extension to standard regression techniques to enable a more nuanced assessment of the influence of local neighbourhoods on fear. Drawing on social disorganisation theory and the impact of objective disorder in the local environment, I will introduce a series of environmental measures derived from the census to characterise local neighbourhoods. These will be included at the neighbourhood level, and assessed in relation to observed individual differences to provide a test of the importance of contextual explanations for variations in fear of crime. I will then go on to question some of the assumptions implicit in neighbourhood effects research, allowing individual level relationships with fear to vary as a function of neighbourhoods. This will more clearly situate people within their local environment, allowing an examination of how fear of crime is experienced at the neighbourhood level.

4.2 Modelling the fear of crime

As I outlined in chapter 2, the origins of fear of crime research can be traced back to the advent of victimisation surveys, and the increasing prominence that this gave to victims within criminology (Zedner, 1996). In particular, questions covering fear of crime were covered in the early victimisation surveys conducted in America as part of the PCLEAJ in 1967 (Jackson et al., 2006) and then went on to be included in the NCVS that was introduced in 1972. In the UK context, fear of crime has featured prominently in all BCS and associated reports since the first wave was conducted in 1981 (Hough & Mayhew, 1983), with the survey itself strongly influenced by the NCVS.

This close link with national victimisation surveys had a direct impact on the focus of early research, with the use of nationally representative cross sectional survey data resulting in analyses largely restricted to the identification and explanation of general differences in reported levels of fear (Hale, 1996). This initially centred on the apparently contradictory finding that when examined nationally, peoples' levels of fear did not appear to match their objective risk of criminal victimisation with the least at risk of crime reporting the highest levels of fear and vice versa (Mayhew & Hough, 1988).

The early focus on overall differences between objective levels of risk and personal levels of fear for different types of people faced considerable criticism for masking important variations in risk and fear at the local level (Young, 1988). This criticism was largely guided by evidence from a number of local surveys conducted in the 1980s demonstrating that when examined at the local level, fear more closely resembled the risks of crime in the area (Hanmer & Saunders, 1984; Jones et al., 1986; Kinsey, 1984). These studies showed that in local areas with particularly high crime rates, the fear of local residents was noticeably higher than in less crime ridden neighbourhoods. In direct contrast to the aggregate picture resulting from national survey data, evidence therefore suggested that a more nuanced local approach was necessary to accurately model variations in fear of crime.

Around this time we also began to see a resurgence of interest in ecological theories of crime, in part driven by the increased prominence given to social disorganisation theory (originally explicated in the work of Shaw and McKay (1942)), and a growing emphasis on the importance of neighbourhood disorder (Lewis & Maxfield, 1980). This fostered an increased interest in the impact of area based influences on fear of crime, with a number of studies attempting to incorporate the effect of environmental differences to provide a more detailed account of variations in levels of observed fear (Hale, 1996). These approaches have identified important contextual influences on fear, placing a greater emphasis on the impact of the wider social and physical environment (for a full review see chapter 3).

4.2.1 Modelling area differences in fear

Two methodologically distinct approaches to analysing the effect of contextual influences on levels of fear can be identified in early research. These have demonstrated important neighbourhood level influences associated with differences in fear that have been explained with reference to social disorganisation and the impact of disorder. However, both methodological approaches suffer from important limitations which highlight the need for an integrated approach to better incorporate local contextual influences.

One such method of examining contextual influences on fear was to use the clustered sample designs common in survey research to construct aggregates of individual level measures at the cluster level (see for example Sampson & Groves' (1989) test of the central tenets of social disorganisation). These were then used in place of individual level measures and examined at the cluster level as a function of contextual measures taken from various administrative sources. These data were analysed using standard analytic techniques to provide a focus on the macro differences between areas, instead of the micro differences between individuals. This ensured that area measures were examined at the correct level of influence, yielding unbiased standard errors and statistical tests.

There are several limitations with this aggregate approach which mean it can only provide a partial picture of the influence of areas on individual outcomes. Most notably perhaps, by restricting the analysis to the aggregate level, all variations between individuals within each area are removed from these analyses. Whilst area based differences may be identified, it is not possible to make any inferences about individual differences or how these may be related to area differences. This is an inefficient use of the available data, limiting the scope of substantive inference (Goldstein, 2003).

This also results in a 'shift of meaning' of fear of crime and the other individual measures that are aggregated to the area level (Snijders & Bosker, 1999). These measures are now averages for the area, rather than corresponding to the responses of particular individuals living within that area. Whilst some measures may make conceptual sense when treated at the aggregate level, reflecting characteristics such as area disadvantage and its ethnic structure, it is less clear what the meaning of an aggregate of fear of crime at the neighbourhood level actually represents. This has resulted in studies routinely making erroneous conclusions about the area influences on individual levels of fear using data that should be restricted to a focus on the area influences on average levels fear at the area level, an error commonly referred to as the ecological fallacy (Alker, 1969).

A further problem relates to the reliability of estimates derived by aggregating individual responses to the cluster level. The reliability of aggregate measures is directly linked to the number of responses used to construct them. Typically a minimum of 30 responses within each area is required to obtain reliable estimates (Ludtke et al., 2007; Snijders & Bosker, 1999). This is problematic when using clustered sample data where unbalanced cluster sizes can be fairly common, resulting in measures estimated with varying reliability. It is therefore difficult to be sure of the extent to which results are a function of the uneven sample sizes in each area, as opposed to a reflection of real area differences.

Other studies have used clustered sample designs to identify the areas that respondents are resident in, and then taken contextual data from administrative sources and linked it directly to respondent level data within single level regression models (see for example Hale et al., (1994)). Covariates describing differences between areas can then be incorporated alongside individual level variables to assess the effects of area characteristics on levels of fear.

However, this method is also problematic, failing to account for the fact that area level attributes occur at a higher level of aggregation than individual attributes. The implication of this is that they will be shared by all of the individuals living within the same locally defined area, so there will be complete dependency across individuals from the same cluster on these area level measures. When a number of survey respondents are all clustered in an area that is described by a common area measure, the sample size that the estimates of the area effect are based on will be artificially inflated if it is treated as an individual level variable (Snijders & Bosker, 1999). For example, although we may have a sample of 200 respondents, if they are geographically clustered within 20 areas then estimates of area characteristics will be based on the sample of 200 individuals when they should in fact be based on the 20 areas. The implication of this is that standard errors will be underestimated, increasing the likelihood of making type I errors (Goldstein, 2003).

Treating area level data as further individual level information also erroneously assumes that all of the differences between areas are accurately captured by the included contextual effects (Snijders & Bosker, 1999). This is generally not a realistic assumption given the range of potential influences at the area level. This also means that it is not possible to accurately assess the relative contribution of the included area level effects, or how well a proposed model fits the data.

4.2.2 Multilevel examinations of fear of crime

In response to these problems some more recent studies have begun to adopt a multilevel framework to examine area differences in fear of crime. A multilevel approach allows for multiple levels of influence on the outcome variable, with individual and area effects incorporated at the correct level of influence (for a detailed explanation of multilevel modelling see section 4.5). This correctly accounts for the higher than average similarity between residents of the same local area, and ensures that neighbourhood level measures are incorporated as ecological effects. However, despite the clear benefit this offers for an integrated assessment of individual and ecological influences on fear, studies using these models are still relatively scarce because of a lack of suitable data.

The first studies to incorporate between area variability along with individual differences in fear were conducted by Taylor et al., (1984), and Covington and Taylor (1991). Both of these studies are based on the same data, using responses from 1,557 individuals taken from 66 Baltimore neighbourhoods. Drawing on elements of social disorganisation theory, Taylor et al., (1984) demonstrate a direct link between the extent of local ties on levels of fear, which is partially mediated by the degree that people are willing to intervene to solve common problems. In contrast, Covington and Taylor (1991) focus on the ecological influences on fear, identifying significant area level influences of ethnic composition and socio-economic status, in addition to the effect of community integration. Using a measure of objective neighbourhood disorder, they further demonstrate the importance of objective low level signs of neighbourhood decline. The inclusion of these neighbourhood level measures account for 7.5% of the total variation in levels of fear, demonstrating that neighbourhood differences appear to have an important part to play in explaining variations in fear

However, despite incorporating individual and area variability, neither of these studies is fully multilevel. Instead, individual level data is transformed into neighbourhood means and the individual deviations from these means. Whilst this represents a considerable advance over previous studies, it still assumes that all area differences are incorporated in the fixed effects that are included in the model. As a result, it is possible that there is additional unexplained variation in fear at the area level that has not been accounted for (Snijders & Bosker, 1999). Additionally, with the exception of neighbourhood disorder, all neighbourhood measures are aggregates of individual level data, potentially leading to unreliable estimates (Ludtke et al., 2007). Both studies also rely on a global measure of fear of crime, therefore it is unclear the extent that they are accurately capturing variations in fear as opposed to variations in the perception of risk (see the earlier discussion on problems of definition and measurement in section 1.3). Finally, they both rely on data from a single U.S city, limiting their generalisability across cities, and to the UK context.

Using the same data, Snell (2001) extends these analyses by adopting a full multilevel formulation. His study demonstrates that approximately 13% of the initial variance in global fear can actually be attributable to local area differences, considerably more than was suggested by the earlier studies. Snell also extends the earlier analyses by incorporating census data to reflect objective neighbourhood socio-economic status, ethnic composition, and stability. When these measures are included he finds that they explain approximately 70% of the neighbourhood variation in fear, demonstrating strong support for their inclusion. Snell then goes on to demonstrate that the effect of these structural characteristics is mediated by the influence of perceived disorder. However, this study also suffers from some of the same limitations as the early analyses, with the 'global' measure of fear less than optimal. Additionally, the small sample of neighbourhoods taken from a single city significantly limits the scope of the area component of the model, suggesting the need for a cross-city comparison. Finally, the large effect of disorder may reflect the decision to use perceived disorders rather than a more objective measure (Taylor, 2001).

Wilcox-Rountree and Land (1996b) also use multilevel models to examine variations in fear of crime. Using a considerably larger dataset from 300 neighbourhoods across 100 census tracts in Seattle, they assess the ecological impact on general measures of safety, as well as burglary specific fear. This study found that neighbourhood differences made a significant contribution to both dimensions of fear of crime, and again highlighted the importance of disorder and the extent of social integration. Additionally, they demonstrate an important interaction between disorder and victimisation experience when considering fear of burglary, with the impact of previous victimisation significantly weaker in areas suffering from higher levels of disorder. They argue that this reflects the tendency of neighbourhood differences to 'overwhelm' individual differences when assessed together, providing strong support for models that incorporate the impact of context (Wilcox-Rountree & Land, 1996b). This study also incorporated a measure of objective crime levels based on police recorded data, however this was not significantly related to either measure of fear, and had very little impact on the other neighbourhood level measures. This study was later expanded to examine fear of violence (Wilcox-Rountree, 1998), and perceptions of crime risk (Wilcox-Rountree et al., 2003), with similar findings about the impact of disorder.

Wilcox-Rountree and Land (1996b) also use measures of perceived disorder aggregated to the neighbourhood level, rather than including objective measures of disorder. This means that it is again unclear the extent to which they are actually measuring a neighbourhood construct that is distinct from fear. They also report that their selected sample is likely to under-represent neighbourhoods that have low levels of crime, with neighbourhoods selected to ensure at least one victim per sampled area. It is possible that different effects might be observed in neighbourhood suffering from lower levels of crime, signalling the need for a fuller exploration of a range of different area types. This study also relied on measures of crime at a significantly broader spatial scale than their neighbourhoods were defined at. As a result, the failure to identify a relationship with crime may actually reflect the insensitivity of their measure to local variations in crime.

Robinson et al., (2003) present the only longitudinal multilevel assessment of the impact of disorder on fear. Using a number of different dimensions of fear, they find a significant area contribution that accounts for approximately 18% of the total variation in global fear. In contrast, they find no area level variation in a measure of fear based on 'worry' indicators, suggesting that specific crime fears may be less contextually embedded than the general risk perceptions captured by the 'global' indicator. Robinson et al., (2003) also demonstrate a significant relationship between rising perceptions of disorder and rising levels of fear, what they refer to as 'co-occurring' changes, reflecting the difficulty in separating perceived disorder from fear (271). However, this analysis is based on a sample of 305 residents from 50 neighbourhood blocks, so their failure to identify significant variation in levels of worry may reflect sample size limitations. This also means that important interactions between neighbourhood and individual characteristics may be missed, with only 6 individuals per area cluster limiting the ability to identify complex area level variation.

In a recent study of 45 neighbourhoods in Philadelphia, Wyant, (2008) assesses the extent that individual levels of fear are influenced by the amount of fear from residents in surrounding neighbourhoods. Using a combined measure of fear based on variants of the 'global' fear item, this analysis again demonstrates a significant neighbourhood component, accounting for 12% of the total variance in fear. Wyant also demonstrates a significant neighbourhood level effect of perceived incivilities on fear, which is mediated through neighbourhood level perceptions of crime risk. Importantly, despite significant variation in fear across neighbourhoods, this study finds no evidence that fear is influenced by the levels of fear in surrounding neighbourhoods. Additionally, objective controls for neighbourhood stability and heterogeneity fail to reach significance, although this may again be a reflection of sample size limitations.

Finally, Wittebrood (2002) uses multilevel modelling to examine variations in fear of crime across Europe using the International Crime and Victimisation Survey, demonstrating significant variability between countries. Whilst this study uses multilevel methodology, no attempt is made to examine variations across neighbourhoods within countries. Instead, this analysis treats country as the contextual level of interest, reducing its relevance for the current assessment.

Examining these studies, there seems to be a strong consensus about the existence of an area influence when considering fear of crime. However some important methodological limitations are evident that highlight the need for a more detailed integration of individual and ecological analyses. To briefly summarise, with the exception of Wittebrood (2002), all of these studies are restricted in their scope to one city area. This makes generalisations to the wider population problematic, with potential differences in the structure of different cities highlighting the need for external validation. Extending the scope beyond a single city would also enable the assessment of the extent that the identified ecological mechanisms remain stable across different city contexts, where there will be different crime profiles and socio-demographic structures.

Additionally, most of these studies are based on limited sample sizes at the area level where between 50 and 66 neighbourhoods have been used (with the exception of Wilcox-Rountree et al., (1998; 2003; 1996b)). Whilst simulation research has indicated that multilevel models will produce robust estimates of fixed effects and variance components with samples of around 50 areas, it is possible that a more complex area based variance structure would be evident if a larger sample of neighbourhoods were used (Maas & Hox, 2005). The limited cluster sizes used in many of these analyses may also mask important complexity, with Wilcox-Rountree and Land (1996b) the only study to identify an influence of cross level interactions between individual and ecological predictors of fear. They also tend to rely on global measures of fear, which have been shown to behave differently to crime specific measures. Additionally, with the exception of Covington and Taylor (1991), these studies all rely on measures of perceived disorder, which Taylor (2001) and Tseloni (2007) have argued may be better conceived of as another dimension of fear, or as a parallel process, rather than as a cause of fear. Finally, all of these studies are based on data from America, highlighting a clear need for similar multilevel based studies in the UK to examine whether the ecological processes that have been identified also hold in the UK context.

4.3 Introducing Multilevel models

Multilevel analysis - sometimes referred to as hierarchical linear modelling, random effects modelling, random coefficient modelling, or mixed modelling - is a statistical method that was developed to analyse data with a hierarchically clustered structure. A hierarchically clustered structure refers to the grouping of observations within larger analytic units that is common in many kinds of data. For example, in educational research data is typically collected about individual pupils, but these pupils are usually clustered within different schools, which themselves may be grouped within neighbourhoods.

Similarly, in a nationally representative survey data is usually collected about individuals, but this data will typically be collected using a clustered design that collects data from a sample of small geographic areas to minimise costs. We might then think of these small geographic areas as themselves being clustered within different regions. Importantly, when referring to a hierarchically clustered structure, the different cluster levels are defined as directly nested within each other, such that all individuals from the same local area must also belong in the same region. This type of clustering can be represented diagrammatically, as in figure 4.1.

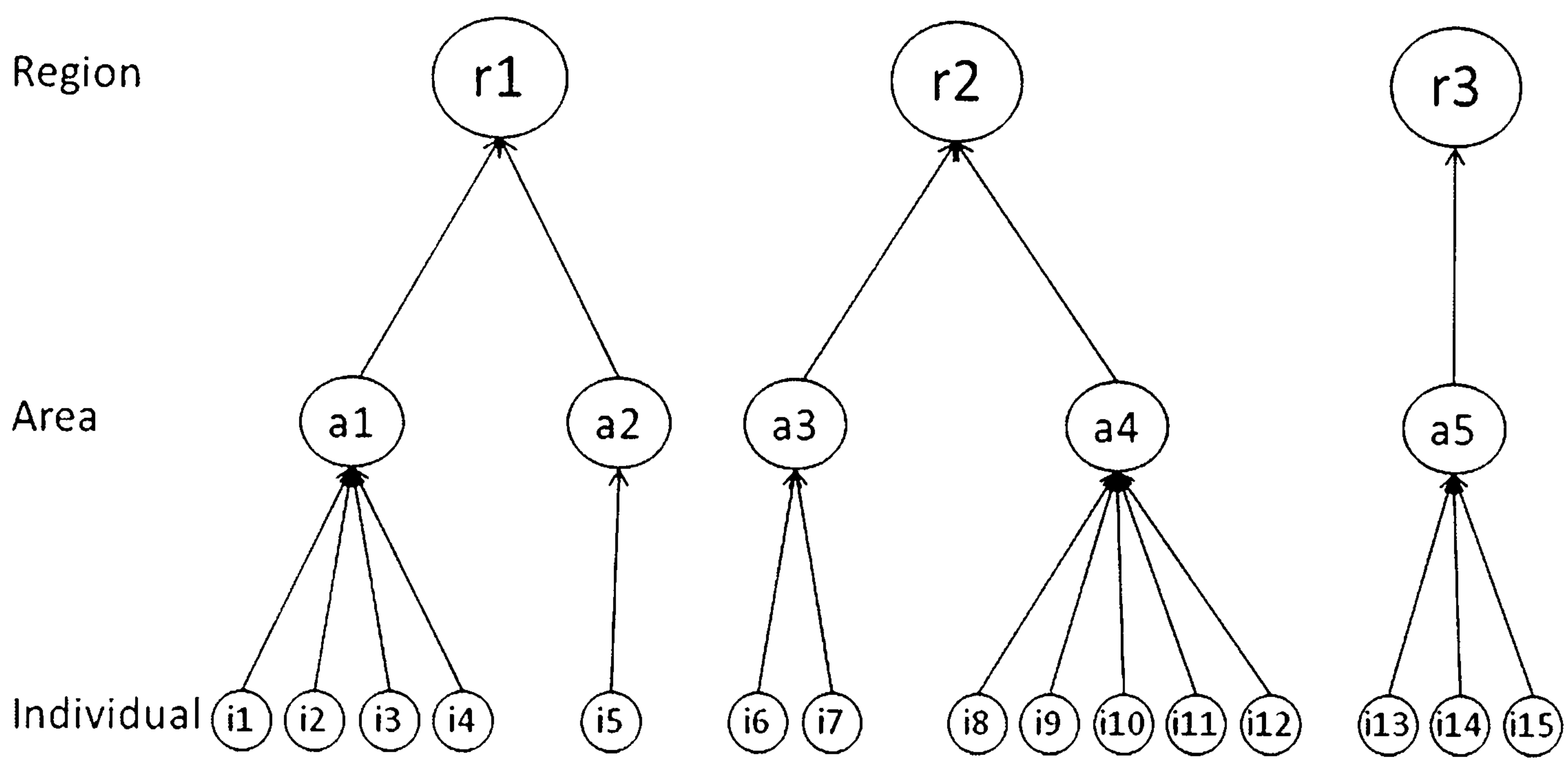

Figure 4.1 Multilevel Data Structure

In the diagram, at the lowest level we identify the first 15 individuals from a survey sample, labelled i1-i15. These 15 individuals have been sampled from 5 separate local areas, represented by the second level in the diagram, labelled a1-a5. These local areas are themselves taken from three separate regions, r1-r3, representing the highest level of clustering in the data. It is clear from the diagram that all individuals from the same local area are also clustered within the same region, indicating that the data is hierarchically nested.

One implication of this clustering of observations within larger analytic units is that it often results in higher than average correlations between observations from the same cluster and lower average similarities between observations from different clusters. This might be because of selective factors involved in the grouping of individuals, joint exposure to similar influences, mutual interactions within an area, or a combination of all three of these influences (Kish, 1967: 163). When this is the case, the assumption of independence between observations on which standard statistical analysis is based is no longer valid. Instead the potential existence of group level processes that influence, and are influenced by, the observations within them must be acknowledged and adjusted for (Goldstein, 2003). Failure to do so can often lead to an underestimation of standard errors and an increased likelihood of making type I errors (Hox, 2002). It also suggests that important higher level influences are potentially being missed.

Hierarchical data is the norm in survey research, where a complex sample design is usually employed to maximise the precision of estimates for a given cost (Lynn, 1998). First, surveys typically select a random sample of areas, before taking samples of individuals (or more commonly households) from within each selected area. This reduces the fieldwork costs per achieved interview, by limiting the distance that interviewers need to travel between each household in their assignment, enabling the collection of a larger number of interviews for a fixed cost. Here, the negative effects of dependency on individual level estimates are well known and a number of methods have been outlined by survey methodologists to correct for it; either by increasing the distance between units; using systematic sampling within each cluster to reduce homogeneity; increasing the number of sampled areas; or correcting estimates after data collection (Kish, 1967). Such corrections involve the calculation of the degree of similarity amongst observations from the same cluster, known as the intraclass correlation (ICC) and using this to adjust the sample size on which estimates are based. Therefore, for survey methodologists the effects of clustering have primarily been viewed as a necessary nuisance arising from the sample design that should be corrected for prior to any analysis.

In contrast, the multilevel approach treats the similarities between observations from the same unit as a theoretically interesting source of variation in the data to be examined, rather than simply adjusted out (Goldstein, 2003). By separating the variation resulting from differences between observations *within* the same cluster from that which results from differences *between* clusters, multilevel analysis provides an integrated framework for examining how group level processes are related to individual level processes. As a result, this approach enables researchers to combine a focus on macro differences between areas with a micro focus on the individuals that inhabit those areas. This makes it the ideal solution to the problems outlined above with early attempts to examine the neighbourhood level influences on individual levels of fear of crime.

In its simplest form, multilevel analysis extends the single level regression model by allowing the intercept to be different in each area, with a constant relationship assumed between the dependent variable and all independent variables across all areas. This enables the estimation of the amount of variation that exists between different areas, along with the variation that exists between individuals within each area. This is commonly referred to as the random intercept model and is outlined below, adapted from Rasbash et al., (2004). The random intercept model forms the starting point for the analysis that I will be conducting in chapters 5 and 6.

Equation [4.1] is a single level regression model with a constant intercept β_0, an independent variable x_1 and a residual error term e, that is assumed to be independently and identically distributed with a mean of 0 and constant variance, denoted by σ_e^2.

$$y = \beta_0 + \beta_1 x_1 + e \quad [4.1]$$

To include an area component along with the individual model, first it is necessary to extend the standard regression notation in several ways, leading to the more general regression equation [4.2]. A subscript i has been used to denote that the regression is at the level of the individual, enabling the extension of the model to include a higher level of influence related to area differences. An additional term x_0 has also been included which is multiplied by the intercept and error terms. This is a constant of value 1 which is usually omitted from single level regression notation for simplicity. The constant is required in the multilevel specification to enable the grouping of error terms when the model is extended.

$$y_i = \beta_0 x_0 + \beta_1 x_{1i} + e_{0i} x_0 \quad [4.2]$$

To form the basic multilevel model, equation [4.2] is extended to allow for a different intercept in each area. This is achieved by separating the model into two components, an individual and an area level model. Taking the individual level first, a subscript j is added to the y_i and the x's to represent the inclusion of an area component, producing equation [4.3]. This indicates that the regression equation now applies to the i^{th} individual from the j^{th} area. The subscript j is also attached to the intercept coefficient β_0, with the notation here meaning that the intercept is allowed to vary across areas. The intercept coefficient β_{0j} now refers to the overall intercept across all areas.

$$y_{ij} = \beta_{0j} x_0 + \beta_1 x_{1ij} + e_{0ij} x_0 \quad [4.3]$$

Equation [4.4] is the accompanying area level model, used to describe the variation in the intercept between areas. By assuming that the included areas are a random sample from a larger population of areas, a single random error term is included to summarise the variation in the dependent variable across all areas. The equation therefore states that the overall intercept β_{0j} from the individual level model, is composed of the average intercept across all areas β_0 and the residual difference from the average intercept for each area, represented by the error term u_{0j}. This residual is assumed to be normal, independently and identically distributed with variance σ^2_{u0}.

$$\beta_{0j} = \beta_0 + u_{0j} \quad [4.4]$$

The area level equation can then be substituted into the individual level equation, forming equation [4.5].

$$y_{ij} = (\beta_0 + u_{0j})x_0 + \beta_1 x_{1ij} + e_{0ij}x_0 \qquad [4.5]$$

By multiplying out the equation and grouping the error terms, equation [4.5] is rearranged to form equation [4.6], the multilevel random intercept model. In contrast to the single level model there are now two error terms, one associated with the individual level, e_{0ij}, and one with the area level, u_{0j}. Lines two and three indicate that both error terms are assumed to be independent and normally distributed with mean of 0 and variances σ^2_{u0} and σ^2_{e0}. These variance terms represent the unexplained variation in the response variable between areas and between individuals within areas respectively (Goldstein, 2003). Henceforth, this additional notation will be omitted. The x_0 terms have been removed from equation [4.6] for brevity.

$$\begin{aligned} y_{ij} &= \beta_0 + \beta_1 x_{1ij} + (u_{0j} + e_{0ij}) \\ [e_{0ij}] &\sim \mathrm{N}(0, \sigma^2_{e0}) \\ [u_{0j}] &\sim \mathrm{N}(0, \sigma^2_{u0}) \end{aligned} \qquad [4.6]$$

An alternative way of allowing for different intercepts is to fit a separate fixed effect for each area in the sample. However, this is problematic when a large number of areas are included in the sample as it involves the estimation of many additional parameters. Additionally, treating the differences between areas as fixed effects means that it would not be possible to examine why different areas have different average scores. It would only be possible to identify whether such differences exist or not.

Like methods developed by survey methodologists to correct for dependency, the random intercept model produces fixed effect estimates (the β's) and standard errors that reflect the complex structure of clustered survey data. This also provides a measure of the extent to which area differences contribute to the unexplained variation in the model, ρ. This is equivalent to the ICC, and is often referred to as the variance partition coefficient (VPC), and is a straightforward calculation based on the variance estimates, equation [4.7].

$$VPC = \rho = \sigma^2_{u0} / (\sigma^2_{e0} + \sigma^2_{u0}) \qquad [4.7]$$

Importantly, the random intercept model can easily accommodate differential cluster sizes (Hox, 2002). When dealing with differential cluster sizes, each cluster is weighted according to the number of observations included in it. Clusters with a small number of observations make a smaller contribution to estimates of the cluster level variance and contextual effects. This reflects the fact that estimates from these small clusters will be less reliable because they are based on a smaller number of observations. A further benefit of the random intercept model is that it is not restricted to two levels of variation. Following the methodology set out in Goldstein (2003), it is straightforward to extend the model to include multiple additional sources of higher level variation. This enables a more realistic representation of complex data structures to be specified.

In this thesis, I use this multilevel approach as an integrated methodology for incorporating contextual effects alongside an individual level analysis of fear of crime. By treating differences between areas as random coefficients, I am able to assess whether significant variation exists between local areas in addition to the variations in fear between individuals. This forms the essential first step in a systematic and robust assessment of the impact that neighbourhood differences have on the reported levels of fear of individuals.

4.4 The British Crime Survey

To model individuals' reported levels of fear of crime, data from the BCS is used. This is a nationally representative victimisation survey of adults aged over 16 living in private residential accommodation in England and Wales. The survey was first conducted in 1982 and there have been 15 rounds of the survey, with data collected continuously since 2001.

Victimisation surveys were introduced as an alternative method of assessing crime trends during the 1960s in the US, spurred on by a large body of literature that had begun to highlight the problems with official crime figures (Maguire, 2007). This focused on the problem of the so called 'dark figure of crime', with considerable underestimation of the extent of crime resulting from variations in police practices of recording crime, and the reporting behaviour of victims. The principal objective of victimisation surveys was therefore to produce an alternative picture of the extent of crime. Taking a representative sample of the population, details of the victimisation experience of respondents could be collected and used to generate estimates of the extent of crime. These were soon considered to provide a more accurate picture than recorded figures, bypassing problems of differential reporting and recording practices (Maguire, 2007). In addition to estimates of the extent of crime, many victimisation surveys also include a range of additional questions relating to victims of crime, perceptions of the criminal justice system and fear of crime. This makes them an ideal resource for this analysis.

The BCS is generally recognised as a world leader in victimisation surveys and following a methodological review in 2001 is now one of the largest social surveys conducted in Britain. Initial surveys asked a sample of approximately 10,000 people per year about their experiences of victimisation and attitudes to the criminal justice system. This has been greatly expanded with samples of upwards of 40,000 respondents interviewed each year since 2001 (Lynn & Elliot, 2000). The increased sample size has enabled estimation of crime levels within each Police Force Area (PFA), increasing the utility of the survey as a performance indicator for police forces.

Like most national surveys conducted in Britain, a complex multistage sample design is used to collect interviews for the BCS. This is a clustered sample that is first stratified by Police Force to ensure sufficient numbers of interviews within each PFA. The survey is also stratified by population density and the proportion of adults in non-manual occupations to ensure important subgroups are well represented and to maximise participation. Using the small user postcode address file, whole postcode sectors are first selected to be used as primary sampling units (PSU). A sample of 32 households is then selected from within each PSU with probability proportional to the size of the area. Finally, within each household a single individual is randomly selected using a Kish grid (for more detail on the sampling procedure, see the recent technical report from Bolling et al., (2008)).

The sample design produces a sample of respondents from geographically clustered local areas across England and Wales. This makes it ideal for a multilevel treatment of fear of crime, where the resultant dependency is an important source of additional information. For this analysis I will be using three years of data covering the period from 2002 to 2005. This will keep the sample temporally close to the 2001 census, which is important as contextual data will be taken directly from the census to characterise local neighbourhoods. It also capitalises on the sample re-design that was fully integrated by 2002, with a considerably larger sample of respondents selected each year increasing the number of respondents within each neighbourhood cluster (Lynn & Elliot, 2000). In contrast to many UK surveys, the response rate of the BCS has remained largely stable over time and can be considered good by current standards, with rates of 74.4%, 74.1% and 74.8% for 2002/03, 2003/04 and 2004/05 respectively.

There are some important limitations with the BCS and victimisation surveys more generally, which mean they cannot offer a full picture of the extent of crime. Firstly, because it is a victimisation survey it does not include details on crimes that do not have an easily identifiable and contactable victim. Therefore murder is not covered, neither are white collar crimes. In this analysis, victimisation experience is of secondary importance, used as an independent variable; therefore this limitation is not problematic. The coverage of the survey is also restricted, with no coverage of individuals under the age of 16, or those living in institutions like halls of residence, care homes, and prisons.

4.5 Defining neighbourhoods

An important first step in testing the contribution of social disorganisation and low level disorder to individual levels of fear of crime is to develop a workable neighbourhood boundary definition. The first real definition of neighbourhoods can be found in the urban sociological work of Park and Ernest (1916), where they were described in general terms as "subsections of a larger community – a collection of both people and institutions occupying a spatially defined area influenced by ecological, cultural, and sometimes political forces" (147). However, from these beginnings, a more detailed definition of neighbourhoods has been a divisive subject, with much of the critical thinking put forward by qualitative studies at odds with the neighbourhood classifications that have been adopted in more statistical approaches.

The lack of consensus over a definition of neighbourhoods can be partly seen as a reflection of the different focuses from qualitative and quantitative neighbourhood studies. Quantitative studies have focused more on developing working definitions to enable comparisons between neighbourhoods, whilst qualitative studies have been more interested in examining the internal dynamics within single communities. This division reflects data limitations associated with quantitative treatments of neighbourhood effects, necessitating a definition that is supported by sufficient administrative data. The result is a clear gap between theoretical considerations about what constitutes a local neighbourhood motivated by more qualitative community studies, and the spatial measures that are incorporated within empirical assessments of neighbourhood effects (Lupton, 2003).

Considering the conceptual treatments of neighbourhood that have developed out of community studies, neighbourhoods are conceived of as both physical and social spaces whose boundaries are defined in relation to the subjective meanings that they have for the individuals living in them (Weiss, 2007). From this perspective, neighbourhoods and their boundaries are defined at the individual level, based on individual perceptions of the characteristics of the area. These include physical characteristics such as physical barriers, landmarks and roads, as well as social characteristics of the area such as demographic structure, its political character, and the extent of friendship networks (Chaskin, 1998). Focusing on the individual allows neighbourhoods to be defined and experienced differently by different people, depending on the relative importance of these physical and social characteristics. Therefore, different people may place different emphasis on the extent that the neighbourhood is a place for activities to occur, a set of social relationships, a place defined by its relationships with institutions, or a symbolic unit with a recognised identity (Chaskin, 1998).

In addition to viewing neighbourhood boundaries as dependent on the experiences and perceptions of the individual, community studies also allow for multiple overlapping neighbourhood definitions to be important for each person. Neighbourhoods can refer, then, to different spatial zones depending on the type of social interactions that are being examined. Kearns and Parkinson (2001) identify three general spatial scales at which the neighbourhood might exist; the home area, the locality, and the urban region. These are defined in general terms, however in reality the spatial scales are more flexible, varying considerably depending on the type of person and the characteristics of the natural environment.

Within this schema, the home area is typically defined as the area within a 5-10 minute walk of the individual's home. This small neighbourhood classification is the most inclusive residential grouping, with boundaries primarily defined by interactions with others and the friendship networks that this fosters. It is therefore seen as important for engendering a sense of belonging and community (Kearns & Parkinson, 2001). The second neighbourhood layer reflects the wider area in which residential activities take place, and is typically defined by the structure of the housing market and the level of local service provision. Additionally, the physical structure of the area is generally taken as more important for delineating the boundaries of this wider neighbourhood (Kearns & Parkinson, 2001). The final layer, described as the urban region, is broader still. This is defined primarily by the individual's employment connections and the location of leisure interests. This also incorporates the wider social networks that are relevant to individuals (Kearns & Parkinson, 2001). Finally, qualitative studies also focus on the importance of the relations between places in determining how neighbourhoods are defined by residents. Therefore, the way that people define their local neighbourhood can be thought of as partially a reflection of comparisons with the areas that surround them, and their beliefs about how the neighbourhood is perceived by others (Chaskin, 1998).

In contrast to these theoretically driven definitions adopted by qualitative research, in quantitative neighbourhood effects research decisions on how to define and operationalise local areas have been largely guided by the availability of relevant area based data (Sampson et al., 2002). These move away from treating neighbourhoods as the subjective domain of individuals, towards more generally defined spatial units that apply to all residents within them. This has led to neighbourhoods being defined on the basis of a range of geographic boundaries, with fairly limited consideration given to the relevance of the area boundary to the research question being assessed (Lupton, 2003). Neighbourhood effects are therefore often assessed in relation to differences between administrative units such as cities, census tracts and city blocks in the American context, and electoral wards, postcode sectors and regions in the UK context.

Focusing on UK research, electoral wards are commonly used to classify neighbourhood boundaries. However, these can be considered a somewhat problematic measure of local areas. This is because they vary considerably in size and scale, from less than 1,000 to more than 30,000 residents, making comparability difficult (Gibbons et al., 2005; Macallister et al., 2001). They also represent political boundaries rather than clear geographic boundaries, which Lupton (2003) has argued makes them somewhat arbitrary as measures of a local area. Ward boundaries are also frequently subject to shifts in location, making them problematic when analyses are conducted over a number of years.

Postcode sectors, which are generally the PSU in national surveys, have also been used to assess area based variations, with Tseloni (2005) successfully adopting this area geography in her examination of variations in levels of crime. Using these would be the most obvious approach to examine area differences in the current analysis, fully capitalising on the clustered sample design used by the BCS and resulting in a selection of areas containing fairly even numbers of respondents. However, PSU boundaries cover fairly broad areas that have no real meaning beyond their postcode classification. Additionally, like wards there is considerable variation in the size of postcode sectors, making it difficult to argue that they all refer to a similar neighbourhood definition. Finally, there is also very little data made available at this spatial scale, requiring look-up tables to link data to this geography, a procedure that Vickers (2006) has shown to be prone to considerable misclassification errors.

Some more recent neighbourhood studies have begun to use more carefully defined area classifications that go some way to dealing with the limitations identified in much quantitative area effects research (see for example Johnston et al., (2005c)). These have been based around the construction of 'bespoke neighbourhoods' that are specific to each individual in a sample, formed by clustering enumeration districts (the smallest geographic unit defined for the collection of census data) that are in the closest spatial proximity to each respondent (Johnston et al., 2005a; Macallister et al., 2001). This results in local areas that are specific to each sampled individual, with each local neighbourhood being smaller and more statistically stable than other available geographic units. In addition, these 'bespoke neighbourhoods' have been defined at a number of spatial scales, from the nearest 500 individuals to the respondent up to the nearest 10,000, allowing more detailed analyses of area level influences at different levels of aggregation.

However, whilst constructing neighbourhoods specifically for each individual captures the fact that people often rely on different neighbourhood definitions to others around them, it makes them unsuitable for multilevel analyses. This is because it is no longer possible to identify discrete geographic boundaries that individuals are clustered within, with different boundaries applied to each person. As a result, it fails to incorporate the dependency amongst bespoke neighbourhoods that share some of the same geographic space. Additionally, because each person belongs to a unique bespoke neighbourhood, this type of approach requires contextual data that is specific to the individual, restricting the breadth of available data. This makes it particularly unsuitable for the current analysis, with the sensitive nature of victimisation data meaning that it was not possible to obtain contextual data at such a specific spatial scale.

4.5.1 Super Output Areas

The current analysis adopts a neighbourhood classification that can be considered as somewhat analogous to the bespoke neighbourhoods outlined above, resulting in a more theoretically relevant neighbourhood classification than has been used in quantitative studies of area effects to date. This is the newly introduced census Super Output Area (SOA) geography. These areas were constructed using a methodology similar to the creation of 'bespoke neighbourhoods', and were introduced as a stable geography for disseminating local area statistics collected from the 2001 round of the census onwards. However, rather than defining areas that are specific to each respondent, the constructed boundaries are common to all households within a local area. This has the benefit of making them suitable for multilevel analyses.

The increased internal stability when compared with other potential area geographies makes them particularly suitable for this analysis, where the principal focus is on the shared influence of local areas on individuals. Additionally, SOA cover a significantly smaller local area than the neighbourhood boundaries that have typically been used in area studies. This represents a considerable advance over existing studies, enabling a more detailed assessment of small area influences on individuals' levels of fear. It therefore allows us to examine more clearly how characteristics of the area immediately surrounding the individual influence their levels of worry about becoming the victim of crime.

Currently census output geography is based on a four level hierarchy derived from combinations of census output areas (the 2001 equivalent of enumeration districts), themselves constructed from postcode units (Martin, 1998). Output areas were the lowest geographic unit used to collate data from the 2001 census. These are groups of approximately 150 households that have been clustered together on the basis of geographic proximity and social homogeneity as measured by the type of dwelling and the nature of tenure (Martin, 2001).

Output areas are then combined using the same grouping criteria (proximity and homogeneity) to form Lower layer SOA (LSOA). These each contain approximately 600 households, with 34,378 in total covering England and Wales (ONS, 2006). These are the lowest level of the hierarchy from which census data are made publicly available. However, because of their small spatial scale, the amount of data available at this level is restricted to maintain respondent confidentiality.

In the same way that LSOAs were constructed from combinations of output areas, LSOA are then combined to form Middle layer SOA (MSOA). In constructing MSOA there was an additional consultation phase with local authorities and residents to ensure that they represented meaningful geographic units. Each MSOA contains an average of 2,500 households, with a minimum of 1,000 households and a total of 7,193 covering England and Wales. The boundaries for all MSOA in England and Wales can be examined online through the neighbourhood statistics section of the ONS website (see http://www.neighbourhood.statistics.gov.uk)

A final level of the hierarchy, Upper layer SOA (USOA), constructed from groups of MSOA has also been proposed. However, currently the exact size and structure of these units has not been finalised, with a provisional requirement of 25,000 households in each.

For this analysis LSOA were judged to be unsuitable for use as local neighbourhoods because there is only limited clustering of sampled respondents within each LSOA, with approximately 6 individuals clustered within each area across the three years of BCS data. This is a fairly low level of clustering that reduces the ability to identify more complex area based influences on population subgroups at the local area level. Additionally, the Home Office has restricted the availability of contextual data at this spatial scale, which has been judged to represent a confidentiality risk that might result in the identification of individual respondents (in violation of the confidentiality agreement that each respondent signs when completing the questionnaire).

As a result, the middle level of the hierarchy (MSOA) has been selected, with an average cluster size of 20 respondents using the three year BCS data set. This is a sufficient number of respondents to construct more complex models of area variations in fear. MSOA are also small enough to act as a reasonable approximation for the locality of the respondent, and are more consistent in size than the alternative geographies that have previously been used to measure context effects. The consultation stage with local authorities when these boundaries were constructed is an additional benefit, ensuring that they represent 'meaningful' geographic areas that do not cross clear physical boundaries like major roads or waterways (ONS, 2006). This is a clear benefit of MSOA, with physical boundaries recognised as one of the principle influences on people's definition of their local neighbourhood (Lupton, 2003). The use of MSOA represents a significant advance over earlier methods of defining local neighbourhoods in survey research. However, like all other empirical assessments of neighbourhood effects, the selection of these spatial units has primarily been influenced by data availability. This means that although they offer many benefits over other spatial units that have previously been used, they cannot directly incorporate many of the elements that have been identified in theoretical treatments of the neighbourhoods as important.

In the three year combined BCS dataset, this results in a total of 105,110 respondents clustered within 5,208 MSOA across England. Data from Wales has been omitted because of the restricted availability of census data, and some inconsistencies in the available measures in Wales when compared to England (in particular there are no available measures of crime). This is a considerably larger number of local areas than has been used in previous multilevel treatments of fear of crime. Additionally, data is collected for the whole country, in contrast to existing treatments that have generally been restricted to a focus on local areas within single cities. The average cluster size is 20 individuals, with cluster sizes ranging from 1 to 119 before missing cases are removed. The high degree of variability in the number of people within each MSOA cluster is a reflection of the independent construction of these MSOA boundaries, with no requirement that they match the post-code sector boundaries used to collect the BCS sample. As a result, even though BCS sample points will have a relatively stable number of people in them, the number of individuals in each MSOA can vary widely.

As I outlined earlier in the treatment of multilevel models (section 4.5), the unbalanced nature of this data is not problematic within a multilevel framework. Instead the increased uncertainty associated with estimates from areas with smaller samples is incorporated in the results. This is achieved by allowing areas that have larger sample sizes to make a bigger contribution to the final estimate of area variability, whilst estimates from smaller groups are pulled towards the mean (Hox, 2002). There has been some debate over the best way to deal with areas that only contain 1 respondent, where no distinction can be made between individual and area level effects because the two are confounded. In general the consensus seems to be that it is less problematic to simply include this data, although it will make no contribution to estimates of the area level variance (Hox, 2002; Snijders & Bosker, 1999).

4.5.2 The broader administrative geography

An additional benefit of using MSOA to represent local neighbourhoods is that during the consultation phase, steps were taken to ensure that they were congruous with various administrative boundaries. This includes CDRP, also sometimes known as community safety partnerships, enabling the specification of CDRP boundaries as an additional, higher geographic level within this analysis. There are two principal motivations for including CDRP as a higher level of variation.

The first is that it is analytically interesting to examine whether there is additional geographic variation in fear beyond the influence of the local neighbourhood of respondents. CDRP are statutory partnerships within each Government office region formed as a result of the Crime and Disorder Act (1998) to work together to reduce crime and anti-social behaviour within communities. They represent various responsible authorities including police, local authorities and community groups and are specifically focused on reducing crime. Therefore, if significant variations in fear exist between CDRP this might have important implications for policies levelled at CDRPs.

The second reason for the inclusion of a higher level of clustering is that it serves to place neighbourhoods within the wider geographic context of the area. Neighbourhoods in close proximity to one another often share similar characteristics, and will be influenced by one another (Lebel et al., 2007). As a result, it is important to incorporate this potential source of area based homogeneity within any analysis looking at the impact of neighbourhood effects. This is particularly important from a methodological perspective, because a failure to account for this additional source of spatial dependency could lead to underestimated standard errors of contextual effects in much the same way that individual estimates are affected by failure to account for clustering within neighbourhoods (Griffith et al., 2003).

There are 376 CDRP throughout England and Wales. Using three years of the BCS results in data from 353 CDRP, with an average of 15 MSOA within each CDRP and a range from 1 to 95. Additionally there is an average of 298 respondents per CDRP, with a maximum of 1,370.

4.6 Measuring fear with the British Crime Survey

A number of items are included in the BCS that are intended to measure levels of fear of crime. Two of these items adopt the 'global' fear of crime format, covering feelings of safety during the day and at night (Hale, 1996). As I outlined in chapter 2, these items have been heavily criticised as measures of fear for, amongst other things; lacking any direct reference to crime or fear; mixing actual and hypothetical situations; and mixing fear with risk assessments (for a full assessment of these problems see Ferraro & LaGrange, (1987); and Farrall et al., (1997)). As a result of the criticisms levelled at these global measures, they have been excluded from this analysis.

In addition to the 'global' fear questions, eight items are included in the survey that measure levels of worry about becoming the victim of specific criminal events. These items have also faced considerable criticism, most notably in the work of Farrall and colleagues (see for example Farrall & Gadd, (2004a)). However, they are generally accepted as a significant improvement over the earlier 'global' measures and are the most appropriate measures of fear available in the BCS. These are specifically designed to tap into what Hough (2004) has described as a stable mental state representing a diffuse anxiety to potential victimisation. As such, they do not reflect the immediate emotional response to specific fearful occasions, instead capturing more general feelings of worry and anxiety about crime. These eight items are all measured on a four point likert-scale, with responses ranging from 'not at all worried' (1), to 'very worried' (4). Question wording and order within the survey has remained consistent since these questions were first introduced to the BCS in 1984, although questions 3 and 4 were added in 1988, and 8 was added in 1994.

1. How worried are you about having your home broken into and something stolen?
2. How worried are you about being mugged or robbed?
3. How worried are you about having your car stolen?
4. How worried are you about having things stolen from your car?
5. How worried are you about being raped?
6. How worried are you about being physically attacked by strangers?
7. How worried are you about being insulted or pestered by anybody, while in the street or any other public place?
8. How worried are you about being subject to physical attack because of your skin colour, ethnic origin, or religion?

Of the eight worry items included in the BCS to measure levels of fear, four have been omitted from the current analysis. Questions 3 and 4, measuring worry about vehicle crime, are only asked of respondents that report owning a vehicle (75.1% of the total BCS sample). These items have been omitted to limit the focus to general worries experienced by all respondents in the sample. Two additional items, measuring worry about being raped (question 5), and worry about being attacked based on ethnic origin or religion (question 8) have also been omitted as a result of high levels of non-response. In particular these two items suffer from significantly higher proportions of responses coded as 'not applicable' than the remaining four items (table 4.1). In total 10% of responses to question 5 are coded as 'not applicable', and more than 18% of responses to question 8 are similarly coded.

Table 4.1: Percentage of 'Not Applicable' Responses by Item (2002-2005)

Question	Percentage
1. Having your home broken into and something stolen?	0
2. Being mugged or robbed?	0.2
3. Having your car stolen?	24.9
4. Having things stolen from your car?	25.1
5. Being raped?	10.3
6. Being physically attacked by strangers?	0.2
7. Being insulted or pestered by anybody, while in the street or any other public place?	0.3
8. Being subject to physical attack because of your skin colour, ethnic origin, or religion?	18.4

Examining this in more depth reveals that, not unexpectedly, there are considerably more male respondents coded as 'not applicable' to the question measuring worry about rape across the three years, with 21.5% 'not applicable' compared with 1.2% of women. Equally there are considerably more White respondents (19.5%) coded as 'not applicable' to the question measuring worry about attack based on race or religion than BME respondents (0.2%, 0.2% and 1.6% for people of Asian, Black and mixed origin respectively).

However, there is some confusion about why these questions have such high proportions of 'not applicable' codes. In early rounds of the BCS the item measuring worry about rape (question 5) included an interviewer filter so that men were not asked. This interviewer filter was later dropped from the survey and all worry questions are now asked of all respondents. In spite of this, close inspection of responses by interviewer from 2004/05 reveals considerable clustering of 'not applicable' responses within specific interviewers on both worry about rape and worry about racial attack. This suggests that some interviewers might be self coding most or all male/White respondents as 'not-applicable' on these items. In contrast other interviewers seem to be asking these questions of all respondents and only using the 'not applicable' code when instructed to do so by the respondent. Being unable to accurately identify who has been asked these questions and the high degree of interviewer clustering, makes these unsuitable for inclusion in general fear scales.

4.7 Constructing measures of fear

Early fear of crime research focused on the correlates of a single 'global' measure of fear based on responses to the safety alone at night item. Later studies have criticised this research and highlighted the importance of crime type when thinking about fear, in particular the distinction between fear of personal and household crime (Box et al., 1987; Hale et al., 1994). The statistical distinction between fear of personal and household crime has also recently been demonstrated in a factor analytic study by Jackson et al., (2007), with important differences identified between the two types of fear. The remaining four BCS items will therefore be used as indicators to construct measures of fear of these two crime categories. Three of the items will be used as a measure of fear of personal crimes, with the remaining item used to represent fear of household crime.

4.7.1 Fear of personal crime

Three of the four items relate to fear of personal crime; worry about being mugged or robbed; worry about being physically attacked by strangers; and worry about being insulted or pestered while in the street. To correct for the potential impact of measurement error, these three items were combined using principal components analysis (PCA) to form a personal crime fear index. This involves a linear transformation of the three included items, maximising the combined variance that is accounted for by a single factor. This index has high internal scale reliability, with all three items displaying factor loadings above 0.8 as shown in table 4.2. Additionally, the derived index is standardised with a mean of 0 and unit variance. Higher scores on this index represent higher levels of fear of personal crime.

Table 4.2: Principal Components Analysis of Fear of Personal Crime Items

Item	Rotated Factor Loading
Worry about being mugged or robbed	0.868
Worry about being physically attacked by strangers	0.910
Worried are you about being insulted or pestered by anybody, while in the street or any other public place	0.843
Number of Cases	104,476

An alternative approach would be to model the relationship between the three worry indicators and the underlying fear of personal crime latent variable within a structural equation model (SEM) framework. This would deal more efficiently with the measurement error associated with each of the three worry items by correcting for it in a single step along with the individual level structural model. Within the SEM framework, it would also be possible to simultaneously model the individual and area influences on fear, resulting in a fully integrated methodology for examining the area influences on fear; a multilevel SEM.

However, there are two reasons why this method was not adopted in this analysis. First, the multilevel SEM is currently restricted to two levels (Muthén & Muthén, 2007). In the current analysis it is hypothesised that the wider administrative locality may also make an important contribution to variations in fear of crime, and is required to ensure neighbourhood context effect estimates are corrected for dependency. This means that the ability to specify three levels of influence is particularly important, despite the resultant increase in the size of the estimated individual level variance that will result from the weaker correction for measurement error. Second, the multilevel SEM approach is computationally intensive, restricting the number of fixed effects and random coefficients that can be estimated. This also limits the complexity of the contextual model that can be specified to account for neighbourhood differences (see chapter 5).

4.7.2 Fear of household crime

A single question asking about worry about burglary is used to measure household crime (question 1). This item has been kept separate to enable an assessment of the differences in the area effects on personal and household crime. This keeps the research consistent with recent treatments of fear of crime which have highlighted the important distinctions between fear of personal and household crimes, outlined in Ferraro, (1995) and Hale (1996). Like fear of personal crime, this has been standardised with a mean of 0 and standard deviation of 1 to place it on the same scale as the personal fear index outlined above.

To examine the area influences on fear of household crime this standardised dependent variable will be modelled with a simple linear random intercept model. This decision has been made in favour of the two alternative approaches that are available to model single item ordinal scales within a multilevel framework. The first alternative method is to directly model worry about burglary as an ordinal variable with four ranked response categories, referred to in the multilevel literature as a multilevel multivariate ordinal regression model. This treats each response option as a separate threshold on an underlying continuous latent variable, enabling the estimation of the relative odds of moving into a higher fear category for unit increases in the individual covariates (Goldstein, 2003). The model thus accurately reflects the ordinal nature of the dependent variable. However this approach is computationally intensive, resulting in a complex individual level model structure that is most suited to a two level analysis restricted to random intercepts (Snijders & Bosker, 1999). When the models in this analysis where specified as a three level random intercept model they failed to converge, suggesting that this method is unsuitable for dealing with the large and complex BCS data structure. As a check on the final models, a two level random intercept model was also specified. This produced fixed effect estimates in line with the estimates from the three level model assuming a continuous distribution for fear of property crime.

The second option is to collapse worry about burglary into a dichotomous measure, distinguishing those who worry from those who do not. The dichotomous outcome can then be examined using a multilevel extension to the binary logistic regression model. However, the binary logistic model misses potentially important information about the original four category dependent variable by replacing it with a simplified two category measure. It does not, therefore, represent the most efficient method to deal with this item. In addition, the use of a logistic model means that the results must be presented as odds ratios, making comparisons with fear of personal crime more difficult. Finally, because maximum likelihood methods are too computationally intensive when dealing with binary data, a quasi-likelihood linearization method is used to transform the data so they can be estimated in a continuous response model. This quasi-likelihood method produces unreliable fit statistics, which means that it is not possible to use the -2*loglikelihood to judge model fit in the binary logistic model (Rasbash et al., 2004).

All fear of household crime models were estimated using both the linear and the binary logistic approach. Results were approximately equivalent using both methods, so the linear models will be presented in the results section of this chapter to ensure comparability with fear of personal crime.

4.8 Results I: Does social context influence fear of crime?

As a first step in assessing the influence of the local neighbourhood and wider administrative area on individual levels of fear, a simple random intercept model with no fixed effects will first be estimated. This model is referred to in multilevel literature as the unconditional random intercept model, or sometimes the variance components model. This will act as an initial indication of whether there is significant variation in fear across neighbourhoods and CDRP. The model is similar to the random intercept model outlined above in equation [4.6], although it has now been extended to three levels to incorporate the influence of CDRP clustering. Additionally, no individual level covariates are included in the model, allowing a direct examination of how the variance in fear is partitioned between individuals, neighbourhoods and CDRP, equation [4.8]. As before, each error term is assumed to be normally distributed with a mean 0.

$$\mathrm{Y}_{ijk} = \beta_0 + \left(v_{0k} + u_{0jk} + e_{0ijk}\right) \qquad [4.8]$$

As two levels of geographic clustering have been adopted in the analysis, there are now three error terms in the model; v_{0k}, u_{0jk} and e_{0ijk}. This means that the unexplained variance in fear of crime is partitioned at three nested levels; the part that is the result of differences between individuals σ^2_{e0}; the part that is attributable to unexplained differences between local neighbourhoods σ^2_{u0}; and the part attributable to broader CDRP level differences σ^2_{v0}. The subscripts indicate that the covariates in the model now relate to the average effect on fear for the i^{th} individual, living within the j^{th} neighbourhood which is grouped within the k^{th} administrative area.

The inclusion of two area levels means that the calculation of the VPC, outlined above in equation [4.7], is somewhat more complex. Instead of a single estimate, there are now three important variance estimates to consider; the VPC at the neighbourhood level (equation [4.9]); the VPC at the CDRP level (equation [4.10]); and the overall higher level VPC (equation [4.11]). All three of these estimates give us important information about the impact of local neighbourhoods and broader administrative areas on fear of crime.

$$VPC_{Neighbourhood} = \sigma^2_{u0} / \left(\sigma^2_{e0} + \sigma^2_{u0} + \sigma^2_{v0}\right) \quad [4.9]$$

$$VPC_{CDRP} = \sigma^2_{v0} / \left(\sigma^2_{e0} + \sigma^2_{u0} + \sigma^2_{v0}\right) \quad [4.10]$$

$$VPC_{Total} = \sigma^2_{u0} + \sigma^2_{v0} / \left(\sigma^2_{e0} + \sigma^2_{u0} + \sigma^2_{v0}\right) \quad [4.11]$$

All models are estimated using Mlwin, employing an iterative generalised least squares (IGLS) algorithm detailed in Goldstein, (2003). This is a maximum likelihood estimation procedure, which identifies values for the unknown parameters that are included in the model that will be the most likely to result in the sample data that has been observed. This involves generating a reasonable starting value for each of the unknown parameters in the model (usually based on a single level regression), and then iteratively trying to improve on these estimates to identify the values that will maximise the chances of observing the sample data (Myung, 2003). This can be a computationally intensive procedure. However, when dealing with large sample sizes it has the benefit of producing estimates that are asymptotically efficient and consistent (Hox, 2002).

4.8.1 Fear of personal and household victimisation

Table 4.3 contains the variance estimates from the unconditional random intercept models relating to fear of personal and household crime. In each case the dependent variable is a standardised measure with unit variance, with this variance partitioned at the individual and two area levels.

Table 4.3: Unconditional Random Intercept Models

	Personal Crime Effect (S.E)	Household Crime Effect (S.E)
RANDOM EFFECTS		
CDRP Level	.051 (.005)**	.030 (.003)**
Neighbourhood Level	.047 (.002)**	.031 (.002)**
Individual Level	.903 (.004)**	.934 (.004)**
-2*Loglikelihood	289790.6	293880.7
Number of cases	*104,476*	*105,054*

*** P<(.01)*
**P<(.05)*

Looking first at fear of personal crime, approximately 10% of the total unexplained variability is partitioned at the area levels, with a VPC_{Total} of .098. This is comprised of an equal contribution from differences between local neighbourhoods and differences between CDRP, with a $VPC_{Neighbourhood}$ of .047 and a VPC_{CDRP} of 0.51. The standard errors associated with each estimate reveal that these are highly significant proportions of the total variability, demonstrating that it is important to incorporate these sources of variance when examining differences in individual levels of fear of personal crime.

Turning to fear of household crime, the proportion of variance attributable to local neighbourhood and CDRP differences appears somewhat smaller, with 6% of the total variance partitioned at the area levels and an equal contribution from neighbourhood and CDRP differences. Despite accounting for a smaller proportion of the total variance in fear of household crime, this is still highly significant. Importantly, the reduced size of the area contribution does not necessarily mean that areas are less important to fear of property crime. Instead, this may reflect the failure to correct for measurement error when looking at fear or household crime, with the additional unexplained variation inflating the relative contribution of individual differences and thus making the area contribution appear smaller.

4.9 The problem of selection bias

The unconditional random intercept models outlined above demonstrate the existence of clear neighbourhood level variations in fear of crime. This suggests that there are important neighbourhood level processes resulting in different average levels of fear from residents of different local neighbourhoods. Additionally there appear to be broader influences on levels of fear that are related to differences between CDRP. Consequently the models clearly demonstrate that any assessments of individuals' fear of crime need to incorporate the influence of neighbourhood and broader administrative boundaries. However, before we can say with any degree of certainty that unexplained neighbourhood effects really exist, it is important to discuss the problem of selection bias.

The problem of selection bias is common to all neighbourhood effects research, and has been the subject of considerable debate. This refers to the fact that, in reality, people are not randomly distributed across neighbourhoods. Instead there is a degree of individual choice about which neighbourhood people live in (Oakes, 2004). A failure to account for the tendency for people to select themselves in to particular neighbourhoods based on individual characteristics means that we are potentially missing an important source of variability at the neighbourhood level. What we may attribute to objective differences between neighbourhoods might better reflect the differential selection of individuals with particular sets of characteristics into certain types of neighbourhood (Sampson et al., 2002).

For example, we may attribute the higher levels of fear from people living in certain neighbourhoods to some objective characteristics of the neighbourhood that lead the people living in them to report higher levels of fear than people living in other neighbourhoods. However, it is equally possible that the higher levels of fear in particular neighbourhoods actually reflect a general tendency of more fearful people to move to those types of neighbourhood. This means that the cause of higher levels of fear is an individual characteristic rather than characteristics of neighbourhoods. A failure to account for this selection process will result in a confounding of the effect of neighbourhood differences with the effects of characteristics of individuals. This can lead either to the overestimation or underestimation of neighbourhood effect sizes (Buck, 2001).

Several methods have been outlined to overcome the problems associated with selection bias, with some focusing on improving the initial study design process, and others attempting to deal with self selection through model refinements. These are all intended to enable the separation of neighbourhood effects from the effects of individual characteristics that lead people to select themselves into particular neighbourhoods. Considering extensions to the study design, experimental studies represent the gold standard in addressing the problem of self selection (Sampson et al., 2002). Essentially this involves the random allocation of individuals or families to different neighbourhood conditions. By randomly allocating individuals to different neighbourhoods, this allows a direct assessment of the extent that neighbourhood conditions affect various outcomes, which is not confounded by selection bias. However, in general experimental studies of neighbourhood effects are both ethically and financially unfeasible, with only one well known example that has adopted a variant on this methodology, the 'Moving to Opportunity' study (Kling et al., 2004).

The 'Moving to Opportunity' study was set up to test whether families who moved from inner-city, high poverty areas to low poverty areas showed improved outcomes for children and adults, relative to a control group that were not moved. This was intended to demonstrate whether neighbourhood effects were really apparent, or whether they were really the result of self selection of particular types of people into particular types of neighbourhood. This involved the random assignment of families with children living in high poverty areas to one of three groups (Kling et al., 2005). Two of these groups were given housing vouchers and were required to move to a low poverty area, whilst the third group received no assistance, allowing researchers to separate the role of neighbourhood context from selection bias arising from residential mobility decisions (Sampson et al., 2002).

Seven years after the initial experiment, results from the study appear somewhat mixed. Significant improvements in female youth education levels and physical health were evident in the intervention groups when compared with the controls, along with similar positive effects on adult mental health (Kling et al., 2005). However, the study also showed adverse effects of the intervention on male youth when compared to the control group, and no effect of the treatment on adult earnings. From these results, it appears that neighbourhoods can be influential for some individual outcomes, but the effects are not universal. Despite providing the best example of an experimental test of neighbourhood effects, this method still suffers from the problem of differential take-up, with residents choosing whether or not to be involved in the study, meaning that it cannot definitively demonstrate neighbourhood effects (Oakes, 2004).

Oakes (2004) proposes an alternative method which also focuses on the adoption of an experimental design, the community experiment. In contrast to the 'Moving to Opportunity' study, where families were randomly allocated to different status neighbourhoods, Oakes advocates the random allocation of interventions to neighbourhoods. The random allocation of interventions to neighbourhoods is presented as a more feasible method for constructing an experimental design, avoiding some of the ethical constraints associated with the random allocation of people to neighbourhood conditions. This again enables an assessment of the impact of neighbourhood differences on individual outcomes that is not confounded by the background characteristics of the individuals within each neighbourhood, with the additional benefit that individuals cannot select themselves in or out of the program. However, this method has not yet been implemented in practice, so there is no clear way to evaluate its efficacy.

Whilst it is clear that these methods represent the most complete approach to separating neighbourhood effects from selection bias, the intense data requirements mean that they are beyond the scope of the majority of context effect analyses. Researchers have therefore begun to adopt an instrumental variable (IV) approach, to better control for the potential impact of selection bias. The IV approach involves the identification of some variable or variables (the instruments) that are uncorrelated with the error term, and correlated strongly with the explanatory variables that are included in a model (Oakes, 2004). These are then regressed on each of the independent variables of interest, with the predicted scores from these regressions used in the final analysis. This means that the final model uses only the part of the variability in the dependent variable that is uncorrelated with any omitted variables to estimate its' relationship with the neighbourhood effects, ensuring that estimates are not affected by omitted variable bias (Angrist & Krueger, 2001). Unfortunately, these instruments are often difficult to identify, requiring a clear justification of how they might be correlated with the neighbourhood effects of interest but not the error term (Angrist & Krueger, 2001). This means they are often based on assumptions that are implausible and un-testable (Harding, 2003). In this analysis there were no clearly identifiable instrumental variables that could be incorporated within the models.

As a result of a lack of suitable alternatives, the potential effect of selection bias is accounted for with the inclusion of covariates within the individual level fear of crime model that are closely associated with social mobility (Buck, 2001). These include socio-economic status, ethnicity, marital status, and education level. By including these covariates in the individual level model, estimates of the size of neighbourhood effects will be conditioned on potential selection mechanisms that lead to the uneven distribution of people across areas. Whilst it is possible that other unobserved effects could still bias results, the range of covariates included in the individual level fear of crime model go some way to mitigating the effect of selection bias.

4.10 The individual level correlates of fear

A range of individual level covariates will be included in the models to account for individual level variations in fear of crime, and to act as controls for selection bias. This is an important stage in integrating individual and area level explanations for fear of crime within a multilevel framework, with a number of important individual differences indentified in the existing literature that need to be incorporated to understand the complex relationship between people and the local context in which they experience fear (for a full review see chapter 1). This also allows the impact of the correction for within area dependency on individual level estimates to be examined. Including an individual level model has an additional benefit when dealing with uneven cluster sizes, because in this situation the higher level variance will also incorporate the variance resulting from the differential sample composition within each area. To obtain a proper estimate of the impact of neighbourhoods it is therefore necessary to control for potential differences in the individual composition of each area (Hox, 2002).

All individual level covariates are grand mean centred. This has no impact on fixed effect estimates but changes the value and meaning of the intercept to refer to the predicted level of fear for an average resident. Centring variables leads to a more readily interpretable random part of the multilevel model, which is particularly important when the model is extended to allow all included coefficients to vary across neighbourhoods (the implications of centring are outlined in detail in chapter 6).

The individual level covariates included in this model have been selected on the basis of existing research on the individual correlates of fear of crime, broadly covering the influences of vulnerability (including a direct measure of physical vulnerability), direct victimisation experience, and the influence of the media (for a full discussion of the individual level theories of fear, see chapter 2). The individual level model also includes a polynomial age function and the interaction between gender and age. These were included as a result of initial exploratory analysis of the individual level fear model, suggesting the relationship between age and fear was non-linear, and differentially felt by men and women. This has also been found in studies by Ferraro (1995) and Moore and Shepherd (2007). Table 4.4 provides summary details of all the individual level covariates that are included in the model.

Table 4.4: Individual Level Fear of Crime Variables

Covariate		Percentage
Gender (*Ref: Male*)	Male	44.8
	Female	55.2
Age	16-24	8.4
	25-44	34.6
	45-64	31.8
	65+	25.3
Ethnicity (*Ref: white*)	White	93.9
	Asian	1.8
	Black	2.7
	Mixed/other	1.5
Education (*Ref: No qualifications*)	No qualifications	33.8
	GCSE	25.0
	A level	21.1
	Degree	15.3
	Other (foreign)	4.7
NS-SEC (*Ref: Professional/managerial*)	Professional or Managerial	31.9
	Intermediate Occupation	11.6
	Small Employer	8.4
	Lower Supervisory Role	10.4
	Routine or Semi Routine	30.8
	Never Worked	3.4
	Student	3.6
Marital Status (*Ref: Married*)	Married or de Facto	56.6
	Separated or Divorced	11.8
	Single	19.4
	Widowed	12.1
Personal victimisation	Non Victim	93.8
	Victim	6.2
Household Victimisation	Non Victim	80.7
	Victim	19.3
Newspaper readership (*Ref: No paper*)	No Paper	22.5
	Tabloid	43.8
	Broadsheet	15.7
	Local	12.0
Health (*Ref: Not ill*)	No illness	72.6
	Non-Limiting Illness	7.9
	Limiting Illness	19.4
Length of residence	Less than 12 months	6.0
	12 months - 2 years	5.0
	2 years - 5 years	13.2
	5 years - 10 years	13.2
	More than 10 years	62.6

The crimes included in previous personal and household victimisation experience have been selected to match the official classifications used in Home Office research. Personal crime covers assault, robbery, theft from the person, and 'other' personal theft, whilst household crime includes bicycle theft, burglary, theft in a dwelling, 'other' household theft, theft of and from vehicles, and vandalism (Walker et al., 2006). Following the methodological redesign in 2001, victimisation experience now refers to the 12 months prior to the interview and not the previous calendar year.

This is generally believed to have resulted in improved and more consistent estimates of victimisation experience because of the more straightforward recall period (Lynn & Elliot, 2000).

The decision to combine three years of BCS data means it is also important to control for this potential influence on results. Figure 4.2 demonstrates a consistent drop in levels of fear across crime types over the three years of collected data (most notably between 2002/03 and 2003/04). A failure to control for this within the analysis could lead to biased estimates. As a result, a fixed effect is included that denotes the year in which the respondents were interviewed.

Percentage Worried by Crime Type (2002-2005)

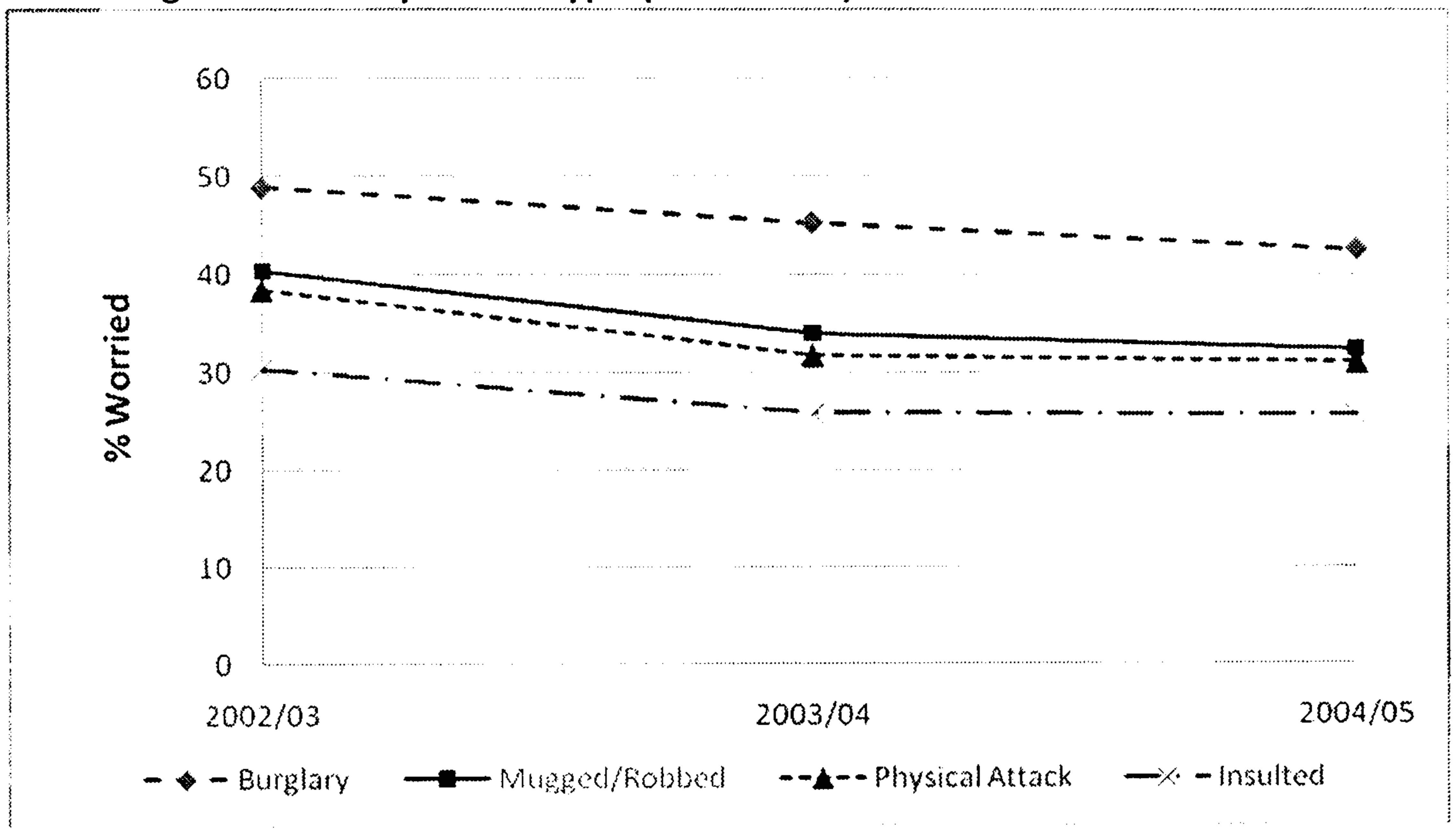

Figure 4.2

The BCS employs a complex questionnaire structure, with large sections of the survey only asked of random subsamples to maximise the number of questions that can be included. This has resulted in a potentially interesting set of individual covariates being omitted from this analysis; the impact of perceived risk. For a detailed assessment of the relationship between perceived risk and fear of crime the reader is directed to Ferraro (1995). Across the three years of included data, these items are only asked of a random sample of 25% of respondents. This means that there are too few individuals within each MSOA to conduct a meaningful area level analysis. The BCS also asks a series of questions intended to measure perceived levels of disorder. However, in line with the criticisms of Taylor (2001) and Tseloni (2007) these are viewed as a parallel construct to fear of crime so will not be used in the current analysis (see chapter 3 for a full discussion of this issue). Instead, interviewer assessments of the level of disorder in the local environment will be included in the contextual models outlined in chapter 5, reflecting the status of disorder as a contextual explanation for variations in fear.

4.11 Results II: Explaining individual differences in the fear of crime

Having identified that significant variation in fear of crime across neighbourhoods and CDRP exists, two nested models of increasing complexity are estimated for each dimension of fear. This begins with a single level regression model including individual level covariates, and is then extended to the multilevel random intercept model. Adopting this strategy will enable assessment of the contribution of neighbourhoods and CDRP conditional on the uneven sample composition within each cluster. This will also control for selection bias and reduce the likelihood of identifying spurious neighbourhood relationships by ensuring that individual differences have been accurately modelled first.

Like the unconditional random intercept model, the unexplained variance in fear of crime is partitioned at three nested levels; the part that is the result of differences between individuals σ_{e0}^2; the part that is attributable to unexplained differences between local neighbourhoods σ_{u0}^2; and the part attributable to broader CDRP level differences σ_{v0}^2. In addition to correcting fixed effect estimates and standard errors for within area dependency, this model will produce estimates of the proportion of unexplained variation in fear attributable to differences between areas, having controlled for the potential impact of uneven sample composition within each cluster.

4.11.1 Fear of personal victimisation

Looking first at fear of being the victim of personal crime, table 4.5 contains the fixed effect estimates from both the single level regression model and the extended random intercept model. The first column includes fixed effect estimates and standard errors from the single level model, along with an estimate of the remaining unexplained variance at the individual level. The second column includes the equivalent estimates from the random intercept model, along with an estimate of the remaining variance partitioned at the individual, neighbourhood and CDRP levels. The table also includes estimates of the deviance statistic (-2*loglikelihood) from each model, which is used to judge improvements to overall model fit from the multilevel extensions to the single level regression model (Hox, 2002).

Table 4.5: Random Intercept Model (Personal Crime)

		Model 1: Single Level Effect (S.E)	Model 2: Random Intercept Effect (S.E)
FIXED EFFECTS			
Constant		.08 (.01)**	.06 (.01)**
Gender (*Ref: Male*)	Female	.46 (.01)**	.46 (.01)**
Age	Age	-.005 (.0003)**	-.005 (.0003)**
	*Female	-.01 (.0003)**	-.01 (.0003)**
	Age^2	-.0002 (.00001)**	-.0002 (.00001)**
Education (*Ref: No qualifications*)	GCSE	-.07 (.01)**	-.05 (.01)**
	A level	-.11 (.01)**	-.09 (.01)**
	Degree	-.19 (.01)**	-.18 (.01)**
	Other (foreign)	-.06 (.02)**	-.05 (.01)**
Ethnicity (*Ref: White*)	Asian	.46 (.02)**	.33 (.02)**
	Black	.35 (.02)**	.13 (.02)**
	Mixed/other	.31 (.02)**	.18 (.02)**
Direct Victimisation *(Ref: Non-victim*	Personal Crime	.29 (.01)**	.26 (.01)**
	Household Crime	.19 (.01)**	.15 (.01)**
Newspaper readership (*Ref: No paper)*	Tabloid	.13 (.01)**	.11 (.01)**
	Broadsheet	-.02 (.01)	-.02 (.01)
	Local	.09 (.01)**	.09 (.01)**
NS-SEC (*Ref: Professional/managerial)*	Intermediate Occupation	.05 (.01)**	.04 (.01)**
	Small Employer	-.07 (.01)**	-.05 (.01)**
	Lower Supervisory Role	.05 (.01)**	.05 (.01)**
	Routine or Semi Routine	.08 (.01)**	.08 (.01)**
	Never Worked	.02 (.02)	.01 (.02)
	Student	.12 (.02)**	.13 (.02)**
Marital Status (*Ref: Married)*	Separated or Divorced	-.04 (.01)**	-.07 (.01)**
	Single	.02 (.01)*	-.01 (.01)
	Widowed	-.02 (.01)	-.04 (.01)**
Health (*Ref: Not ill)*	Non-Limiting Illness	.11 (.01)**	.10 (.01)**
	Limiting Illness	.19 (.01)**	.18 (.01)**
Residence	Length of residence	.01 (.002)**	.004 (.002)*
Year	Survey Sweep	-.07 (.004)**	-.07 (.004)**
RANDOM EFFECTS			
CDRP level			.037 (.003)**
Neighbourhood level			.036 (.002)**
Individual Level		.881 (.004)**	.814 (.004)**
-2*Loglikelihood		276924.7	272342.9
Number of cases		*102,133*	*102,133*

*** P<(.01)*
**P<(.05)*

The single level model (model 1) conforms to existing findings about individual level differences in fear of personal crime, and accounts for approximately 12% of the variance in fear. In line with previous research, fear of personal crime is significantly higher amongst women, net of other individual differences. The interaction between age and gender, and the quadratic age term results in a smaller estimated effect of age on levels of fear for men, and a reduction in the gender gap amongst older respondents. This can be seen more clearly in figure 4.3.

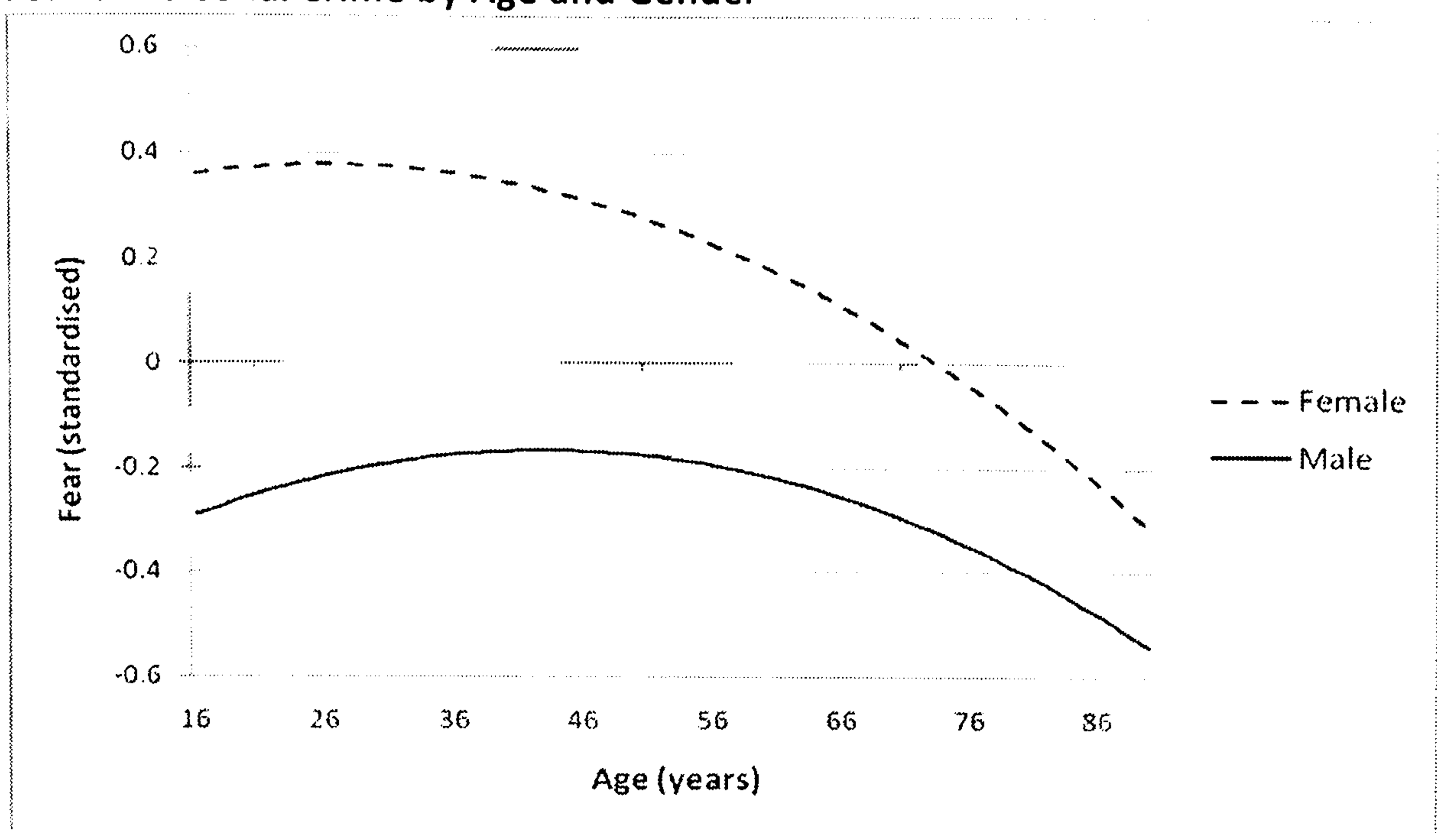

Figure 4.3

Fear of crime is also higher amongst people with poor health, with the highest levels of fear amongst people who have a limiting illness. This provides some support for the importance of physical vulnerability in relation to fear, beyond the effect of gender differences. In line with the predicted effect of social vulnerability, fear of crime is higher amongst BME groups when compared with White people and is also higher amongst those identified as more socio-economically disadvantaged (measured by NS-SEC and education level).

Turning to the effect of previous victimisation, experience of household and personal crime are both important predictors of fear of personal crime. Additionally, there is a larger difference in fear identified between victims of personal crime and non-victims, when compared with victims of household crime. Finally, the effect of the media on fear also conforms to existing studies, with significantly higher levels of fear amongst readers of newspapers that devote a larger proportion of their news space to the reporting of violent crimes (tabloid and local newspapers).

The random intercept model (model 2) confirms the finding from the unconditional model that area differences make an important contribution to individual levels of fear. This is indicated by the significant proportion of unexplained variance that has been re-partitioned as the result of differences between areas. This has been partitioned both at the local neighbourhood level and broader CDRP level and accounts for approximately 8% of the remaining unexplained variation in fear of crime. Additionally, the model reveals that an equal proportion of variance has been partitioned at each of the two higher levels included in the model, with estimates of .036 at the local neighbourhood level and .037 at the CDRP level. Therefore just as differences between local neighbourhoods are associated with different average levels of fear from residents, differences between CDRP are associated with different average levels of fear from the local neighbourhoods they are comprised of.

This is a smaller contribution from local neighbourhood and CDRP differences than was estimated in the unconditional random intercept model, dropping by 23% at the neighbourhood level (from .047 to .036) and 27% at the CDRP level (from .051 to .037). These drops in the estimated proportion of the remaining unexplained variance that is partitioned at the neighbourhood and CDRP levels reflect the uneven composition of clusters within the sample. They can be interpreted in the equivalent way to an R^2 at the specified level of the model, demonstrating that a considerable proportion of the variance at the neighbourhood and CDRP level is actually explained by individual covariates. This shows the importance of incorporating a suitable individual level model before making assessments of the impact of higher levels of clustering. The area contribution appears small when compared to the contribution of differences between individuals within local areas. However, to place this effect in context, when assessed against the single level model the inclusion of area differences make a contribution of roughly half the magnitude of all of the included individual level measures, and a larger contribution than any single individual level effect. Additionally this area effect controls for individual differences and the potentially uneven sample composition within each area.

Extending the model with a random intercept also results in clear changes to some of the fixed effect estimates included at the individual level. Most notably the estimated higher level of fear for BME groups compared to White people is considerably lower in the extended model, dropping from .46 to .33 for an Asian and from .35 to .13 and .31 to .18 for Black and mixed or other origin residents respectively. This is a clear indication of group level processes that are associated with the effect of being from a BME group that are not accurately captured in the single level model. In the random intercept model, these individual level covariates relate to within neighbourhood effects. Therefore, within neighbourhoods the effect of belonging to a BME group is estimated to be considerably smaller than when it is treated as a global effect. This suggests that part of the effect estimated in the single level model is actually a reflection of significant differences *between* neighbourhoods in the effect of ethnicity, rather than the effect of differences *within* neighbourhoods.

However, the random intercept model does not lead to significantly inflated standard errors. This is somewhat contrary to expectations, but can be explained in relation to the change in effect size estimates. As a result of many of the effect size estimates dropping in magnitude, the relative size of the standard errors has actually increased in the random intercept model. This reflects the more accurate treatment of the structure of the data in the multilevel case.

The importance of adjusting for area differences is also reflected by changes to the fit statistic in the random intercept model, with a reduction in the -2*loglikelihood of 4582 with 2 degrees of freedom [$p<0.001$] when compared against the single level model. Significance is assessed as a one tail Chi^2 difference test (Goldstein, 2003), which shows that the random intercept model represents a significant improvement over the single level model. To test the effect of correcting for the additional clustering of neighbourhoods within the wider geographic boundaries represented by the third level of the model, the additional improvement in fit from the inclusion of CDRP as a higher level of aggregation was assessed. This was done by comparing the three level random intercept model against a two level model where variance was only partitioned between individuals and local neighbourhoods. This reveals that both levels make a significant contribution to model fit, with the two level model improving model fit by 3584 with 1 degree of freedom [$p<0.001$] when compared against the individual level model, and the inclusion of CDRP further reducing the deviance statistic by 998 with 1 degree of freedom [$p<0.001$]. The three level model, then, is a justifiable extension to the two level model, enabling us to better account for the complex data structure.

4.11.2 Fear of household victimisation

Fear of being the victim of household crime is modelled using the same strategy as fear of personal crime, with two models again specified. Table 4.6 shows the estimated coefficients for these models, with the first column displaying estimates from the single level household model, and the second column relating to the extended random intercept model.

Table 4.6: Random Intercept Model (Household Crime)

		Model 1: Single Level Effect (S.E)	Model 2: Random Intercept Effect (S.E)
FIXED EFFECTS			
Constant		.09 (.005)**	.07 (.01)**
Gender (*Ref: Male*)	Female	.14 (.01)**	.14 (.01)**
Age	Age	-.005 (.0003)**	-.004 (.0003)**
	*Female	-.002 (.0003)**	-.002 (.0003)**
	Age^2	-.0002 (.00001)**	-.0002 (.00001)**
Education (*Ref: No qualifications*)	GCSE	-.06 (.01)**	-.04 (.01)**
	A level	-.10 (.01)**	-.08 (.01)**
	Degree	-.16 (.01)**	-.14 (.01)**
	Other (foreign)	-.05 (.02)**	-.03 (.01)*
Ethnicity (*Ref: White*)	Asian	.33 (.02)**	.24 (.02)**
	Black	.27 (.02)**	.17 (.02)**
	Mixed/other	.24 (.02)**	.18 (.03)**
Direct Victimisation *(Ref: Non-victim)*	Personal Crime	.16 (.01)**	.15 (.01)**
	Household Crime	.28 (.01)**	.25 (.01)**
Newspaper readership (*Ref: No paper*)	Tabloid	.10 (.01)**	.09 (.01)**
	Broadsheet	.001 (.01)	.02 (.01)
	Local	.08 (.01)**	.08 (.01)**
NS-SEC (*Ref: Professional/managerial*)	Intermediate Occupation	.03 (.01)**	.02 (.01)*
	Small Employer	-.01 (.01)	.002 (.01)
	Lower Supervisory Role	.06 (.01)**	.05 (.01)**
	Routine or Semi Routine	.07 (.01)**	.05 (.01)**
	Never Worked	.06 (.02)**	.05 (.02)**
	Student	-.06 (.02)**	-.06 (.02)**
Marital Status (*Ref: Married*)	Separated or Divorced	-.11 (.01)**	-.12 (.01)**
	Single	-.07 (.01)**	-.09 (.01)**
	Widowed	-.08 (.01)**	-.09 (.01)**
Health (*Ref: Not ill*)	Non-Limiting Illness	.08 (.01)**	.08 (.01)**
	Limiting Illness	.12 (.01)**	.11 (.01)**
Residence	Length of residence	.02 (.002)**	.02 (.002)**
Year	Survey Sweep	-.06 (.004)**	-.05 (.004)**
RANDOM EFFECTS			
CDRP level			.022 (.002)**
Neighbourhood level			.023 (.001)**
Individual Level		.938 (.004)**	.894 (.004)**
-2*Loglikelihood		284832.0	282454.8
Number of cases		*102,696*	*102,696*

*** P<(.01)*
**P<(.05)*

Like fear of personal crime, all estimated coefficients from the individual level model (model 1) are in line with existing research findings. Fear is therefore higher fear amongst people identified as more physically vulnerable, BME groups and more socio-economically disadvantaged people. Victims of crime again experience significantly higher levels of fear than non-victims, although when looking at fear of household crime victims of household crime display the largest difference in fear. Additionally, readers of tabloid newspapers are again identified as significantly more fearful of crime, with fear also higher amongst readers of local newspapers.

In contrast to fear of personal crime, the size of the gender gap is considerably smaller when examining fear of household crime. The interaction with age is also different, identifying the highest levels of fear amongst middle aged groups for men, shown in figure 4.4. The increase in fear to middle ages likely reflects the reduced likelihood of younger people being home owners, and hence being less affected by the consequences of household crime. The inclusion of these individual level covariates explains approximately 6% of the unexplained variance in fear. This is a smaller contribution than the individual covariates made when looking at fear of personal crime, again likely reflecting the failure to incorporate a measurement error correction within the model.

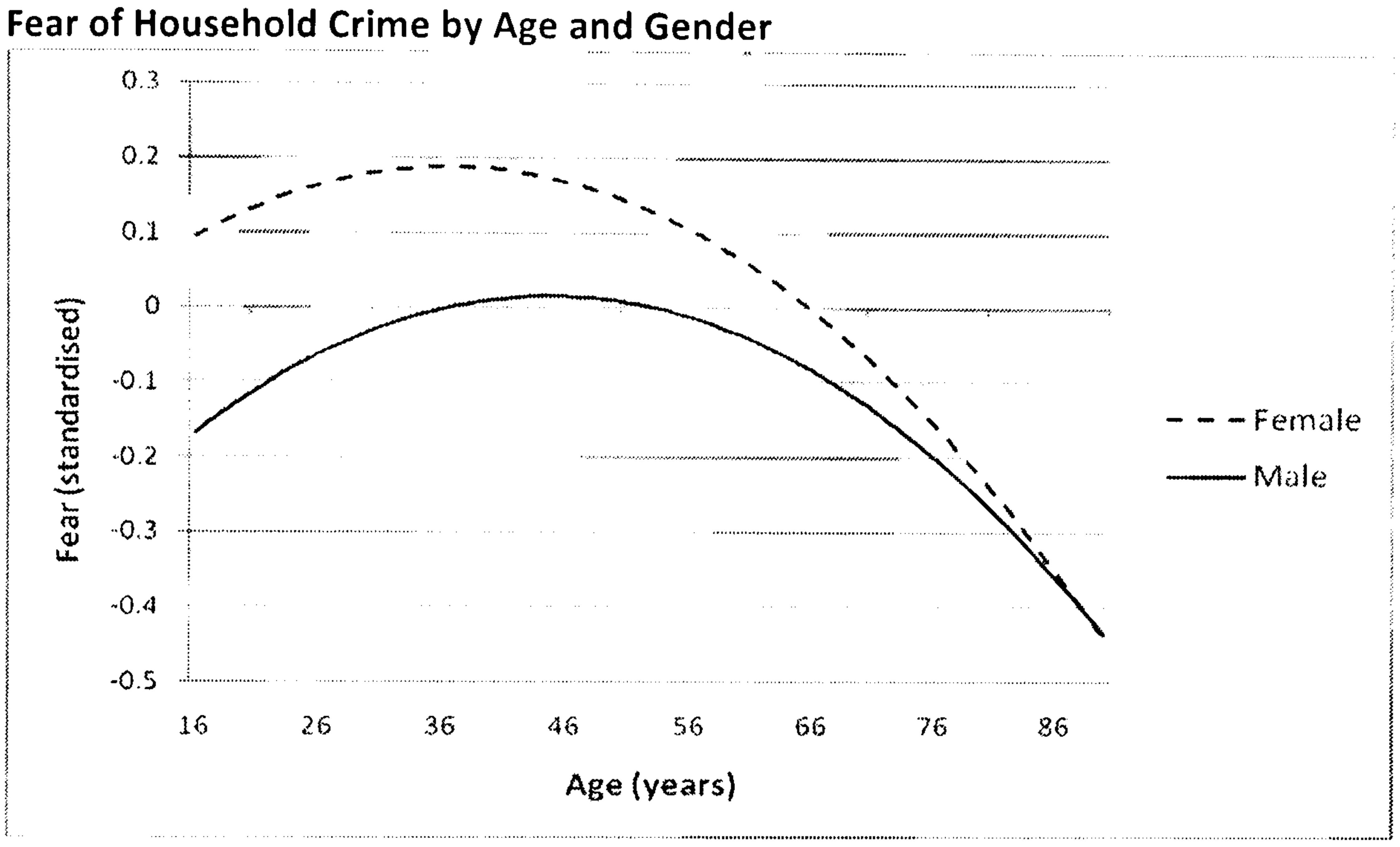

Figure 4.4

The random intercept model (model 2) confirms that local areas have a significant effect on individual level differences in fear, accounting for 5% of the total remaining unexplained variance. This is split evenly between the local neighbourhood and broader administrative geography. The inclusion of individual covariates has again resulted in a significant reduction in the unexplained variation attributable to neighbourhood and CDRP differences, further demonstrating the importance of correcting for uneven sample composition. When considering neighbourhood differences, there is an R^2 equivalent drop of 26% when compared with the unconditional model. Similarly, when looking at the effect of CDRP differences, there is a drop of 27%.

The random intercept model behaves similarly to the fear of personal crime model when considering changes to the fixed effect estimates, with notable reductions in the size of some effect size estimates when compared with the single level model. Again, BME groups are the most affected by the more complex model specification, with the size of the difference in fear compared to Whites dropping from .27 to .17 for Black people, .33 to .24 for Asians and .24 to .18 for those of mixed or other origin. Like fear of personal crime there appear to be important differences between neighbourhoods when considering the differences in fear between White and BME groups that are masked when adopting a single level approach. With the exception of the intercept term there is no clear reduction in precision resulting from the extended model, with the standard errors of estimates remaining largely consistent when measured to three decimal places. This is again attributed to the changes in fixed effect estimates.

Like fear of personal crime, the influence of area differences is not trivial, resulting in a considerably better fit than the single level model. This leads to a reduction in the deviance statistic of 2377 with 2 degrees of freedom [p<0.001]. The drop in the deviance statistic is highly significant at conventional levels of confidence, and suggests that the influence of local areas is important. Consequently the multilevel approach is again justified, improving our understanding of the complex influences on individuals' levels of fear. Testing the validity of two separate area levels confirms that including CDRP differences provides a better representation of the data structure than restricting the analysis solely to the influence of local neighbourhoods. This is demonstrated by a drop in the -2*loglikelihood of 1714 with 1 degree of freedom [p<0.001] when local neighbourhood clustering is incorporated, and a further 663 with 1 degree of freedom [p<0.001] when CDRP differences are included as an additional level.

4.12 Discussion I: The importance of social context

In this chapter I set out to examine whether the local neighbourhoods that people live in contribute to variations in levels of fear of crime, conditional on the individual level effects that have been well documented as correlates of fear. Additionally, this chapter has examined the possibility that the broader administrative area that people live in influences levels of fear beyond the impact of the immediate neighbourhood. More specifically the CDRP that each person is resident within was included in the analysis, in addition to information about the specific MSOA that they belonged to. This chapter therefore forms the important first step in a fully integrated assessment of the part that local social context plays in individual levels of fear of crime.

By capitalising on the broad coverage of the BCS and the clustered design of the sample, a random intercept multilevel model has been used to assess the extent of unexplained variations in fear of crime at the area level. Additionally it has been possible to define neighbourhoods at a significantly smaller spatial scale than previous analyses, enabling a significantly more local conceptualisation of the neighbourhood. This has several advantages over the methods that have traditionally been used to assess area effects, including corrected effect size estimates and the ability to incorporate additional data about area level characteristics at the correct level of influence alongside individual level data.

The individual level models both provide evidence in support of the findings from existing literature on individual differences in fear of crime. Women and more physically vulnerable people are thus identified as more fearful of both crime types, with a more notable difference in fear when considering fear of personal crime. Fear is also higher amongst BME groups and socio-economically disadvantaged people, both groups that have been identified as more socially vulnerable in previous research. The importance of victimisation experience is also confirmed, with recent victims significantly more fearful than non-victims. Furthermore, these effects are shown to be partly crime specific, lending support to the notion that different crime types elicit different fearful reactions. Fear is also higher amongst tabloid and local newspaper readers, which has previously been used as evidence that the media contributes to shaping people's fear. However, this effect comes with the caveat that the current analysis cannot demonstrate that it is the media influencing levels of fear, rather than that fearful people are more likely to seek out particular media sources.

Results for both fear of personal crime and fear of property crime indicate that important area level variations in fear of crime are evident, net of the observed individual differences. The extended model has therefore resulted in a significant re-partitioning of the unexplained variance in fear, with areas identified as an important source of unexplained variation in addition to individual differences. Considering fear of personal crime this has been estimated at approximately 8% of the total remaining variance, with an estimate of 5% at the area level when examining fear of property crime. Whilst this appears to be a relatively small contribution, there are several reasons to suggest that it is non-trivial and requires further investigation.

Liska (1990) argues that even a small contribution at the macro level should not be underestimated when assessed in relation to the micro level, and that this can be "pivotal in conceptually linking macro and micro level theories" (298). Therefore when adopting a multilevel modelling approach, assessments of the importance of area contributions cannot be made simply by examining their relative magnitude. Instead it is important to consider how the introduction of these additional sources of variability impact on the overall fit of the model and how the extended structure affects existing individual estimates. In this analysis the extension to a random intercept model results in a significant improvement in model fit, with the -2*loglikelihood dropping by 4582 (2 df) when considering personal crime and 2377 (2 df) when considering property crime. This is a large drop and indicates that the model is a significantly better representation of the underlying structure of the data.

The extended model also results in some clear changes to the effect size estimates associated with several of the individual covariates. This demonstrates that the picture of fear of crime is considerably different when assessed within neighbourhoods, compared with examining the individual level across all areas. This is further evidence that individual differences in fear are differentially affected by the local context in which they are experienced. It also indicates that simple corrections for clustering will not accurately reflect the uneven sample compositions within each area. Therefore, even before considering the meaning of the area component, a failure to account for the differential composition of local areas can result in some misleading conclusions about the size of some individual differences.

When considered in relation to the few existing studies that have examined worry about crime using a multilevel approach, the estimates from the current analysis are comparable. Whilst Snell (2001) uses a global measure of fear, the estimated contribution from neighbourhoods of 13% of the total variability is roughly comparable to the neighbourhood contribution to fear of personal crime in the current analysis. This is also in line with the work of Wyant (2008), where 12% of the unexplained variance in fear was attributed to local area differences. The estimated 5% contribution when considering fear of household victimisation is significantly higher than the work of Wilcox-Rountree and Land (1996a), who estimated the influence of the local neighbourhood at less than 1% of the total variance when examining fear of household crime. Additionally, Robinson et al., (2003) found no significant neighbourhood variation in worry about crime, although they did demonstrate a significant neighbourhood contribution when using other measures of fear. Since these studies were all focused on neighbourhoods within a single city, it is clear that the broader scope, but smaller spatial scale, of the current analysis has identified some important differences between neighbourhoods, even when controlling for wider geographic differences. Currently, no similar studies have been conducted in the UK, therefore the current analysis provides valuable evidence that neighbourhood variation in fear of crime also applies in the UK context.

It is therefore evident that fear of crime should not be approached purely in relation to differences between individuals linked with notions of vulnerability and victimisation experience. Instead the environmental context that people live in has an important role to play in influencing levels of fear.

Just as crime levels have been shown to vary significantly across local areas, fear of crime has an important area component that should be incorporated in any assessment of the causes of fear. This provides strong initial support for claims that local context is important and that a purely national focus is likely to distort the true picture of experiences of fear.

However, this chapter has gone a step further by allowing for the added contribution of the wider administrative geography. This has indicated that both area levels are important and make an independent contribution to the overall variation in fear of crime. It may not, then, be sufficient to simply attribute variations to differences between local neighbourhoods, with broader geographic influences also coming in to play, tied to CDRP. The clustering of neighbourhoods within CDRP provides initial evidence of the existence of spatial dependency, with levels of fear more likely to be similar amongst neighbourhoods in close proximity to one another (Elffers, 2003). A similar finding was reported in recent work by Wyant (2008), who showed some evidence of spatial dependency using data from 45 neighbourhoods in Philadelphia. This suggests that there may be processes at the neighbourhood level which are shared between neighbourhoods in close proximity to one another. Consequently, the inclusion of CDRP as an additional level of clustering will act as an important control in subsequent models, ensuring that contextual effect estimates are corrected for the influence of spatial dependency.

In this chapter, I have demonstrated significant contextual variability that should be incorporated to produce a more accurate account of fear of crime. Drawing on social disorganisation theory, in chapter 5 I will introduce a set of characteristics capturing the economic and demographic structure of local neighbourhoods, along with measures of the housing and crime profile. I will also incorporate a measure of local disorder within the local neighbourhood, another outcome of disorganised communities that has been linked to higher levels of fear of crime. I will demonstrate that the fear of crime is not just driven by individual differences, rather important contextual effects are operating at the community level which shapes the fear of the individuals living within them.

In chapter 6 I will further extend the random intercept model to provide a fully integrated explanation for variations in fear of crime. This will test whether individual explanations for fear of crime are applicable across all types of neighbourhood, or whether individual differences in fear are actually context specific. I will then examine how these variations across neighbourhoods are related to the structural characteristics introduced in chapter 5, linking the effects of social disorganisation and low level disorder directly to the experiences of local residents.

CHAPTER 5: EXAMINING THE LOCAL NEIGHBOURHOOD INFLUENCES ON FEAR OF CRIME

5.1 Introduction

In Chapter 4, I demonstrated the importance of incorporating variability across areas when examining individuals' levels of fear of crime, confirming the existence of important contextual effects beyond individual differences in fear. By adopting a multilevel modelling framework I demonstrated that a significant proportion of the variability in fear occurs at the area level, further distinguishing the influence of the local neighbourhood from wider CDRP. This resulted in a significant improvement in model fit over a single level model that did not accurately incorporate the area structure. Additionally this led to more conservative estimates of some individual level effects when these relationships were considered *within* neighbourhoods. This raises the important question, what is it about the local neighbourhood and CDRP that leads to differences in the levels of fear of residents?

Having established that significant variation in fear of crime exists between neighbourhoods and CDRP, in this chapter I extend the simple random intercept model to assess the validity of contextual explanations that focus on the impact of the areas in which people live; namely social disorganisation and the impact of low level disorder. To test social disorganisation theory, I have constructed a set of structural dimensions of neighbourhood difference derived from the 2001 census of England. Social disorganisation theory states that neighbourhood disadvantage and residential mobility lead to a breakdown in the organisational traditions of local communities, reducing their ability to control the behaviour of residents and outsiders (Shaw & McKay, 1942). This results in the atomization of local communities as residents withdraw from social life, leading to increased fear and further disorganisation. Social disorganisation theory also highlights the impact of ethnic diversity, which further reduces the informal controls available to local residents and leads to the creation of insider and outsider groups. To capture these influences, I use a factorial ecology approach to construct ecological indices, based on multiple indicators of the neighbourhood structure.

Low level disorder is the other dominant neighbourhood level theory used to explain variations in fear of crime. This has been identified as another consequence of disorganisation, with higher levels of disorder resulting in reduced informal controls available to communities (Skogan, 1990). Proponents of the disorder perspective argue that low level disorder in the neighbourhood acts as a signal to residents of the extent that the neighbourhood is in decline, causing people to perceive their risks of crime to be higher. This in turn prompts increased fear from residents. To capture the impact of disorder, I include a measure of disorder based on interviewer assessments of the local area surrounding each respondents home. To reflect the position of disorder as a consequence of disorganisation that promotes fear, this is expected to mediate the relationship between the structural dimensions of social disorganisation and fear of crime.

In chapter 6, I will extend the individual level model to allow for differential individual level relationships in different neighbourhoods, enabling an examination of the effect of being a particular type of individual in a particular type of area. This will link the individual explanations for fear directly to the contextual explanations provided by social disorganisation and neighbourhood disorder, more realistically treating neighbourhoods as specific to individual residents. This is a significant advance over existing treatments, providing a fully integrated analysis of the individual and area level influences on fear.

5.2 Introducing contextual effects to the random intercept model

Incorporating contextual data at the correct level of influence in a multilevel framework is a straightforward extension to the random intercept model outlined in chapter 4, equation [4.6]. This is based on the equations outlined in Rasbash et al., (2004). As I explained in chapter 4, the random intercept model was constructed by substituting an area level equation, [4.4], into an individual level regression equation, [4.3], to form equation [4.5], and then grouping together the error terms to form the final multilevel model. One benefit of the random intercept model is that it enables researchers to include area level variables at the correct level of influence. This is done by incorporating contextual variables within the area model originally shown in equation [4.4], forming equation [5.1].

$$\beta_{0j} = \beta_0 + \alpha_1 w_{1j} + u_{0j} \qquad [5.1]$$

In multilevel notation, coefficients at the area level are typically represented by $\alpha's$, with the $x's$ replaced by $w's$ to differentiate the area level variables from the individual level variables. A j

subscript is also included to indicate that they are measured at the area level, as shown in equation [5.1]. By including these variables in the area model, the complete dependency amongst area level variables from individuals within the same area is accounted for. As a result, estimates are adjusted to reflect the number of areas in the sample rather than the number of individuals, ensuring standard errors are correctly estimated. Because the areas are assumed to be a random sample from a larger population of areas, this also allows us to make inferences to areas in general, rather than restricting the analysis to the areas that happen to have been included in the data (Goldstein, 2003).

When the area level model is substituted back into the individual level equation we again have a random intercepts formulation, equation [5.2], though now there is also a contextual variable w_{1j}, measured at the area level. The constant terms, x_0, have again been omitted for brevity. In the same way that individual characteristics are included in the individual model to account for unexplained variation that has been partitioned at the individual level, these contextual characteristics are included within the area level model to explain the variation that has been partitioned at the area level. These area characteristics are common for all individuals living within them, and are used to describe how residents are affected by the local area.

$$y_{ij} = \beta_0 + \beta_1 x_{1ij} + \alpha_1 w_{1j} + \left(u_{0j} + e_{0ij}\right) \qquad [5.2]$$

5.3 The data

The models that I use in this chapter build on the random intercept models that were estimated in chapter 4. Therefore the core individual level data is the same combined three years of the BCS, with a sample size of 105,110 and an average of 20 respondents within each of the 5,208 MSOA (for full details, see chapter 4). This is a sufficient area level sample to make an assessment of the differences between neighbourhoods, and a large enough number of individuals within each area to look in more detail at the nature of these differences.

To test for the effect of social disorganisation, crime and low level disorder on fear of crime, and how these notions relate to individual level theories of fear, in this chapter I use contextual information to characterise the sample of neighbourhoods. Measures have been selected to capture the principal structural dimensions of local areas that have been identified in existing research on fear of crime, summarised in Hale et al., (1994). In 'contextual analysis models' this type of neighbourhood data is often based on aggregating measures from the individual level sample to the cluster level. However, as I outlined in chapter 4, this can be problematic when there are a small number of units within each cluster, with estimates typically suffering from a high degree of measurement error and a low degree of reliability (Ludtke et al., 2007). As a result of this limitation with the use of aggregate measures, the neighbourhood indices I use are primarily derived from the census, and based on data from the full neighbourhood population (Sampson et al., 2002).

Neighbourhood measures have been selected from population data made available from the 2001 census, covering all of England. The 2001 census includes a range of items covering the geo-demographic and structural character of each neighbourhood in England. This is based on aggregated responses from all the individuals living within each defined area, with all characteristics represented as proportions. By deriving data from sources independent of the BCS, we have greater confidence that they accurately represent the effect of neighbourhood differences, rather than the composition of the BCS sample within each selected area (Sampson et al., 2002).

For the purposes of this analysis, data have been obtained from all MSOA in England, with measures selected based on previous research that has incorporated the impact of social disorganisation and disorder (see for example Hale et al., (1994); Lowenkamp et al., (2003); Sampson & Groves (1989); and Taylor & Covington (1993)). The measures broadly cover; the ethnic make-up of the neighbourhood, the extent of disadvantage, the occupation structure, household types, housing details, signs of disorder, recorded levels of crime, and the population structure of the area. The data therefore cover many distinct aspects of the neighbourhood structure, and represent the range of suitable census measures available at this level of aggregation. The contextual measures from the census have been supplemented by administrative data obtained from the neighbourhood statistics division of the ONS. This data details the proportion of the population on income support, along with information about the amount of land classified as domestic, non-domestic and green-space. These measures provide further detail about each neighbourhood, with a particular emphasis on the physical structure of the area. Additionally, a measure of recorded crime is included from the index of multiple deprivation, and one measure is constructed from BCS interviewer collected data.

As I demonstrated in the previous chapter, there are important variations in levels of fear between CDRP. This represents an additional interesting source of information about the contextual nature of fear of crime, with potentially interesting differences based on variations in policing strategies and the functioning of the various agencies that are active within each area. Unfortunately, there is a distinct lack of data available at this level of aggregation. This means that it has not been possible to explore this additional source of variability beyond the simple random intercept variance. Whilst it would have been possible to construct a partial dataset including some details about policing numbers and crime levels, this would require some partnerships, and all sampled respondents from within them, to be omitted from further analysis due to a lack of available data. Missing data can be a significant problem when considered at the area level, with the loss of one CDRP potentially equating to a loss of data from 98 neighbourhoods and more than 1,000 individuals. Additionally, unlike data taken from the census there is very little consistency in the way that this data has been collected within each CDRP. This is problematic because it means that there is no way to judge the accuracy of the information obtained, or to be sure that the same thing is being measured in each partnership.

The inclusion of CDRP as a higher level of influence beyond local neighbourhood effects will still serve an important purpose for this analysis. Retaining CDRP as a higher level of clustering will correct neighbourhood effect size estimates for the impact of within CDRP dependency, in the same way that the basic multilevel structure corrects individual estimates and standard errors for area clustering (Griffith et al., 2003). Consequently, by including CDRP as a higher level of area clustering, the increased likelihood that two neighbourhoods within close proximity to one another will be more similar than two randomly selected neighbourhoods is anticipated and incorporated in the analysis.

5.4 Measuring social disorganisation and disorder

The analysis is based on the full range of available census measures, giving a significantly more detailed account of how neighbourhood differences affect levels of fear of crime than has been possible in previous analyses that rely on single indicators to characterise neighbourhoods (see for example, Hale et al., (1994); Wilcox-Rountree & Land, (1996a); and Snell (2001)). This includes measures of physical characteristics of the local area, which have largely been ignored in quantitative studies of neighbourhood effects (Lupton, 2003). Table 5.1 provides summary details for all of the measures obtained from the census and ONS data sources.

Table 5.1 : Summary of Neighbourhood Characteristics

Neighbourhood Measure	Mean (%)	Minimum (%)	Maximum (%)	Standard Deviation
Working population on income support	3.8	0	22	2.8
Working population unemployed	3.4	1	12	1.7
Non-Car owning households	26.3	3	74	14.3
Working in professional/managerial role	31.8	7	70	12.2
Working in agriculture	1.5	0	19	2.1
Lone parent families	2.7	0	10	1.3
Single person, non-pensioner households	15.4	5	60	6.6
Terraced housing	25.7	1	88	16.3
Flats	13.5	0	90	13.8
Vacant property	3.1	0	22	2.1
Local authority housing	13.1	0	78	13.1
Owner occupied housing	29.3	2	68	10.3
Domestic property	6.6	0	34	5.2
Commercial property	3.5	0	49	4.1
Green-space	51.9	0	99	28
Population density (people per square KM)	30.2	0.06	230.1	30.4
More than 1.5 people per room	0.6	0	11	1
In migration	10.9	4	59	5
Out migration	10.2	5	49	3.9
Asian	4.5	0	82	9.8
Black	2.3	0	57	5.5
Mixed Ethnicity	1.3	0	11	1.2
Resident population under 16	30.1	4	37	3.6
Resident population over 65	16	2	49	4.8
Number of neighbourhoods				6,781

Source: Census 2001

The classification and predicted influence of these census items is informed by social disorganisation theory, outlined in detail in chapter 3. A number of measures have been selected to characterise the three structural dimensions of social disorganisation described in the original treatment of Shaw and McKay (1942); neighbourhood socio-economic status, population mobility and the ethnic composition of the area. These three dimensions of neighbourhood difference have also featured in other assessments of the ecological influences on fear, making them important measures for the current analysis (Hale, 1996). Reflecting Sampson and Groves (1989) extended treatment of social disorganisation, measures have also been selected to capture the level of urbanisation and the influence of family disruption on fear of crime.

Neighbourhood Socio-Economic Status

The socio-economic status of the local neighbourhood forms a central part of social disorganisation theory, with more socio-economically disadvantaged neighbourhoods associated with fewer available resources to tackle local problems and signs of disorder, consequently leading to higher levels of fear (Hale et al., 1994). Additionally, the socio-economic status of the local area has been used as a measure of the organisational participation of residents, with more disadvantaged neighbourhoods offering fewer opportunities for local residents to participate in the community, which in turn reduces the degree of community cohesion and the availability of informal social controls (Sampson & Groves, 1989). This is then linked to reduced abilities to maintain social order, resulting in higher levels of crime and fear. The socio-economic status of the neighbourhood has also been linked to fear indirectly through crime rates, with more disadvantaged areas also often suffering from higher levels of crime than less disadvantaged areas.

To incorporate disadvantage in this analysis, a number of census measures have been selected that capture aspects of the socio-economic structure of the local neighbourhood. Looking first at the economic structure of the neighbourhood, two characteristics are included; the proportion of the resident population of working age on income support; and the proportion of households that do not own a car. Averaged across all neighbourhoods, the proportion of the working aged population on income support is approximately 4% of the total working population. Additionally, approximately 26% of households do not own a car, with a maximum of 74% of the resident population reporting they do not own a car.

Turning to the occupation structure of the area, the proportion of the working age population that are unemployed, and the proportion classified as working in a managerial or professional role are used to characterise the impact of differential employment opportunities. Across all neighbourhoods, the proportion unemployed is low, at approximately 3%. Despite this, some particularly disadvantaged neighbourhoods can be identified, with a maximum of 12% of the working population unemployed. Additionally, on average 31% of the resident working population is classified as working in a managerial or professional role.

A measure has also been included to capture differences in the housing structure of each area, detailing the proportion of housing identified as terraced accommodation. On average 23% of the housing in an area is terraced, although in some neighbourhoods they account for up to 85% of all households. Along with details of the housing type in an area, two measures are included to describe particular types of household within each area; the proportion of local authority housing; and the proportion of owner occupied accommodation. Finally, the level of intensive overcrowding is included to help identify the most disadvantaged local neighbourhoods. Specifically this details the proportion of households with more than 1.5 people per room. In general only a small proportion of households are classified as overcrowded (average 0.6%), although some areas are characterised by as much as 11% of housing overcrowded.

Residential Mobility

Within the original treatments of social disorganisation, the extent of population migration into and out of the local neighbourhood was directly tied to the level of socio-economic disadvantage. This gave prominence to the importance of residential stability for fostering local community networks and social relations between residents. These networks and relational structures have primarily been presented as an important source for facilitating local social control, providing communities with increased social resources for organising effectively to prevent disorder (Taylor & Covington, 1993). Residential mobility has also been linked to higher levels of fear by highlighting the potential impact that population instability has in restricting the development of local support networks between residents, leading to greater perceived consequences of crime (Sampson & Groves, 1989).

The level of population turnover is captured with measures of the level of migration into and out of the local neighbourhood within the last 12 months. These provide clear details of the extent that the area is in transition, displaying similar average proportions moving into and out of the local neighbourhood (11% and 10% respectively). There is a high degree of variability between neighbourhoods, and some areas are characterised by particularly high levels of net migration. In addition to these direct measures of the level of population mobility, the proportion of properties in the MSOA that have been left vacant is used to characterise the extent that areas have experienced a net outflow of residents. Additionally, the proportion of local residents who live alone, but who are not pensioners is also included to capture the more transient young working population. Across all local neighbourhoods in England, an average of 15% of households is identified as one-person non-pensioner properties, with this figure ranging from 5% to 60% across all neighbourhoods.

Ethnic diversity

Ethnic diversity has also been identified as an important influence on levels of disorganisation, restricting the formation of strong community networks and fostering suspicion of people from different ethnic groups. In addition to the links with disorganisation, this has then been linked to fear of crime as a result of a higher incidence of crime, and higher levels of socio-economic disadvantage within neighbourhoods that have higher proportions of non-White residents (Babb et al., 2007; Hale, 1996). The effect of ethnic diversity has typically been characterised in studies by incorporating the proportion of the population identified as non-White, or of particular ethnic groups. Across England, the majority of areas have a fairly low proportion of BME residents, with an average of 2.3% of the resident population classified as Black, 4.5% classified as Asian, and 1.3% of mixed or other ethnic origin. There are some areas that have a very different ethnic structure and experience a high degree of ethnic clustering, with a maximum of 57% of the population identified as Black, 11% of mixed origin, and up to 82% of the neighbourhood identified as Asian.

However, using the proportions of residents from different BME groups does not represent a true measure of the extent of diversity, instead acting as a basic measure of the ethnic composition of the neighbourhood. A more detailed characterisation of the level of ethnic diversity in the local neighbourhood can be found in studies that focus on the effect of ethnic heterogeneity, reflecting the level of integration of BME groups within a neighbourhood. Here, the presence of 'insider' and 'outsider' groups within an area is given prominence. 'Insider' groups are those individuals that share the same ethnicity, whilst 'outsider' groups are those of different ethnicities. There are two dominant theories about the impact of the existence of 'insider' and 'outsider' groups, which have primarily been used to explain differences in people's levels of trust; generally labelled as conflict and contact theories (Putnam, 2007).

Theories of the effects of ethnic diversity that fall within the rubric of conflict theories, state the importance of the presence of 'others' in reducing social solidarity. This can lead to inter-group tensions, fostering out-group suspicions, which in turn lead to higher levels of fear. These inter-group tensions also result in the reduced likelihood of the effective socialisation of residents within a neighbourhood, making them less likely to intervene to solve problems like low level disorder (Taylor & Covington, 1993). In contrast, contact theory argues that increased ethnic heterogeneity actually results in higher levels of social solidarity, by fostering increased tolerance of those identified as 'outsiders' (Putnam, 2007). From this perspective, increased contact with those that are different actually serves to enhance the community bonds within a neighbourhood, strengthening the available informal social controls within the community to deal with low level disorder. This is a more long term predicted outcome of heterogeneity that has received considerably less empirical support than conflict theory.

Putnam (2007) also presents us with a third possible effect of ethnic heterogeneity, labelled constrict theory, which he directly relates to the levels of trust within a community. From this perspective, the effect of higher levels of ethnic heterogeneity is not just that people's suspicion of 'outsider' groups is higher, but that they will also experience higher levels of suspicion of other 'insiders'. He suggests that this means that residents of more heterogeneous neighbourhoods will tend to "withdraw from collective life, to distrust their neighbours regardless of the colour of their skin" (Putnam, 2007: 150). Whilst this withdrawal from community life has generally been used to explain differences in levels of trust, it can also be processed in relation to fear of crime which can be viewed as an expression of reduced trust in neighbours. It is therefore plausible that the mechanisms linked to heterogeneity will have a similar effect on fear.

In this study, the ethnic composition of the neighbourhood is characterised by the degree of ethnic heterogeneity, in line with more recent treatments of neighbourhood ethnicity. The level of ethnic heterogeneity is assessed in this analysis using a fractionalisation index. This is based on the herfindahl concentration formula, displayed below in equation [5.3].

$$Diversity = 1 - \sum_{i=1}^{n} s_i^2 \qquad [5.3]$$

In this equation, s_i reflects the population share of ethnic group i, out of a total of n groups. To calculate the index score, we sum the squared proportion shares for each ethnic group, and subtract this from one. This gives us the probability of two randomly selected individuals from the same locality being of different ethnic origin, with a higher score (from 0 to 1) representing a neighbourhood with a more mixed population. The ethnic fractionalisation index has regularly been used to characterise the differences in the level of ethnic heterogeneity between different countries. However the availability of local area ethnicity data makes it a suitable index for the current analysis.

Urbanisation

Sampson and Groves (1989) also incorporated urbanicity within their treatment of social disorganisation theory, reflecting the extended scope of their analysis beyond a single city. Despite finding no direct link to disorganisation in their original assessment, there are several reasons to include it within the current treatment of fear of crime. The difference in the levels of fear of urban and rural residents is not a new idea, with urban residents repeatedly shown to have higher levels of fear (for a recent example see Allen (2006)). This is generally explained in relation to the limited mechanisms to exert social control in urban areas when compared to the strong community structures that are often present in rural locations (Hale et al., 1994). This reduced capacity to exert social control within urban areas has primarily been linked with the higher levels of population mobility within urban areas (Sampson & Groves, 1989), but has also been associated with a reduced ability to create and maintain social networks (Merry, 1981b). Finally, an indirect effect of urbanisation through the higher crime rates in urban areas has been used to explain the higher levels of fear in urban areas (Jones et al., 1986).

However, the effect of urbanisation has typically been based on the simple distinction between rural and urban areas based on the number of households within a given area, with no ability to distinguish between varying degrees of urbanisation. This effect has also been difficult to separate from other potential neighbourhood influences, making a more complex appraisal that controls for other contextual measures an important extension to existing research. In this analysis I incorporate a number of measures to more accurately describe the level of urbanisation, focusing particularly on the land usage in the local neighbourhood. The inclusion of multiple measures enables a more sensitive assessment of the influence of urbanisation that is not restricted to a simple dichotomy between urban and rural. This also relates to a more compact geographic area than has been used in previous studies, providing a clearer picture of the effect of urbanisation at the neighbourhood level.

Three measures have been selected which characterise the type of land usage within each neighbourhood. These detail the amount of land covered by domestic property, commercial property, and green-space, with averages of 7%, 3.5% and 52% of land defined as domestic, commercial and green-space respectively. These are intended to provide an alternative characterisation of the area that specifically focuses on the physical structure of the neighbourhood. In addition to these measures, the proportion of the population working in agriculture is used to characterise more rural locations, with an average of 2% working in an agricultural occupation and a maximum of 19%.

Finally, the population density of the local area is used as a further measure of urbanisation. There is considerable variation in the population densities across neighbourhoods, with the number of people ranging from less than one to 230 per sq km. From this it is clear that whilst neighbourhoods might all contain a fairly stable number of households, some will cover a wide geographic area whilst others will relate to much smaller areas. This makes it important to be able to control for these differences within any analysis of the contextual influences on fear.

Family disruption

Sampson and Groves (1989) also identify the degree of family disruption as an important neighbourhood characteristic that should be incorporated within assessments of social disorganisation theory. They highlight parental supervision as a key source of informal control over the actions of neighbourhood youth. This in turn is believed to increase the levels of low level disorder and public anxiety about crime. Like urbanicity, they find no direct link between family disruption and social disorganisation theory, leading them to suggest it has an independent effect on crime. This is included in the current analysis because of its close link to low level disorder, which has regularly been identified as an important source of fear in existing research.

As a result, a direct measure of the extent of family disruption that details the proportion of households within the area that are lone parent families is included in this analysis. Across England, approximately 3% of all households are identified as lone parent households, with some neighbourhoods having up to 10% classified as lone parent families. Additionally, two measures of the age structure of the neighbourhood are included. These detail the proportion of the resident population that is aged below 16, along with the resident population aged over 65.

Disorder

Low level disorder in the local neighbourhood has regularly been identified as an important correlate of fear of crime, with a large body of research referring to incivilities, broken windows, disorder, signs of crime and perceived neighbourhood problems (for a full review see chapter 3). Disorder is also closely tied to social disorganisation theory, with low level disorder signalling that a neighbourhood lacks the mechanisms to informally control the behaviour of residents and outsiders. The structural precursors to social disorganisation can therefore also be identified as the structural precursors to low level disorder, which in turn leads to higher levels of fear as residents judge their risks of crime to be greater.

However, most studies of the relationship between disorder and fear rely on questions that ask people about their perceptions of low level disorder within the local area, rather than capturing physical signs of disorderly behaviour in the local community. Taylor (2001) has convincingly argued that these measures should not be treated as equivalent to actual disorder, and that they could better be described as alternative measures of fear of crime (see also Tseloni (2007)). This suggests that the high correlations often observed are a reflection of the fact that perceptions of disorder actually represent another dimension of fear. Additionally, Taylor (2001) highlights the high degree of variability in perceptions of disorder amongst residents from the same neighbourhood as a demonstration that they are unsuitable as measures of disorder.

In response to these criticisms, I include an independent measure of low level disorder within this analysis, derived from interviewer assessments of the extent of disorder in the area. This is based on the combined score on three items covering the extent of litter, vandalism (graffiti and damage to property), and run down property in the area immediately surrounding the respondents home. These are aggregated across all individuals from the same MSOA to construct a summary measure of the extent of disorder within the neighbourhood. The measure ranges between a score of 0 and 9, with higher scores representing a higher prevalence of signs of disorder. This is not a true measure of disorder, relying on interviewers accurately assessing the levels of disorder within the local neighbourhood. However, it does go some way to mitigating the problems evident with basic perception measures, using data that is independent of respondents.

Recorded crime levels

In addition to the structural dimensions of the local neighbourhood, I also include a measure of the level of recorded crime. Traditionally, treatments of neighbourhood variations were used to explain differences in the levels of crime in different neighbourhoods. However, Sampson and Groves (1989), and later Hale et al., (1994) incorporated these structural dimensions as important influences on levels of fear independently of the level of crime. Therefore, to separate these influences from the potential impact of crime, it is necessary to also include a measure of the level of recorded crime. This will also help provide a clearer picture of the relationship between crime rates and fear of crime, with the significantly lower spatial scale more directly relevant to the local experience of residents.

The apparent lack of a consistent relationship between recorded crime figures and levels of fear has greatly influenced theorising on the mechanisms influencing fear of crime (Hale, 1996). However the rejection of a significant relationship has often been based on the inclusion of crime figures at a broad spatial scale. This makes it likely that important local level variations are being missed and consequently that the effect of crime is being underestimated. To remedy this, an index measure of recorded crime levels in the immediate neighbourhood is used in the current analysis. This is part of the official index of multiple deprivation (Noble et al., 2004).

Using a measure of crime at a much lower spatial scale makes it possible to more accurately assess how the very local experience of crime is reflected in the levels of fear of residents. As such, it comes significantly closer to representing the real experiences of crime at the local level, which Young (1988) highlighted were important in his assessments of fear using local crime surveys. It is expected that this will result in a clearer relationship than has previously been demonstrated in national fear of crime research, with fears more closely resembling the reality of crime at the local level. Unfortunately, as this is an index that has been constructed by an external source it is not possible to assess whether levels of fear are directly related to specific types of recorded crime. Instead, the index incorporates details from 33 different recorded offences across four major crime types that have occurred in the local area of approximately 500 households around the respondent's home.

This is based on geo-coding of the location where the crime was recorded by the police. Table 5.2 contains details of all of the offences that have been included in this index, including the crime type that they belong to.

Table 5.2: Crime Types Included in Index

Major Crime Type	Offence
Burglary	Burglary in a Dwelling
	Aggravated Burglary in a Dwelling
	Burglary in a Building other than a Dwelling
	Aggravated Burglary in a Building other than a Dwelling
Theft	Aggravated Vehicle Taking
	Theft from the Person of Another
	Theft from a Vehicle
	Theft or Unauthorised Taking of Motor Vehicle
	Vehicle Interference and Tampering
Criminal Damage	Arson
	Criminal Damage to a Dwelling
	Criminal Damage to a Building other than a Dwelling
	Criminal Damage to a vehicle
	Other Criminal Damage
	Racially-aggravated Criminal Damage to a Dwelling
	Racially-aggravated Criminal Damage to a Building other than a Dwelling
	Racially-aggravated Criminal Damage to a Vehicle
	Racially-aggravated other Criminal Damage
	Threat etc. to Commit Criminal Damage
Violence	Murder
	Manslaughter
	Infanticide
	Attempted Murder
	Causing Death by Aggravated Vehicle Taking
	Wounding or other Act of Endangering Life
	Other Wounding
	Harassment
	Racially-aggravated other Wounding
	Racially-aggravated Harassment
	Common Assault
	Racially-aggravated Common Assault
	Robbery of Business Property
	Robbery of Personal Property

Source: Noble et al., (2004)

The index measure is constructed by calculating the incidence of each crime type within a local area and combining these to form a final score for the overall incidence of crime in the neighbourhood. This score is then used to rank local neighbourhoods in terms of their relative crime level, producing the final index measure of the relative level of crime (Noble et al., 2004). Within each of the four crime types, each offence contributes an equal weight to the incidence score, therefore the incidence level in each crime type is simply the sum of all of the individual offences divided by the total resident population.

The level of recorded crime is treated in the following models as an individual level measure, despite actually being measured at the LSOA level. As I outlined in section 4.7, this is a spatial scale that lies between the individual and the MSOA level. This means that there is potentially additional dependency amongst individuals within the same LSOA that might be missed by treating this measure as an individual characteristic. All subsequent models were therefore tested for the possible effect of this additional source of dependency by utilising a four level random intercept framework, including LSOA as a further source of variation. This had no noticeable effect on results with the ICC at this lower spatial scale estimated to be non-significant, giving us confidence that the current specification is justified.

5.4.1 Characterising neighbourhoods with a factorial ecology approach

Amongst many of the measures that have been selected for inclusion within this analysis there is a high degree of multicollinearity, reflecting their status as multiple indicators of a few principal dimensions of neighbourhood differences. Multicollinearity is a common problem with the use of neighbourhood level data which can lead to estimation problems, inflated standard errors and unstable results when many highly correlated variables are included within the same analysis (Agresti & Finlay, 1997). As a result of this potential model limitation, I have adopted a factorial ecology approach to generate a series of structural indices that characterise the strong correlations amongst the identified neighbourhood characteristics. This follows the methodology adopted by Morenoff and Sampson (1997) in their study examining variations in violent crimes across neighbourhoods.

Factorial ecologies are an exploratory approach to ecological analyses that have been used by researchers to uncover dimensions of area differentiation. To do this, the statistical methods associated with factor analysis are adapted by replacing individuals with areas as the unit of analysis, enabling researchers to identify the underlying dimensions of neighbourhood difference (Rees, 1971). The most common method used to identify the underlying dimensions in a factorial ecology is PCA, which transforms the observed correlated variables into a set of uncorrelated factors (Agresti & Finlay, 1997). These uncorrelated factors are linear combinations of the observed variables, such that the first factor explains the maximum possible variance amongst the observed variables, and each additional factor explains progressively less of the remaining variance. This results in a set of uncorrelated indices that are linear transformations of the observed variables, from which all of the factors that account for a pre-specified proportion of the total variance are retained. This usually involves retaining all factors that account for more variance than is attributable to any single variable included in the analysis, as represented by their eigen value (Agresti & Finlay, 1997).

This approach often involves a second transformation of the factors, referred to as a rotation, which re-scales the retained factors to make their interpretation clearer. There are two types of main rotation available, orthogonal and oblique, with orthogonal rotation generally used in factorial ecologies. This is an exploratory procedure which attempts to make the distinction between each of the factors, and the variables that are highly correlated with each factor, more apparent, whilst retaining the uncorrelated structure between factors (Rees, 1971). This rotation procedure is done to enable the straightforward labelling of each factor based on the variables that are highly correlated with it. In contrast, oblique rotation allows the extracted factors to be correlated with one another.

Since the peak of their popularity in the 1960s, factorial ecologies have become less prominently used as forms of research in their own right (Johnston et al., 2005a). However, a number of more recent analyses have fruitfully used these techniques to generate indices of relative neighbourhood difference to be incorporated in analyses (see for example Buck, (2001); Johnston et al., (2005a); Morenoff & Sampson (1997); and Propper et al., (2005)). These focus primarily on the benefits of factorial ecology approaches as a method for summarising neighbourhood level data, enabling a more detailed assessment of how different dimensions of neighbourhood variability influence different social outcomes. This approach is suitable for the current analysis, enabling a more accurate assessment of the distinct dimensions of local neighbourhood difference that are predictors of fear of crime.

Importantly, no preconceived hypotheses about the relationships between neighbourhood measures are specified using this methodology. Using this exploratory method enables an assessment of the extent that the neighbourhood dimensions identified above are suitable descriptions at the very local level. The factorial ecology is conducted on data from all local neighbourhoods in England. As a result, the neighbourhood dimensions that are uncovered will be reliable indicators of the differences across local neighbourhoods.

A multilevel analysis using a factorial ecology approach to generate indices of neighbourhood differences can be thought of as a two stage process. First the factor model is estimated to identify the common area level factors that characterise the variance in the available items. Then the extracted factors from this model are included as contextual effects in the multilevel model. Using a multilevel SEM approach, it would be possible to estimate the measurement model for the contextual effects and the multilevel random intercept model in a single step. This approach was not adopted in the current analysis because of the restriction to two levels of influence. Additionally, the multilevel SEM approach is computationally intensive, leading to estimation problems when a large number of coefficients are being estimated. I felt that the potential added value from an additional level of influence to control for dependency was a more important consideration than the small reduction in measurement error resulting from the use of a fully integrated SEM approach.

The factorial ecology model uses a principal components extraction with an orthogonal rotation procedure to retain all factors which account for more variance than the average neighbourhood variable (eigen values above 1). This results in five factors being extracted which accounted for 82% of the total variation in the 21 items included in the analysis. The level of recorded crime, low level disorder, and the measure of ethnic fractionalisation were not included within the factorial ecology because these measures are already composite indicators, and it was felt to be important not to further abstract these measures from their initial meanings. The rotated factor loadings for each extracted factor are included in table 5.3. An oblique rotation procedure was also examined, however none of the retained factors exhibited high correlations with one another, so the increased simplicity and interpretability of the orthogonal approach was judged appropriate.

Table 5.3: Rotated Factor Loadings from Factorial Ecology

Neighbourhood Measure	Socio-economic disadvantage	Urbanicity	Population Mobility	Age Profile	Housing Profile
Working population on income support	**.890**	.245	.191	.138	.092
Lone parent families	**.847**	.222	.002	.263	.153
Local authority housing	**.846**	.064	-.009	.146	-.168
Working population unemployed	**.843**	.293	.173	.118	.125
Non-Car owning households	**.798**	.417	.363	-.010	.057
Working in professional/managerial role	**-.787**	.002	.153	.146	-.368
Owner occupied housing	**-.608**	-.249	-.349	-.572	.053
Domestic property	.104	**.921**	.165	.052	.112
Green-space	-.214	**-.902**	-.180	-.011	-.043
Population density (per square KM)	.245	**.824**	.262	.150	-.135
Working in agriculture	-.126	**-.663**	-.006	-.183	-.030
In migration	-.074	.102	**.916**	.069	.071
Out migration	-.019	.162	**.903**	.119	.134
Single person, non-pensioner households	.355	.364	**.743**	.134	-.092
Commercial property	.378	.432	**.529**	.019	-.093
More than 1.5 people per room	.428	.472	**.507**	.197	-.326
Resident population over 65	-.052	-.210	-.271	**-.892**	-.021
Resident population under 16	.427	.040	-.464	**.635**	.190
Terraced housing	.323	.263	.102	.274	**.689**
Vacant property	.319	-.118	.485	-.173	**.530**
Flats	.453	.359	.489	.008	**-.524**
Eigen Value	9.3	3.3	1.9	1.4	1.3

Examining the rotated factor loadings shows how much each neighbourhood measure is correlated with each extracted factor, with higher scores representing a stronger influence of a particular variable on that factor. This enables us to identify which measures are making a notable contribution to each factor and hence attach descriptive labels to each of them. These extracted factors fall largely in line with the classifications identified in Sampson and Groves (1989) extended treatment of social disorganisation theory, with a few notable exceptions. When examined using the factorial ecology approach, the proportion of lone parent households is identified as an indicator of socio-economic disadvantage, rather than as a measure of family disruption. As a result, a general measure of the age profile of the local area is extracted, capturing the combined influence of the indicators of the population age structure. Additionally, the measures capturing the types of housing that are present in the neighbourhood form a separate dimension of neighbourhood difference.

The first extracted factor accounts for 44% of the total variance amongst the items. This factor clearly reflects the socio-economic structure of the local area. Neighbourhoods identified as more disadvantaged (and thus scoring higher on this factor) are more likely to have higher proportions of the population unemployed or on income support, and lower proportions of the population working in managerial or supervisory roles. Additionally more 'disadvantaged' areas are likely to have a larger proportion of lone parent families and those who do not own a car. Finally, these areas will be characterised by a higher proportion of local authority housing, and a lower proportion of property that is owner occupied.

The second extracted factor is a measure of the neighbourhood level of urbanicity. This factor accounts for an additional 16% of the variation in the included items. Areas characterised as having a higher degree of urbanisation (higher scores) will tend to have higher population densities and higher proportions of domestic housing, as well as a reduced proportion of land identified as green-space and fewer residents working in the agricultural sector.

The third extracted factor accounts for a further 9% of item variation. This details the level of population mobility in the local area, with neighbourhoods that have a higher proportion of people moving into and out of the area scoring higher on this index. Additionally, areas scoring higher on this index will have higher proportions of non-domestic property and a higher level of overcrowding. A higher score on this factor is also associated with a higher proportion of single-person non-pensioner households, suggesting that this measure may partially be capturing neighbourhoods that are characterised by a younger and more mobile workforce.

The fourth factor accounts for 6% of the variation in the items. This factor relates specifically to the age profile of the local area. Areas scoring higher on this index will have a higher proportion of younger people living in the area (aged below 16), and a lower proportion of elderly respondents (aged 65+). They will also have somewhat lower proportions of owner occupied properties. This factor does not fully match earlier definitions of family disruption, although it can still be used to characterise neighbourhoods that will have larger youth population, and hence an increased likelihood of unsupervised teen groups (Hale et al., 1994). The final factor accounts for another 6% of the variation in the included items. This factor appears to be characterising the housing profile of the area, with the proportion of housing identified as terraced, vacant and flats all demonstrating higher factor loadings.

5.5 Results III: Social disorganisation, disorder and the fear of crime

To test the effects of social disorganisation and disorder on fear of crime, the contextual effects described above are incorporated within the random intercept models from chapter 4. Including these contextual measures within the area level model means that they are treated as area effects rather than as individual level effects. As a result, estimates of significance are based on the 5,208 sampled neighbourhoods, controlling for the composition of the individuals within them. Additionally, the effect of dependency between neighbourhoods in close proximity to one another is corrected for by nesting neighbourhoods within broader CDRP boundaries. Buck (2001) highlights the potential existence of non-linear neighbourhood effects, and advocates the inclusion of polynomial terms within contextual models. These were tested for in the current analysis, however no significant quadratic terms were identified, and so these were omitted from the final models. Interaction terms between contextual effects were also tested for, but no significant interactions were identified.

5.5.1 Fear of personal crime

Table 5.4 contains effect size estimates from the random intercept model with contextual variables at the neighbourhood level. This also includes details of the remaining unexplained variance partitioned at the individual, neighbourhood, and CDRP levels. Model 1 includes measures of the 5 structural dimensions of social disorganisation that were included in Sampson and Groves (1989) extended theory. This also includes details of the housing structure of the local neighbourhood, the additional neighbourhood measure that was derived from the factorial ecology. In model 2 the level of crime and low level disorder in the local area are added to the contextual model to examine how they affect the relationship between disorganisation and fear.

Table 5.4: Contextual Effects Models (Personal Crime)

		Model 1: Social Disorganisation Effect (S.E)	Model 2: Disorder and Recorded Crime Effect (S.E)
FIXED EFFECTS			
Constant		.07 (.01)**	.07 (.01)**
Gender (*Ref: Male*)	Female	.46 (.01)**	.46 (.01)**
Age	Age	-.004 (.0003)**	-.004 (.0003)**
	*Female	-.01 (.003)**	-.01 (.003)**
	Age^2	-.0002 (.00001)**	-.0002 (.00001)**
Education (*Ref: No qualifications*)	GCSE	-.04 (.01)**	-.04 (.01)**
	A level	-.08 (.01)**	-.08 (.01)**
	Degree	-.17 (.01)**	-.17 (.01)**
	Other (foreign)	-.05 (.01)**	-.05 (.01)**
Ethnicity (*Ref: White*)	Asian	.29 (.02)**	.29 (.02)**
	Black	.09 (.02)**	.09 (.02)**
	Mixed/other	.15 (.02)**	.15 (.02)**
Direct Victimisation (*Ref: Non-victim*)	Personal Crime	.26 (.01)**	.26 (.01)**
	Household Crime	.15 (.01)**	.14 (.01)**
Newspaper readership (*Ref: No paper*)	Tabloid	.11 (.01)**	.11 (.01)**
	Broadsheet	-.02 (.01)	-.02 (.01)
	Local	.09 (.01)**	.09 (.01)**
NS-SEC (*Ref: Professional/managerial*)	Intermediate Occupation	.04 (.01)**	.04 (.01)**
	Small Employer	-.05 (.01)**	-.05 (.01)**
	Lower Supervisory Role	.04 (.01)**	.04 (.01)**
	Routine or Semi Routine	.07 (.01)**	.07 (.01)**
	Never Worked	-.0003 (.02)	-.003 (.02)
	Student	.14 (.02)**	.14 (.02)**
Marital Status (*Ref: Married*)	Separated or Divorced	-.08 (.01)**	-.08 (.01)**
	Single	-.02 (.01)*	-.02 (.01)*
	Widowed	-.04 (.01)**	-.05 (.01)**
Health (*Ref: Not ill*)	Non-Limiting Illness	.10 (.01)**	.10 (.01)**
	Limiting Illness	.17 (.01)**	.17 (.01)**
Residence	Length of residence	.004 (.002)*	.004 (.002)*
Year	Survey Sweep	-.07 (.01)**	-.06 (.01)**
CONTEXTUAL EFFECTS (Level 2)			
Social disorganisation	Socio-economic disadvantage	.07 (.01)**	.03 (.01)**
	Urbanisation	.09 (.01)**	.07 (.01)**
	Population mobility	.02 (.01)**	.004 (.01)
	Age Profile	.02 (.01)**	.01 (.005)**
	Housing Profile	-.01 (.01)*	.02 (.01)**
	Ethnic heterogeneity	.24 (.05)**	.23 (.05)**
Crime	Local Recorded Crime		.03 (.01)**
Low level disorder	Objective Disorder		.04 (.01)**
RANDOM EFFECTS			
CDRP level		.020 (.002)**	.019 (.002)**
Neighbourhood level		.032 (.002)**	.031 (.002)**
Individual Level		.814 (.004)**	.814 (.004)**
-2*Loglikelihood		271927.2	271858.9
Number of cases		*102,133*	*102,133*

*** P<(.01)*
**P<(.05)*

Looking at the contextual effect estimates provides us with important details about how people's fear of crime is influenced by social disorganisation, low level disorder and crime. Model 1 provides initial support for the effect of social disorganisation, with all six structural measures demonstrating significant relationships with fear. Incorporating these structural characteristics leads to a large reduction in the unexplained variance in fear attributable to area differences, with the contextual measures thus explaining 29% of the area level variation in fear. This reduction in area level variance appears to occur primarily at the Crime and Disorder Reduction Partnership level, with the variance here dropping by 46%, compared with 11% at the local neighbourhood level. The larger contribution at the CDRP level likely reflects the high degree of similarity amongst neighbourhoods from the same CDRP, highlighting the importance of correcting neighbourhood estimates for dependency within CDRP. This is also associated with a significant improvement in model fit of 416 with 6 degrees of freedom [$p<0.001$].

The most striking result here relates to the effect of the neighbourhood level of ethnic heterogeneity on fear. This indicates that people living in more ethnically mixed areas have higher than average levels of fear, net of all other covariates. Importantly, this effect is evident having controlled for other structural characteristics of neighbourhoods that are also associated with more ethnically heterogeneous areas, including the level of socio-economic disadvantage. Along with the significant effect of the ethnic structure of the area, there are strong effects of the level of socio-economic disadvantage and the degree of urbanisation. The positive coefficient associated with the relative level of neighbourhood socio-economic disadvantage means that people living in areas classified as more socio-economically disadvantaged; typically having higher proportions unemployed and on income support, fewer working in managerial roles and owning cars, and a higher proportion of lone parents, will have significantly higher fear of crime. This controls for the potential selection mechanism within the neighbourhood linked with differing individual socio-economic status. Therefore, it is not simply the socio-economic status of the respondent that has an important influence on levels of fear. Instead there is an additional effect of the economic status of the residents surrounding them in the community.

The effect of urbanisation is also positive, with an effect size of .09, meaning that in areas classified as more urban; with higher population density, and less space defined as green-space, the level of fear of residents will be higher. Smaller effects are evident between the level of population mobility and fear, along with the effect of the neighbourhood age structure and the housing profile of the area. The small effect of population mobility indicates that in neighbourhoods identified as more transitory, the levels of fear from residents will be higher than average. Levels of fear will also be higher than average in neighbourhoods that have a relatively younger age profile and where there are more flats.

In model 2, the effect of recorded crime and low level disorder are added, presenting us with further detail about the contextual influences on fear of crime. This leads to an additional improvement in model fit of 68 with 2 degrees of freedom [$p<0.001$]. The positive effect of recorded crime means that people living in areas with higher levels of recorded crime will also have significantly higher levels of fear, net of the influence of social disorganisation and low level disorder. Importantly, this effect is evident conditional on the individual level model, which controls for the recent victimisation histories of individuals. Similarly, this model confirms the existence of a relationship between low level disorder and fear of crime, net of other neighbourhood characteristics including the level of crime. Therefore, residents living in areas with more signs of low level disorder like vandalism, graffiti and litter will be significantly more fearful than those living in areas with fewer observed signs of disorder.

The inclusion of these two additional contextual measures also leads to different estimates of the effect of the structural dimensions of social disorganisation on fear of crime. There is a large reduction in the strength of the relationship between neighbourhood disadvantage and fear of crime, dropping from .07 to .03, and a smaller reduction in the impact of the level of urbanicity (from .09 to .07). Controlling for the extent of recorded crime and low level disorder in the neighbourhood also removes the significant effect of the level of population mobility on fear and changes the direction of the neighbourhood housing profile. This suggests that part of the effect originally attributed to elements of social disorganisation is actually better explained by the presence of signs of disorder and the crime profile of the local neighbourhood[2]. However, the extended model has very little impact on the relationship between ethnic diversity and fear of personal crime, with people living in more diverse neighbourhoods still identified as significantly more fearful than people living in less diverse neighbourhoods.

5.5.2 Fear of household crime

Table 5.5 includes the equivalent estimates from the fear of household crime models. Model 1 introduces the structural dimensions of social disorganisation theory, along with the additional

[2] The effects of disorder and crime were also examined separately, with each leading to similar sized drops in the magnitude of the other covariates

measure of the neighbourhood housing profile that was derived from the factorial ecology. Model 2 adds the effects of the extent of low level disorder in the neighbourhood, and the recorded levels of crime in the surrounding area.

Table 5.5: Contextual Effects Models (Household Crime)

		Model 1: Social Disorganisation Effect (S.E)	Model 2: Disorder and Recorded Crime Effect (S.E)
FIXED EFFECTS			
Constant		..08 (.01)**	.08 (.01)**
Gender (*Ref: Male*)	Female	.15 (.01)**	.15 (.01)**
Age	Age	-.004 (.0003)**	-.004 (.0003)**
	*Female	-.001 (.0003)**	-.001 (.0003)**
	Age^2	-.0002 (.00001)**	-.0002 (.00001)**
Education (*Ref: No qualifications*)	GCSE	-.03 (.01)**	-.03 (.01)**
	A level	-.07 (.01)**	-.06 (.01)**
	Degree	-.13 (.01)**	-.12 (.01)**
	Other (foreign)	-.03 (.01)*	-.03 (.01)*
Ethnicity (*Ref: White*)	Asian	.22 (.02)**	.22 (.02)**
	Black	.14 (.02)**	.14 (.02)**
	Mixed/other	.16 (.03)**	.16 (.03)**
Direct Victimisation *(Ref: Non-victim)*	Personal Crime	.14 (.01)**	.14 (.01)**
	Household Crime	.25 (.01)**	.24 (.01)**
Newspaper readership (*Ref: No paper)*	Tabloid	.09 (.01)**	.09 (.01)**
	Broadsheet	.02 (.01)*	.02 (.01)*
	Local	.08 (.01)**	.08 (.01)**
NS-SEC (*Ref: Professional/managerial)*	Intermediate Occupation	.02 (.01)*	.02 (.01)*
	Small Employer	.004 (.01)	.003 (.01)
	Lower Supervisory Role	.04 (.01)**	.04 (.01)**
	Routine or Semi Routine	.05 (.01)**	.04 (.01)**
	Never Worked	.04 (.02)*	.04 (.02)*
	Student	-.05 (.02)**	-.05 (.02)**
Marital Status (*Ref: Married)*	Separated or Divorced	-.13 (.01)**	-.14 (.01)**
	Single	-.10 (.01)**	-.10 (.01)**
	Widowed	-.10 (.01)**	-.10 (.01)**
Health (*Ref: Not ill)*	Non-Limiting Illness	.07 (.01)**	.07 (.01)**
	Limiting Illness	.10 (.01)**	.10 (.01)**
Residence	Length of residence	.02 (.002)**	.02 (.002)**
Year	Survey Sweep	-.05 (.004)**	-.05 (.004)**
CONTEXTUAL EFFECTS (Level 2)			
Social disorganisation	Socio-economic disadvantage	.06 (.01)**	.01 (.01)*
	Urbanisation	.04 (.01)**	.01 (.01)*
	Population mobility	-.01 (.01)**	-.03 (.01)**
	Age Profile	.02 (.005)**	.01 (.005)*
	Housing Profile	.02 (.01)**	.01 (.01)
	Ethnic heterogeneity	.10 (.05)*	.10 (.05)*
Crime	Local Recorded Crime		.05 (.01)**
Low level disorder	Objective Disorder		.04 (.01)**
RANDOM EFFECTS			
CDRP level		.016 (.002)**	.014 (.002)**
Neighbourhood level		.021 (.001)**	.020 (.001)**
Individual Level		.894 (.004)**	.894 (.001)**
-2*Loglikelihood		282211.4	282094.3
Number of cases		*102,696*	*102,696*

*** P<(.01)*
**P<(.05)*

Model 1 again demonstrates some initial support for the influence of social disorganisation on levels of fear of household crime, with all 6 included coefficients significantly related to levels of fear of crime. This explains 18% of the variance in fear of crime that was partitioned at the area level, with a 9% drop at the neighbourhood level and 27% at the broader administrative level. The inclusion of these 6 contextual effects also results in a significant improvement to model fit of 243 with 6 degrees of freedom [$p<0.001$].

As with fear of personal crime, people living in areas that are classified as more socio-economically disadvantaged are more fearful, on average, than people living in areas that are less disadvantaged. Additionally, people living in areas with a more urban structure are likely to be more fearful than people living in areas that have more green space and lower population densities. The neighbourhood level of ethnic diversity is again closely related to the levels of fear of residents, with residents of more diverse neighbourhoods reporting higher levels of fear than people living in less diverse neighbourhoods. Additionally, areas with a larger youth population are also associated with higher levels of fear amongst residents.

However, in contrast to the fear of personal crime, the influence of population mobility acts in the opposite direction to that predicted by social disorganisation theory. This means that levels of fear are predicted to be significantly lower amongst residents of neighbourhoods where there is greater population mobility, perhaps reflecting the higher proportions of renters in these areas who are less concerned about household crime. Finally, people living in areas with larger proportions of vacant property and terraced accommodation are significantly more fearful than people living in areas with lower proportions of vacant property and terraced accommodation.

Like fear of personal crime, when the amount of recorded crime and low level disorder in the local area are controlled for (model 2), the contribution of social disorganisation is significantly reduced. Differences in fear based on the neighbourhood level of socio-economic disadvantage and urbanisation are considerably smaller, with both dropping to .01. Similarly, there is a smaller increase in fear amongst residents living in areas with a younger age profile when levels of disorder and crime have been controlled, and the housing profile of the neighbourhood is no longer significantly related to fear of crime. Importantly, the relationship between ethnic diversity and resident's fear of crime is again unaffected by the inclusion of neighbourhood disorder and crime levels.

The extended model shows that in areas characterised by higher levels of crime, the fear of local residents will be significantly higher than the levels of fear for equivalent residents from areas with lower crime rates. This relationship between recorded crime and fear is evident having controlled for the range of neighbourhood characteristics, along with individual differences in fear of crime including people's own experiences of crime. Similarly, people living in areas with more signs of low level disorder including vandalism and graffiti will be more afraid of being the victim of household crime, on average, than people living in areas where vandalism, graffiti, and litter are relatively uncommon. The model therefore provides strong support for the importance of disorder and crime on levels of fear, alongside the effect of ethnic diversity.

Adding in the effects of low level disorder and the crime profile of the local neighbourhood leads to an improvement in model fit of 117 with 2 degrees of freedom, providing support for their inclusion in the model. Additionally, the inclusion of these two contextual measures results in a further drop in the unexplained variation in fear at the neighbourhood level of approximately 5%.

5.6 Discussion II: The role of social disorganisation, disorder, and recorded crime in an examination of fear of crime

In this chapter I have extended the random intercept models introduced in chapter 4 to include a series of contextual measures characterising differences between local neighbourhoods. These measures have been selected to represent the structural dimensions of social disorganisation theory, and to account for the influence of low level disorder and recorded crime on people's fear; the three dominant contextual explanations. Incorporating these measures within the neighbourhood component of the fear of crime model enabled an assessment of how well these theories explain differences in fear of crime across neighbourhoods, conditional on the observed differences already identified in the individual level model. Additionally, by including contextual data from a large number of local neighbourhoods at a smaller spatial scale than many existing treatments of the contextual influences on fear has enabled a more robust assessment of the local neighbourhood processes that influence the levels of fear of their residents.

Two models of increasing detail were specified for each crime type, with the first featuring the structural measures of social disorganisation, and the second extending the model to include the added effects of the level of disorder and recorded crime in the local area. These models provide partial support for the influence of social disorganisation, with higher levels of fear amongst people living in more disadvantaged and ethnically diverse neighbourhoods. Fear is also higher amongst those living in areas with larger youth populations, and areas that have a more urban structure. Additionally, fear of personal crime is higher amongst residents living in neighbourhoods identified as having a more transient population. Social disorganisation theory argues that the higher levels of fear in these neighbourhoods is a reflection of their reduced capacity for informal social control, with fewer available resources and more fragmented community structures limiting the controls available to the neighbourhood. This can lead to a withdrawal from community life, resulting in higher levels of fear.

However, despite providing initial support for social disorganisation theory, there are reasons to suggest that the relationship with fear is more complex. First, the effect of population mobility is somewhat contrary to expectation, with higher fear amongst residents of more stable communities when considering fear of household crime, and only a small increase in fear amongst more transient communities when looking at fear of personal crime. Additionally, when the level of recorded crime and low level disorder in the neighbourhood have been controlled, there is no longer an effect of the extent of population mobility on fear of personal crime. The degree of population mobility into and out of the neighbourhood is a key component of social disorganisation theory, with a higher level of migration representing communities with weakened social bonds and limited community networks between residents, which in turn results in lower levels of social control and higher levels of fear (Taylor & Covington, 1993). Therefore the relationship with household fear does not match our theoretical expectations. Considering household crime, this might reflect the higher proportion of rented properties within these neighbourhoods, with people who rent being less worried about burglary because they are not responsible for the property or have less to steal. The original social disorganisation theory suggests that the effect of population mobility is contingent on the neighbourhood level of disadvantage (Shaw & McKay, 1942), so the interaction between population mobility and the level of neighbourhood socio-economic disadvantage was also tested. However no significant interaction effect was evident for either crime type, leading to further doubt over the importance of population mobility on levels of fear when other important ecological influences have been controlled.

Second, like the effect of population mobility, the size of the effects of socio-economic disadvantage and urbanisation are significantly reduced when the extent of recorded crime and low level disorder in the neighbourhood are incorporated in the models. This suggests that part of the relationship between the structural determinants of social disorganisation and fear of crime is actually a reflection of the higher levels of crime and disorder in more disadvantaged and urban areas. These effects are not completely removed in the extended fear of crime model, however it does indicate that social disorganisation has a smaller impact on levels of fear than research which fails to include the prevalence of disorder and the local recorded crime rate would suggest. This fits with the suggestion that disorder mediates the relationship between the structural determinants of social disorganisation and fear, with disorder having strong parallels with the direct measures of disorganisation used in the study of Sampson and Groves (1989).

Unlike the degree of urbanisation and the level of socio-economic disadvantage, the effect of ethnic diversity on levels of fear of crime is unaffected by the inclusion of disorder and recorded crime. The effect of diversity is particularly interesting because it is present having controlled for the full range of individual and neighbourhood level characteristics, including individual ethnicity and the neighbourhood socio-economic status and recorded crime level. Since BME groups tend to be clustered in areas with higher crime rates, the relationship between ethnic diversity and fear is often described as a function of the level of crime (Newburn, 2007). However, the consistent effect in the current analysis suggests other mechanisms related to diversity that lead to increased fear.

It is possible that the effect of ethnic diversity identified in these models is actually a reflection of the higher proportions of BME groups in these areas, and not the level of diversity. To check this competing explanation, a further model was fitted that also included a measure of the proportion non-white in the area. In this model, the effect of ethnic diversity remained significant, and of a similar magnitude, suggesting that the extent of ethnic mixing has an important and distinct role to play in influencing the levels of fear of local residents.

The impact of ethnic diversity in these models is consistent with recent work that has focused on the impact of heterogeneity on levels of social trust (Putnam, 2007). This showed that net of other neighbourhood and individual differences, individuals living in more ethnically diverse areas will report lower levels of trust than individuals living in areas with a relatively homogeneous population. Treating fear as a sign of low levels of trust, the ideas put forward by conflict theory can be used to explain the relationship evident in this analysis. More heterogeneous areas have a higher proportion of people that an individual would classify as 'outsiders', associated with a tendency for people to withdraw from those around them. This in turn fosters out-group suspicions which limit the development of social support networks, producing higher levels of fear.

Similar to the work of Putnam (2007), selection bias is judged to be an implausible explanation for this positive relationship between heterogeneity and fear. The implication of selection bias when considering the effect of ethnic diversity would be that more fearful individuals would be disproportionately *more* likely to choose to move into neighbourhoods that are more ethnically diverse. Similarly, this would suggest that people who are the least fearful would be the least willing to move into a more diverse neighbourhood. In reality, it is more likely to operate in the opposite direction, with more fearful people being the least likely to move into more heterogeneous neighbourhoods and vice versa. In fact, it is perhaps more likely that the current model is actually underestimating the true effect of heterogeneity. Despite this face validity, there is still the possibility that some unobserved neighbourhood characteristic is actually responsible for neighbourhoods being both more ethnically diverse, and having higher average levels of fear of residents. However, this is unlikely given the extensive neighbourhood and individual controls that are incorporated in this analysis; including the socio-economic status of the neighbourhood, the level of crime, and individual ethnicity.

The extended models demonstrate clear support for the claims of the disorder perspective that the presence of low level disorder in the local neighbourhood leads to higher levels of fear amongst residents (Skogan, 1990). This effect is evident having controlled for the level of recorded crime in the local area, along with the range of individual and contextual controls. Additionally, unlike many treatments of the disorder perspective where the focus is on the correlation between perceived disorder and fear, this model has demonstrated that a relationship exists with interviewer assessments of the level of disorder in the local area (Taylor, 2001). A link between objective disorder and fear has often been difficult to identify, with many studies failing to find a significant relationship. The current models suggest that when measured at a small spatial scale, an important relationship does exist.

There is also a consistent relationship between the level of recorded crime and fear of crime. This is in contrast to many studies which have failed to demonstrate a significant relationship between crime and fear (Hale, 1996). The significant relationship can again be attributed to the increased precision afforded by the large sample of areas that the current estimates are based on, and the smaller spatial scale that recorded crime is measured at in this analysis. The models therefore demonstrate that when examined at the very local level, covering an area that is likely to be well known and regularly monitored by respondents, a higher level of crime does in fact appear to be associated with a more fearful response to crime. This suggests that the failure of many studies to identify a relationship might be better explained as a result of insufficient detail on the location of offences in relation to individuals, rather than as a true reflection of no observable relationship.

The inclusion of these contextual effects resulted in a significant drop in the unexplained variance at the area level, with a drop of 29% for fear of personal crime, and 18% for household crime. This acts as further evidence that these measures represent important dimensions of the neighbourhood influence on fear of crime, beyond those that are present at the individual level. Importantly, the influence of these measures appears to be primarily at the broader CDRP level, indicating a high degree of dependency amongst neighbourhoods within the same CDRP. This means that the included neighbourhood measures are most successful when explaining differences between clusters of neighbourhoods. Although it was not possible to incorporate data directly at the CDRP level, this demonstrates that it is important to retain CDRP as a higher level of nesting to reduce the likelihood of overestimating neighbourhood effects. In the same way that a failure to incorporate the complex area structure when estimating individual level effects can result in erroneous standard errors and effect size estimates, a failure to incorporate the complex clustering of neighbourhoods within CDRP would likely lead to incorrect conclusions.

The apparent similarity amongst neighbourhoods from the same CDRP underlines the importance of being able to effectively characterise broader differences between local areas. The lack of available data at CDRP level is a clear limitation with the current analysis, with unexplained variability partitioned at this level indicating the existence of more general influences on fear. Currently, data is collected inconsistently at CDRP level, with many partnerships failing to provide potentially valuable information that might better explain differences in levels of fear and other social outcomes across CDRP. This results in high levels of missing data, particularly at the individual and neighbourhood level, meaning that the costs of including CDRP level data outweigh the potential gains of this additional source of information. There are clear policy implications of being able to identify attributes of CDRP that are associated with higher levels of fear amongst residents, enabling targeted interventions to try and reduce levels of fear. However, it has not been possible to examine these in the current analysis.

Despite providing support for the effects of contextual variations on levels of fear of crime, there is still considerable remaining unexplained variation across neighbourhoods and CDRP in the levels of fear of crime amongst residents. The failure to effectively explain all neighbourhood level variance in fear of crime might reflect the nature of the neighbourhood indices used. These focus specifically on structural differences between local areas, missing the influence of other contextual effects that more directly describe the social structure of local neighbourhoods, such as the degree of community involvement or collective efficacy (Sampson et al., 1997). In future analyses, a more detailed set of social structure measures may identify additional important effects. However, these would need to be carefully incorporated to limit the problems of reduced reliability that result from aggregation.

In this chapter I have used multilevel modelling to provide a more detailed test of the importance of social disorganisation theory and the disorder perspective for explaining variations in people's levels of fear of crime. This has treated neighbourhood differences as global effects on all types of individual, testing the effects of the structural dimensions of social disorganisation, neighbourhood disorder, and recorded crime on variations in levels of fear. However, differences in fear have also been identified between population groups, attributed to the effect of vulnerability, victimisation experience, and indirect knowledge obtained via the media. Currently, these differences have also been treated as global effects, operating in the same manner across all neighbourhood contexts.

In chapter 6 I will adopt a more complex modelling approach to fully integrate the contextual models introduced in this chapter with the individual level model that I outlined in chapter 4, moving from the random intercept model to the full random coefficients multilevel model (Snijders & Bosker, 1999). This will be done in two stages to examine individual levels of fear within the local context in which they are experienced. First, I will allow for differential individual level relationships within different local neighbourhoods, reflecting the possibility that individual differences in fear might be influenced by local context. Second, I will introduce cross level interactions between neighbourhood differences and individual characteristics to more accurately look at how particular types of people are differentially affected by contextual explanations for differences in fear. By allowing for differential relationships at the local level, this will provide a more realistic account of the complex influences on levels of fear. This recognises that neighbourhood differences can have different meanings for different types of individual, and that a global relationship between individual characteristics and fear is unlikely to accurately reflect the more nuanced local experience of fear (Young, 1988).

CHAPTER 6: EXTENDING THE NEIGHBOURHOOD MODEL

6.1 Introduction

In chapter 4 I demonstrated the importance of incorporating the area structure in analyses of fear of crime, introducing the multilevel random intercept model to include an area based analysis within an individual level treatment of fear. Using this approach I showed that a significant proportion of the variation in individuals' fear of crime is actually better conceptualised as the result of differences at the local neighbourhood and broader CDRP levels. This represented the first step in accurately combining individual and contextual explanations for differences in fear.

In chapter 5 I then introduced a series of contextual measures derived from the census and other administrative sources to explain the variations in fear that result from area based differences. These extended models were able to explain between 18% and 27% of the area based variations in fear. These effects were also supportive of the research findings from single level and contextual models that have explored the impact of social disorganisation and disorder on fear of crime. However, once disorder and the level of recorded crime were included, population mobility (one of the central elements of social disorganisation) was no longer related to differences in fear of crime. Similarly, the size of the relationship between neighbourhood socio-economic disadvantage and fear was significantly reduced. Instead, fear was primarily influenced by the level of ethnic diversity, levels of recorded crime, and the prevalence of low level signs of disorder.

In this chapter I extend the discussion of the contextual influences on fear of crime by questioning the assumption implicit in the random intercept model that all types of individual are influenced by the characteristics of their neighbourhood in the same way. This draws on the more complex treatments of local neighbourhoods that have been introduced by community studies, which suggest that different people perceive the neighbourhood in different ways and hence are affected differentially by the physical and social aspects of their local environment (Lupton, 2003). From this perspective it follows that the individual level relationships that have been identified may not be consistent across neighbourhoods, and that the neighbourhood effects may also be differentially experienced by different types of people.

To do this, I present two further extensions to the random intercept model that was first outlined in chapter 4, providing a more detailed account of the complex relationship between individuals, their localities, and fear of crime. First, I allow individual level relationships to vary across local neighbourhoods, using the full random coefficients specification of the multilevel model. Second, I introduce cross-level interactions between individual level covariates and neighbourhood level contextual effects to examine how area effects differ based on individual characteristics. These represent the final extensions to the multilevel model used to assess the contextual influences on fear, situating the experiences of individuals more directly within their local contexts.

6.2 Linking individual and social explanations for fear of crime

To fully integrate individual and contextual explanations for differences in fear of crime, the random intercept models from chapter 5 are extended to allow all individual relationships to vary across neighbourhoods. This enables us to get considerably closer to the conceptualisation of neighbourhoods put forward by community studies, whereby neighbourhoods have different meanings for different people. By placing individuals directly within their neighbourhood contexts we can identify how the levels of fear of different types of people are influenced by the characteristics of the local neighbourhoods that they live in. This represents a more nuanced test of the importance of the structural dimensions of social disorganisation on variations in fear of crime, as well as providing a more realistic account of how different people are affected by the amount of recorded crime and low level disorder. This also links these contextual theories directly back to the individual level theories posited within early assessments of differences in fear of crime, allowing us to examine whether the effects of previous victimisation experience and greater levels of vulnerability on fear are moderated by the social structure of the local environment in which people live their lives.

The existence of variation in individual level effects across neighbourhoods would indicate that different people's fear of crime is affected in different ways by the effects of social disorganisation and disorder. This would suggest that some types of people are more susceptible to the influence of contextual effects than others, possibly reflecting an increased level of attentiveness to their local surroundings that results from previous experiences of crime, or from increased feelings of vulnerability. Consequently, a failure to incorporate these additional sources of variability in fear across neighbourhoods risks masking contextual effects that are important for particular types of people, incorrectly simplifying the lived experience of fear.

Currently, there is very little evidence to guide us on which individual differences in fear might be affected by local context. Research has largely restricted itself to assessments of individual differences in fear, or the importance of the wider context of fear, with only limited evidence from Wilcox-Rountree and Land (1996a) that victims of crime may be more influenced by their local neighbourhood than non victims. This was shown by a significant interaction between disorder and victimisation experience. However, although not explicitly stated as an interaction between individuals and their local context, more fearful groups are typically identified as more likely to perceive themselves to be at greater risk of crime and less able to effectively deal with the consequences of crime (Killias, 1990). This suggests that they may also be more aware of their local surroundings, and the risk factors in the local environment that indicate they are likely to be a victim, signalling the potential existence of important interactions between fearful groups and neighbourhood characteristics. As a result of the lack of clear evidence from existing research that links individual experiences of fear to contextual explanations, an exploratory approach to the identification of neighbourhood effects that are specific to individuals will be incorporated in this analysis. This is outlined in section 6.5.

6.3 The Random coefficients model

The random coefficients model extends the random intercept model by allowing all individual level coefficients to vary across areas, not just the intercept term (Goldstein, 2003). This is done by relaxing the assumption implicit in the random intercept model that each individual level covariate has a constant effect in each area, instead allowing the strength and direction of these effects to vary across all areas.

To construct the random coefficients model, we begin with the random intercept model from chapter 5, equation [5.2]. This included one area level contextual effect w_{1j}, and one individual level variable x_{1ij}, along with two error terms incorporating the remaining unexplained variance partitioned at the individual and area level. Equation [5.2] was composed of two linked equations. First, an individual level equation [4.3], including subscripts *i* and *j* to locate the regression with the *i*th individual from the *j*th area. A *j* subscript was also attached to the intercept, allowing it to vary across areas. In this equation the intercept coefficient, β_{0j}, therefore refers to the overall intercept across all areas. Second, an area level equation, [5.1], which was used to describe the variation in the intercept across areas. Therefore at the area level the overall intercept was composed of the average intercept across all areas, β_0, and the residual difference from the average intercept for each area, represented by the error term u_{0j}. The area level equation also included the contextual variable w_{1j}, measured at the area level to capture variation across areas in the dependent variable.

To form the random coefficients model, this specification is further extended by allowing the individual level regression coefficient β_1, associated with the variable x_{1ij} in equation [5.2] to also vary by area. This is done with the inclusion of an additional subscript *j*, extending the individual level equation to [6.1].

$$y_{ij} = \beta_{0j}x_{0ij} + \beta_{1j}x_{1ij} + e_{ij}x_{0ij} \qquad [6.1]$$

Adding the subscript indicates the presence of a second area level equation explaining the variation in the regression coefficient, equation [6.2], in addition to the area level equation that outlines the variation in the intercept.

$$\beta_{1j} = \beta_1 + u_{1j} \qquad [6.2]$$

Like the area level model that relates to the intercept, this states that the overall regression coefficient β_{1j} is composed of the average effect across all areas, β_1, and the residual difference from the average effect in each area, u_{1j}. This residual term has a variance, σ^2_{u1}, with the usual assumptions. At the area level, we therefore fit the average intercept and the difference from the average intercept, but we also fit the average coefficient, and the residual difference from the average coefficient in each area. When equation [6.2] is substituted back into the individual level model, it produces equation [6.3]. The x_0 terms have been removed from this equation for brevity.

$$y_{ij} = \beta_0 + \beta_1 x_{1ij} + \alpha_1 w_{1j} + \left(u_{0j} + u_{1j} + e_{0ij}\right) \qquad [6.3]$$
$$\begin{bmatrix} u_{0j} \\ u_{1j} \end{bmatrix} \sim \mathrm{N}(0, \Omega_u), \Omega_u = \begin{bmatrix} \sigma^2_{u0} & \\ \sigma_{u0u1} & \sigma^2_{u1} \end{bmatrix}$$

So we have a residual error term at the individual level, e_{0ij}, with variance σ^2_e. We also have a residual term associated with the intercept, u_{0j}, which has a variance σ^2_{u0}. However, in the random coefficient model there is also unexplained variation around the regression coefficient β_1, represented by the additional residual u_{1j}, which has variance σ^2_{u1}. Finally, because there are now two error terms at the area level, there is an additional covariance term between the unexplained intercept and coefficient variance, σ^2_{u0u1}. This complex area level variation is represented by the variance matrix Ω_u.

The covariance with the intercept is an added layer of model complexity, providing further information about the nature of the variability in the effect sizes across areas. The covariance term informs us of whether the unexplained variability in the relationship between individual covariates and the dependent variable across areas is related to the variability in the intercept term. Additionally, when the covariance term is significant, it can tell us whether there is a positive or negative relationship between the two variances. A positive relationship would indicate that in areas with a higher than average intercept, the effect of the coefficient will also be stronger than average. Conversely, a negative relationship would indicate that areas with a higher than average intercept will have a weaker than average effect of the coefficient.

When more than one individual level coefficient varies across areas, this model also allows for the inclusion of covariance terms between the random coefficients. These can be used to demonstrate interaction effects in the random part of the model, indicating a more complex model structure where particular combinations of individual effects vary across neighbourhoods more than other combinations. Typically these additional covariance terms are constrained to 0, reflecting the lack of a theoretical justification for the added complexity across areas. This is a standard model constraint that significantly reduces the complexity of the variance matrix, reducing the number of parameters that need to be estimated when multiple coefficients are specified as random (Goldstein, 2003; Snijders & Bosker, 1999).

6.3.1 The importance of centring

The inclusion of random coefficients has important implications for the interpretation of the random part of the model, which is now directly linked to the scale of each coefficient that is specified as random. This is because when coefficients vary across neighbourhoods, the position of the intercept becomes important, with linear transformations leading to a different estimated intercept variance, and covariances with each random coefficient (Snijders & Bosker, 1999). This is best illustrated graphically, using a simple example originally included in Hox (2002: 55).

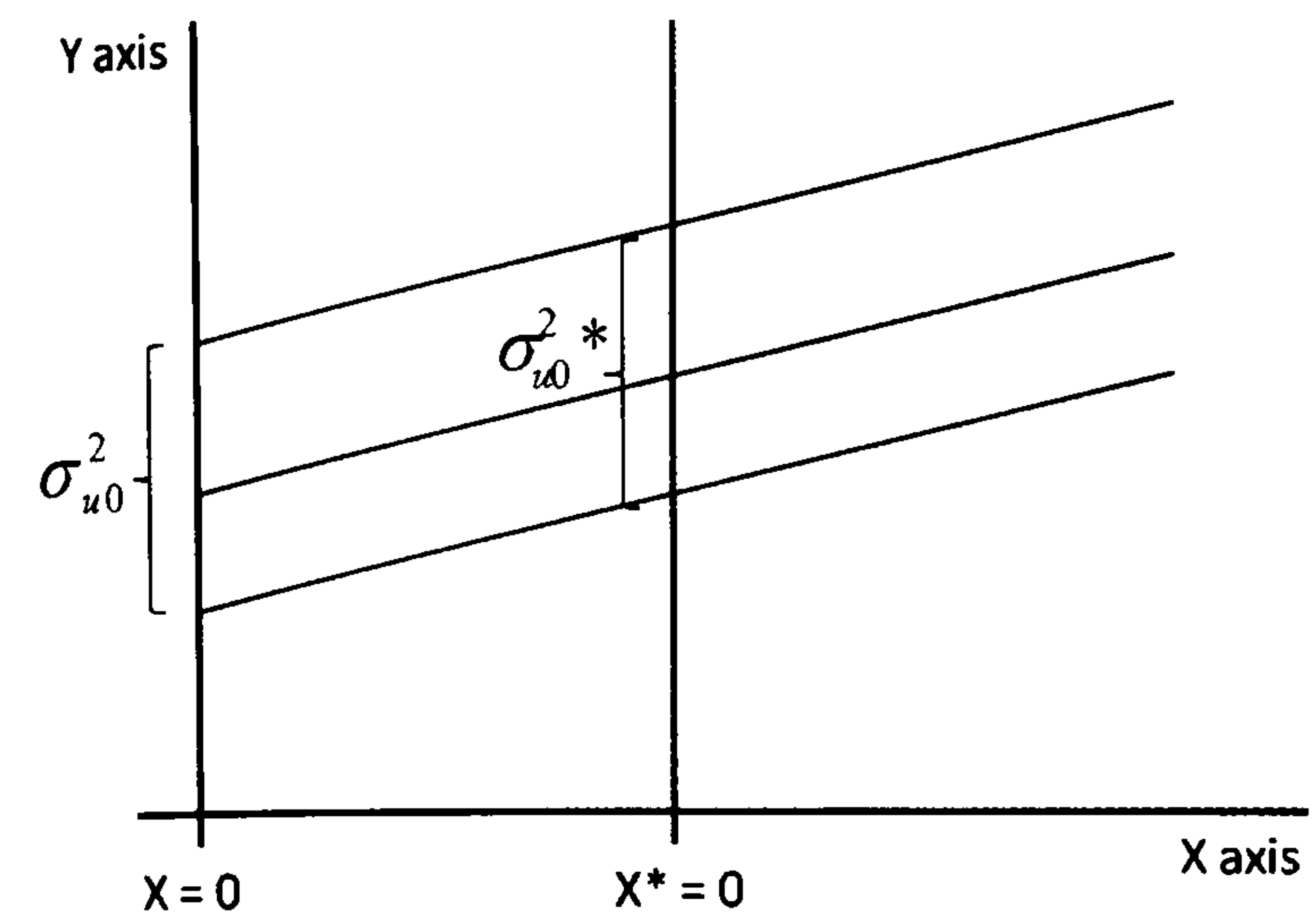

Figure 6.1: Random Intercept Model

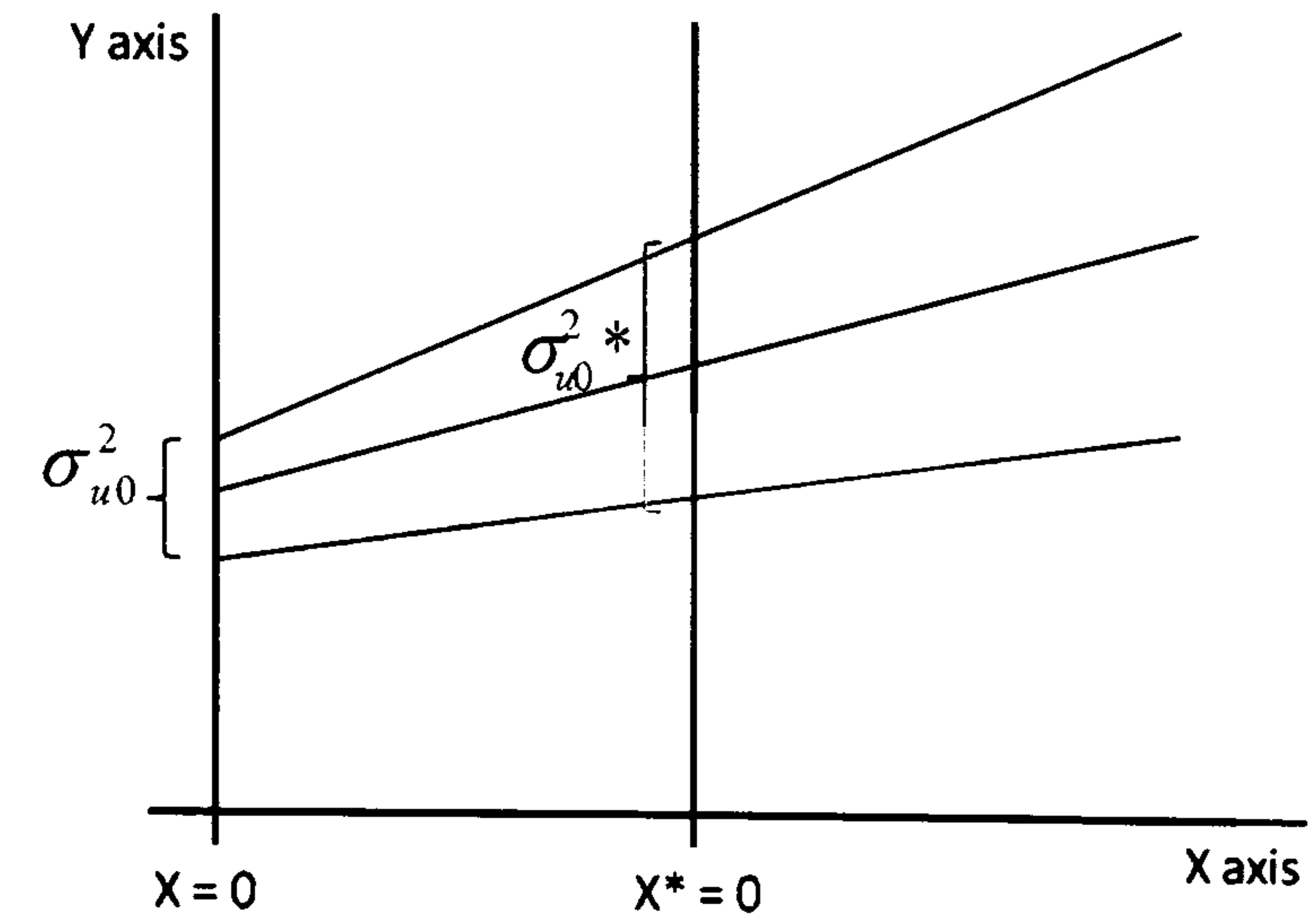

Figure 6.2: Random Coefficients Model

Figure 6.1 is a simple random intercept model, with three groups that each have the same regression slope but different intercepts. Looking at this graph, moving the intercept from X to X* (achieved with a linear transformation of X) has no effect on the intercept variance. This means, that it is not important what the value of the covariate X=0 represents, or even if this is meaningful, the size of the estimated intercept variance will always be the same. In contrast, figure 6.2 is the equivalent random coefficients model, where both the intercept and the slope coefficient are allowed to be different in each group. In this case, it is clear that changing the intercept from X to X* will lead to a different estimated intercept variance, and a different estimated covariance with the slope. In position X, the intercept variance is now estimated to be small, and the covariance with the slope is estimated to be large. In position X*, the intercept variance is much larger, and the covariance is smaller.

This clearly demonstrates that in the random coefficients case, the position of the intercept has important implications for the resultant interpretation of the model. Consequently it is recommended that a meaningful value for the intercept term is used in the random coefficients specification, with grand mean centring regularly used on all included coefficients to ensure easy interpretation of the intercept variance (Hox, 2002). Grand mean centring transforms included covariates so that a value of 0 represents the average score on that variable, meaning that the intercept term refers to the expected value of the outcome variable when all explanatory variables are at their mean. This means that it becomes the expected value for the average person.

In the random coefficients model outlined above, the VPC used to calculate the proportion of variance attributable to area differences refers to the unexplained contribution of areas for the average resident (when the included individual coefficient is 0). It is also possible to demonstrate how the area level contribution varies as a function of the included random coefficient. This is done using equation [6.4], based on the explanation in Rasbash et al., (2002).

$$v.f = \sigma^2_{u0}x^2_{0ij} + 2\sigma_{u0u1}x_{0ij}x_{1ij} + \sigma^2_{u1}x^2_{1ij} \Big/ e_{0ij} + \sigma^2_{u0}x^2_{0ij} + 2\sigma_{u0u1}x_{0ij}x_{1ij} + \sigma^2_{u1}x^2_{1ij} \qquad [6.4]$$

Equation [6.4] is referred to as the variance function (*v.f*). When the included random coefficient is set to 0, the variance function is simply the VPC, relating to the area contribution for an average resident. However, using the variance function means that it is also possible to show how the remaining unexplained area contribution differs as a function of the included random coefficient. When more than one random coefficient is included in the model, this allows us to show how the unexplained contribution of area differences varies as a function of a particular characteristic, for a person who is at the average on all other covariates.

6.3.2 Contextualising individual effects – the inclusion of cross level interactions

Having identified significant variation across areas in the strength of individual level covariates, the next step is to try and explain these additional sources of variance. This is made possible with the inclusion of interactions between the individual level covariates that vary across areas and any contextual effects measured at the area level. These interactions are usually referred to as 'cross-level interactions', because the interaction occurs across two levels in the analysis (Snijders & Bosker, 1999). Cross level interactions allow for a differential effect of particular area characteristics on particular types of people, representing a particularly powerful tool for examining individuals within their specific local contexts (Oakes, 2004).

The incorporation of cross level interactions is achieved in a manner similar to the inclusion of contextual effects outlined in chapter 5. However, instead of restricting them to the area level equation relating to the intercept, contextual variables are also included within the area level model associated with the random coefficients of interest (Rasbash et al., 2004). Returning to our two level example, the area level equation, [6.2], associated with the variable x_{1ij}, is thus extended to form equation [6.5]. This represents the cross level interaction between the individual covariate x_{1ij} and the contextual variable w_{1j}. This term refers to how the individual level effect varies as a function of the included contextual effect.

$$\beta_{1j} = \beta_1 + \alpha_2 w_{1j} + u_{1j} \qquad [6.5]$$

Substituting the area model back into the individual level model, the random coefficient model is extended to form equation [6.6]. Along with the individual and contextual effects, this now has the cross level interaction $\alpha_2 w_{1j} x_{1ij}$ between the individual level covariate x_{1ij} and the contextual measure w_{1j}.

$$y_{ij} = \beta_0 + \beta_1 x_{1ij} + \alpha_1 w_{1j} + \alpha_2 w_{1j} x_{1ij} + \left(u_{0j} + u_{1j} + e_{0ij}\right) \qquad [6.6]$$

6.4 The data

The analysis in this chapter directly extends the models used in chapters 4 and 5, relaxing the assumption implicit in the random intercept model that individual level relationships with fear of crime are the same across all neighbourhoods. Since no new data sources are being utilised, the analysis is based on the same sample of 105,110 respondents from 3 waves of the BCS. These individuals are nested in 5,208 local neighbourhoods (as represented by MSOA) which are themselves grouped within 353 CDRP.

The models that will be extended include a range of individual level covariates that were selected to characterise differences in fear between socio-demographic groups. These were chosen on the basis of existing research to cover notions of vulnerability, direct victimisation experience, and the influence of the media on people's fear of crime. All covariates were grand mean centred to ensure clear interpretation of the intercept and coefficient variances. In addition to this individual level data, the models include contextual data taken from the 2001 census and the ONS neighbourhood statistics archive to account for differences in levels of fear between local neighbourhoods. These measures were incorporated to test the central tenets of social disorganisation theory, along with the effect of low level disorder on fear of crime. The small spatial scale that neighbourhood level data was collected at also enabled a more detailed assessment of the relationship between the level of recorded crime in the local area and fear of crime.

6.5 Results IV: Situating individual experiences of fear within their neighbourhood context

To allow for a differential relationship between individual covariates and fear of crime across areas, the random intercept model including contextual effects at the neighbourhood level from chapter 5 is first extended to allow all individual level coefficients to have a random component at the neighbourhood level. Reflecting the lack of existing research informing us which individual level effects are likely to vary across neighbourhoods, all covariates from the individual level model were examined at this stage. Each coefficient was examined independently, with the reduction in -2*loglikelihood resulting from its inclusion used to judge significance based on the chi-square difference test (Hox, 2002). This is a one-tailed chi-square test reflecting that variances cannot be negative, meaning that our alternative hypothesis is a positive variance (Miller, 1977). Since each random coefficient also includes a covariance term with the intercept, the assessment of significance based on the -2*loglikelihood is adjusted for the loss of 2 degrees of freedom for every added random term (Snijders & Bosker, 1999). The chi-square difference test is used instead of the wald test to judge model fit, which Goldstein (2003) has demonstrated is a less accurate measure of significance when dealing with random coefficients.

All random coefficients identified as significant when examined separately were then estimated within a single model. Any that failed to reach significance in this full model were subsequently set to zero (Hox, 2002). This step by step approach was adopted to limit convergence difficulties that can result when estimating complex variance matrices, and also to ensure that all potential random coefficients were identified. There was no clear theoretical justification for the inclusion of covariances between the random coefficients identified in this full model, so these additional terms were also constrained to 0. This significantly reduces the complexity of the final model, providing a more parsimonious representation of the data structure. Additionally, imposing this constraint reduces the number of degrees of freedom that are lost when multiple coefficients are specified as random (Snijders & Bosker, 1999).

In addition to testing whether the size of individual differences in fear vary across neighbourhoods, variation in contextual effects across broader CDRP boundaries was also tested. This follows the same logic as allowing individual covariates to be random across neighbourhoods, and tests the assumption that the estimated neighbourhood effects are constant across broader area contexts. This might signal the existence of important compositional effects related to the functioning of CDRP that moderate the effect of local neighbourhoods. However, as a result of the lack of available data, it was not possible to examine in any more detail what partnership attributes might lead to the identified variability across neighbourhoods.

Having identified significant coefficient variances across neighbourhoods and CDRP, the final step was to introduce cross-level interactions to account for this variability. Cross-level interactions were tested separately for each random coefficient included in the model, before a final model was specified including all significant interaction effects. These cross-level interactions enable a detailed examination of how people are differentially influenced by the structural dimensions of social disorganisation, and the prevalence of low level disorder and crime within their neighbourhoods. This links these contextual theories back to the individual explanations for variations in fear of crime to provide a fully integrated explanatory model.

6.5.1 Fear of personal crime

Table 6.1 includes estimates from the full random coefficient multilevel model examining fear of personal crime. The first column of figures in the table includes the fixed effects estimates for the individual level covariates and neighbourhood level contextual effects. Where significant variability exists across neighbourhoods or CDRP, these estimates refer to the average effect of the covariate across all neighbourhoods (or CDRP). This also includes estimates of the residual intercept variances at the individual, neighbourhood, and CDRP levels for an average resident (when all coefficients are set to 0). The next column in the table, labelled 'Variance (S.E)', contains estimates of the variance across neighbourhoods in the fixed effects that have been identified as having a significant random component. This means that the assumption of a constant relationship with fear of personal crime is not supported by the data. As a result, the estimated individual level relationships with fear are partially dependent on the neighbourhood that the individuals are clustered within, with different neighbourhoods exhibiting individual level relationships with fear of differing magnitudes. This column also includes estimates of the variance across CDRP in the contextual effects identified as having a significant random component. In the final column, labelled 'Covariance (S.E)', estimates of the covariances between each of the coefficient variances and the unexplained variation in the intercept term at the neighbourhood level are included.

Table 6.1: Random Coefficients Model (Personal Crime)

		Effect (S.E)	Variance (S.E)	Covariance (S.E)
FIXED EFFECTS				
Constant		-.08 (.02)**		
Gender (*Ref: Male*)	Female	.46 (.01)**	.006 (.003)**	.016 (.001)**
Age	Age	-.004 (.0002)**		
	*Female	-.01 (.0003)**		
	Age^2	-.0002 (.00001)**		
Education (*Ref: No qualifications*)	GCSE	-.04 (.01)**		
	A level	-.08 (.01)**		
	Degree	-.16 (.01)**		
	Other (foreign)	-.05 (.01)**		
Ethnicity (*Ref: White*)	Asian	.30 (.02)**	.133 (.023)**	.009 (.006)
	Black	.09 (.03)**	.129 (.029)**	.013 (.007)*
	Mixed/other	.15 (.03)**	.133 (.032)**	.011 (.007)
Direct Victimisation *(Ref: Non-victim)*	Personal Crime	.26 (.01)**	.015 (.010)*	-.009 (.003)**
	Household Crime	.14 (.01)**		
Newspaper readership *(Ref: No paper)*	Tabloid	.11 (.01)**		
	Broadsheet	-.01 (.01)		
	Local	.09 (.01)**		
NS-SEC (*Ref: Professional/managerial)*	Intermediate Occupation	.04 (.01)**		
	Small Employer	-.05 (.01)**		
	Lower Supervisory Role	.04 (.01)**		
	Routine or Semi Routine	.06 (.01)**		
	Never Worked	.001 (.02)		
	Student	.14 (.02)**		
Marital Status (*Ref: Married)*	Separated or Divorced	-.08 (.01)**		
	Single	-.02 (.01)*		
	Widowed	-.04 (.01)**		
Health (*Ref: Not ill*)	Non-Limiting Illness	.09 (.01)**		
	Limiting Illness	.17 (.01)**	.016 (.004)**	.008 (.002)**
Residence	Length of residence	.004 (.002)*	.001 (.0002)**	.001 (.0002)**
Year	Survey Sweep	-.07 (.01)**		
CONTEXTUAL EFFECTS (Level 2)				
Social disorganisation	Socio-economic disadvantage	.03 (01)**		
	Urbanisation	.07 (.01)**		
	Population mobility	.01 (.01)		
	Age Profile	.01 (.005)**		
	Housing Profile	-.02 (.01)**		
	Ethnic heterogeneity	.30 (.02)**	.097 (.041)**	-.016 (.007)**
Crime	Local Recorded Crime	.03 (.01)**		
Low level disorder	Objective Disorder	.03 (.01)**		
RANDOM EFFECTS				
CDRP level		.016 (.002)**		
Neighbourhood level		.030 (.001)**		
Individual Level		.800 (.004)**		
-2*Loglikelihood		271530.4		
Number of cases		*102,133*		

*** P<(.01)*
**P<(.05)*

From this model it is evident that a number of the previously estimated individual level fixed effects actually vary significantly across neighbourhoods, providing further evidence that a national assessment of differences in people's fear of crime is masking variability between local neighbourhoods. This is also a clear indication that contextual influences on fear of crime do not have a uniform influence on all types of people, rather the reality is a more complex relationship between individual and contextual influences. Not all individual level relationships with fear of crime vary across neighbourhoods though, with the effects of age, education, socio-economic status, and marital status displaying consistent relationships with fear across all neighbourhood contexts. Additionally, the neighbourhood level effect of ethnic diversity is shown to vary significantly across CDRP.

Using the variance function outlined in equation [6.4], the remaining neighbourhood and CDRP contribution for an average resident is shown to be the same as the random intercept model. However, there are significant differences in the size of the remaining unexplained neighbourhood contribution across different types of people. The size of the neighbourhood contribution for an average male resident (when all other covariates are set to 0) is 1.8%, compared to 5.3% for an equivalent woman. There is also a significantly larger remaining neighbourhood contribution for BME groups, with an average Asian resident having a neighbourhood contribution of 18.2% (18.6% and 18.2% for the equivalent Black and mixed or other origin resident respectively, compared to 3.6% for an equivalent white resident. Those who have a limiting illness also have a larger contribution from unexplained neighbourhood differences when compared to those that do not (6.3% compared to 3.3%).

Looking in detail at how the individual level relationships vary across neighbourhoods provides us with useful detail about how neighbourhood level differences might have an influence on the fear of crime experienced by individuals. Table 6.2 Includes details of how these coefficient estimates vary across neighbourhoods, demonstrating the range of values of each coefficient across the middle 95% of neighbourhoods. These estimates were calculated based on the methodology of Snijders and Bosker (1999: 85). For example, the variability in the size of the gender difference in fear was calculated as $[.46 \pm 1.96^{*}\sqrt{.006}]$.

Table 6.2: Variance across Middle 95% of Neighbourhoods/CDRP (Personal Crime)				
		Lower Limit	**Effect Size**	**Upper Limit**
FIXED EFFECTS (Across 95% of neighbourhoods)				
Gender *(Ref: Male)*	Female	0.31	**0.46**	0.61
Ethnicity *(Ref: White)*	Asian	-0.41	**0.30**	1.01
	Black	-0.61	**0.09**	0.79
	Mixed/other	-0.56	**0.15**	0.86
Direct Victimisation *(ref: Non-victim)*	Personal Crime	0.02	**0.26**	0.50
Health *(Ref: Not ill)*	Limiting Illness	-0.08	**0.17**	0.42
Residence	Length of residence	-0.06	**0.004**	0.07
CONTEXTUAL EFFECT (Across 95% of CDRP)				
	Ethnic heterogeneity	-0.31	**0.30**	0.91

Gender

Looking first at the effect of gender, when variation between local neighbourhoods is incorporated, significant gender differences in fear of crime across neighbourhoods are evident. As a result, in some neighbourhoods the gender difference is larger than the global average, and in others the difference is significantly less than the average. Looking across neighbourhoods, in areas where the gender difference is strongest, it is estimated to be approximately twice the size that it is in areas where the difference is weakest, ranging from .31 to .61. Importantly, despite demonstrating significant variation, the reported levels of fear from women are always significantly higher than men. This is perhaps unsurprisingly given the wealth of evidence demonstrating women to be more fearful, with very few studies failing to identify a gender gap.

A positive covariance between the random intercept term and the identified variation in the size of the gender difference is also estimated. This positive covariance term indicates that in areas where levels of fear are higher than average, the gender differences will also tend to be larger than average. In contrast, in neighbourhoods where people are generally less fearful than average, the gender gap will be smaller.

Ethnicity

There is also significant variability across neighbourhoods in the size of the difference in fear of BME groups compared to White residents. The extended model demonstrates that whilst BME residents are identified as more fearful than White people when examined on average across neighbourhoods, there is considerable variability in the size of this effect between neighbourhoods. This results in significantly different estimates of the difference in fear between BME and White residents across neighbourhoods. BME residents in some neighbourhoods will be significantly more fearful than suggested by the random intercept model, whereas in other neighbourhoods the difference will be in the opposite direction, with White people identified as more fearful. These significant variance estimates are indicative of important differences in the unexplained neighbourhood characteristics that are influential when considering the levels of fear of BME groups.

The extent of this variability across neighbourhoods is considerable, with the difference in the levels of fear of an Asian compared to a White person varying from a negative effect of -.41 to a positive effect of 1.01 across the middle 95% of neighbourhoods, net of other covariates. Similarly, the difference in fear for someone identified as Black varies from -.61 to .79, and for someone classified as of mixed or other origin the difference ranges from -.56 to .86. This means that the assertion that BME groups are more fearful than their White counterparts does not hold at the neighbourhood level, with approximately 21% of neighbourhoods showing White people to be more fearful than Asians, and even higher proportions of neighbourhoods identifying Whites as more fearful than Black or mixed ethnicity residents (40% and 34%).

There is also a significantly larger contribution of unexplained area differences for BME groups when compared with White people, indicating that the levels of fear of White people are less susceptible to the influence of neighbourhood differences, net of the contextual effects that have already been included in the model. This is further demonstrated by the non-significant covariance terms with the intercept. These indicate that the remaining variability in the effect of being from a BME group is not significantly related to the overall level of fear in the neighbourhood. In areas with higher than average levels of fear, there will not also be a larger difference in the size of the effect of being from a BME group. Instead it appears that the remaining unexplained neighbourhood influences are independent of the overall level of fear.

Previous personal victimisation experience

The higher levels of fear amongst victims of personal crime is also given additional detail by allowing variability across neighbourhoods. Across the middle 95% of neighbourhoods, the difference in fear between victims and non-victims ranges from .02 to .50. This means that despite significant variability across neighbourhoods, previous victims are never identified as less fearful than non-victims, although the magnitude of this difference can be vastly different depending on the neighbourhood context in which people live. Interestingly, the higher levels of fear amongst victims of household crime is shown not to vary across neighbourhoods, suggesting that it is unaffected by neighbourhood context. This is further evidence in support of the importance of distinguishing between these crime types.

A negative covariance term with the intercept is also estimated, suggesting that the gap in fear between victims and non-victims is related to the overall level of fear in the neighbourhood. The negative covariance term means that in neighbourhoods where the levels of fear from non-victims are higher than the overall average, the gap in levels of fear between victims and non-victims will tend to be smaller than average. Conversely, in areas where non-victims are less fearful, the size of the gap will be larger than average.

Health

The difference in fear between people who have an illness that is physically limiting, and those who do not have an illness at all, also varies significantly across neighbourhoods (ranging from -.08 to .42 across the middle 95% of neighbourhoods). The result is that whilst in the majority of neighbourhoods people with a limiting illness are more fearful, in approximately 9% of neighbourhoods people with a limiting illness are identified as less fearful than people who do not have an illness. There is also a small positive covariance term, indicating that the difference in fear will tend to be larger in neighbourhoods where people who do not have a limiting illness are more fearful than average.

In contrast, the difference in fear between those who have an illness that is not physically limiting, and those who do not have an illness at all, is consistently estimated across neighbourhoods. The lack of a significant variance term means that in some neighbourhoods the levels of fear from people with a limiting illness will also be lower than those who have a non-limiting illness. It also means that the levels of fear from people who have a non-limiting illness will always be higher than the fear amongst people who do not have an illness at all.

Length of Residence

Finally, there is also a small degree of variability in the relationship between the length of time that people have lived in the local area, and fear of crime. On average across all neighbourhoods, living in an area for longer is associated with higher overall levels of fear. However, the random coefficient reveals that this effect is actually dependent on neighbourhood context. In some neighbourhoods this relationship is significantly stronger than the overall average, with a larger difference in levels of fear between short and long term residents (with a coefficient as strong as .07 across the middle

95% of neighbourhoods). In contrast, in other neighbourhoods the relationship is actually in the opposite direction, with higher levels of fear reported by short term residents (as low as -.06 across the middle 95%). In fact, in as many as 45% of neighbourhoods, the relationship is negative, suggesting that living in the local neighbourhood longer does not automatically result in higher levels of fear.

A significant covariance with the random intercept is also estimated. This demonstrates that in areas where the levels of fear tend to be higher than average, the relationship between length of residence and fear will also tend to be stronger. In contrast, in neighbourhoods where levels of fear tend to be lower than average, the relationship with the length of residence will be weaker, or negative. This suggests that some of the environmental characteristics that lead people to report higher levels of fear are cumulative in nature, with prolonged exposure leading to a stronger impact on levels of fear. Similarly, the characteristics that result in lower average levels of fear also have a more pronounced effect on long-term residents, resulting in a stronger reduction in fear.

Ethnic heterogeneity

The relationship between the neighbourhood level of ethnic diversity and fear of crime is also given additional detail in the random coefficients model, with significant variability identified across CDRP. This shows that the higher levels of fear amongst residents living in neighbourhoods that are more ethnically diverse does not hold across all CDRP. Instead there is a negative relationship identified in approximately 17% of CDRP. Consequently, across 95% of partnerships, the relationship between ethnic heterogeneity and fear of crime actually ranges from a negative relationship of -.31 to a positive relationship of .91. A negative covariance term is also estimated, suggesting that the effect of heterogeneity will tend to be smaller in CDRP where the levels of fear are higher than average. Unfortunately, the lack of available CDRP data means that it is not possible to explore this variable effect of heterogeneity in more detail. No other neighbourhood effects varied significantly across CDRP, suggesting that the identified relationships are unaffected by the broader administrative context.

6.5.2 Introducing cross level interactions (personal crime)

So far, the random coefficients model has demonstrated that there are clear differences in the size of some individual level relationships with fear across neighbourhoods. However, this has not told us anything about how contextual influences contribute to these differences in fear. To provide a [illegible]ure of how particular types of people are influenced by the characteristics of their local neighbourhoods, table 6.3 extends the random coefficients model to include details of the cross-level interactions between the individual and contextual effects. The existence of cross level interactions was tested for all covariates where significant variability across neighbourhoods was identified. However, reflecting the lack of available CDRP level data, no cross level interactions were included to account for the variability across CDRP in the effect of the degree of ethnic diversity.

Table 6.3: Cross Level Interactions Model (Personal Crime)

		Effect (S.E)	Variance (S.E)	Covariance (S.E)
FIXED EFFECTS				
Constant		-.07 (.01)**		
Gender (*Ref: Male*)	Female	.47 (.02)**	.003 (.003)	.015 (.001)**
Age	Age	-.004 (.0002)**		
	*Female	-.01 (.0003)**		
	Age^2	-.0002 (.00001)**		
Education (*Ref: No qualifications*)	GCSE	-.04 (.01)**		
	A level	-.08 (.01)**		
	Degree	-.17 (.01)**		
	Other (foreign)	-.05 (.01)**		
Ethnicity (*Ref: White*)	Asian	.34 (.03)**	.133 (.024)**	.009 (.006)
	Black	.19 (.04)**	.125 (.028)**	.014 (.007)**
	Mixed/other	.18 (.03)**	.132 (.032)**	.011 (.007)
Direct Victimisation *(Ref: Non-victim)*	Personal Crime	.25 (.01)**	.014 (.010)	-0.01 (.003)**
	Household Crime	.14 (.01)**		
Newspaper readership *(Ref: No paper)*	Tabloid	.11 (.01)**		
	Broadsheet	-.01 (.01)		
	Local	.09 (.01)**		
NS-SEC (*Ref: Professional/managerial)*	Intermediate Occupation	.05 (.01)**		
	Small Employer	-.05 (.01)**		
	Lower Supervisory Role	.04 (.01)**		
	Routine or Semi Routine	.07 (.01)**		
	Never Worked	-.001 (.02)		
	Student	.14 (.02)**		
Marital Status (*Ref: Married)*	Separated or Divorced	-.08 (.01)**		
	Single	-.02 (.01)*		
	Widowed	-.04 (.01)**		
Health (*Ref: Not ill*)	Non-Limiting Illness	.09 (.01)**		
	Limiting Illness	.17 (.01)**	.014 (.004)**	.009 (.002)**
Residence	Length of residence	.005 (.002)*	.001 (.0002)**	.002 (.0004)**
Year	Survey Sweep	-.07 (.01)**		
CONTEXTUAL EFFECTS AND CROSS LEVEL INTERACTIONS				
Social disorganisation	Socio-economic disadvantage	.03 (.01)**		
	*Female	.04 (.01)**		
	Urbanisation	.07 (.01)**		
	*Length of residence	.01 (.002)**		
	Population mobility	.01 (.01)		
	Age Profile	.01 (.01)**		
	*Female	.02 (.01)**		
	Housing Profile	-.02 (.01)**		
	*Female	.02 (.01)**		
	Ethnic heterogeneity	.32 (.06)**	.099 (.041)**	-.016 (.007)**
	*Asian	-.16 (.11)		
	*Black	-.37 (.13)**		
	*Mixed	-.13 (.13)		
Crime	Local Recorded Crime	.03 (.01)**		
	*Personal Crime	.04 (.01)**		
Low level disorder	Objective Disorder	.03 (.01)**		
	*Female	.02 (.01)**		
	*Limiting	.03 (.01)**		
	*Non limiting	-.01 (.01)		
RANDOM EFFECTS				
CDRP level		.016 (.002)**		
Neighbourhood level		.030 (.001)**		
Individual Level		.800 (.004)**		
-2*Loglikelihood		271362.6		
Number of cases		*102,133*		

*** P<(.01)*

**P<(.05)*

As with the random coefficients model, the first column of figures includes the fixed effect estimates, along with the remaining unexplained variance partitioned at the individual, neighbourhood and CDRP levels for an average resident. This also includes all significant cross level interactions between individual and contextual effects. The second column contains estimates of the remaining variability across neighbourhoods in the individual covariates, allowing us to quantify the impact of the included cross level interactions. This also includes the variance in the effect of ethnic diversity across CDRP. Finally, the third column includes estimates of the covariances between the random variances and the neighbourhood level intercept variance.

Eight cross level interactions are estimated that provide further detail about the complex relationships identified between people's fear of crime and the local neighbourhoods in which they live their lives. These all go some way to explaining the variability in individual effects across neighbourhoods, pointing to some clear links between the size of individual effects and the contextual measures included at the neighbourhood level. Reflecting the lack of a significant main effect of the level of population mobility, no significant cross-level interactions were estimated with this structural dimension of the area. However, all other neighbourhood dimensions have significant interactions, demonstrating that their influence is more complex than simply a global effect across all types of individual.

The inclusion of these interaction terms leads to more complex interpretations of many of the individual level effects included in the model. This demonstrates that differences in fear based on gender, ethnicity, victimisation experience, length of residence, and whether someone has a limiting illness are directly linked to the social context in which people are situated. These suggest that more fearful types of people are more susceptible to the fear enhancing effects of social disorganisation, recorded crime and low level disorder, with the levels of fear of these groups generally being more closely linked to changes at the neighbourhood level. All subsequent graphs show the predicted levels of fear when all other covariates are set to 0, relating to an average resident.

Gender

Returning to the differences in fear between men and women, the expanded model identifies four important moderators of the effect of gender. These show that the levels of fear of women are more susceptible to differences in the structure of local neighbourhoods, with the size of the gender difference being directly related to area characteristics, net of other effects. Women are also affected more by the presence of signs of low level disorders in their neighbourhood than men are.

The first interaction term relates the gender gap to the level of neighbourhood socio-economic disadvantage, with a larger difference in fear between men and women evident in neighbourhoods that are identified as experiencing higher levels of disadvantage. The result of this can be clearly seen when represented graphically (see figure 6.3). This reveals that the change in the gender gap occurs because men's fear is not related to disadvantage, whereas women's fear is a function of the level of disadvantage in the neighbourhood.

Fear of Personal Crime by Gender and Neighbourhood Socio-economic Disadvantage

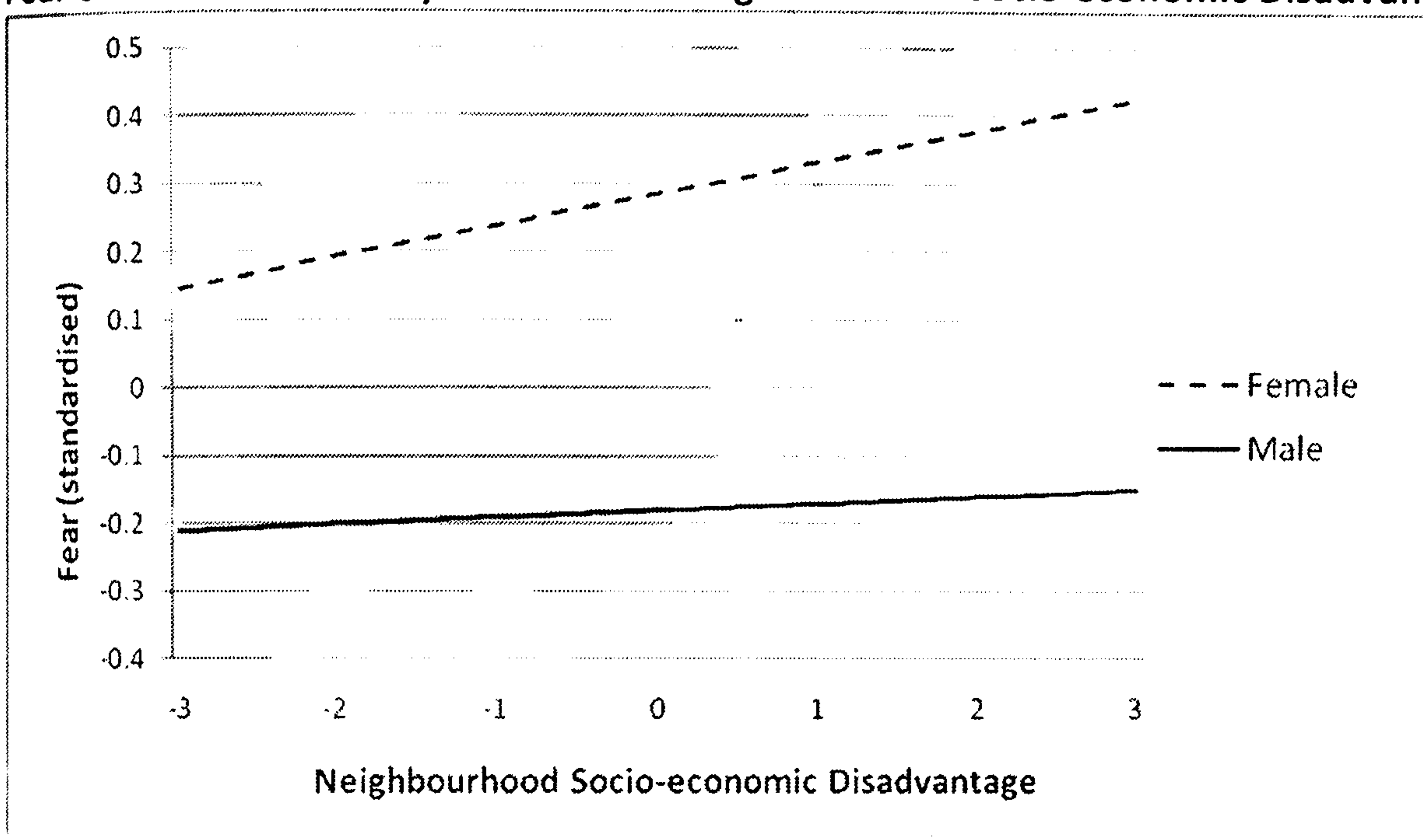

Figure 6.3

Looking at figure 6.3, we see that in areas that have a higher than average level of disadvantage, the gender difference is significantly larger than average. This is represented by the increasing size of the gap between the levels of fear of men and women as we move to the right along the x-axis. In contrast, in areas where the relative level of disadvantage is lower than average, the size of the gender difference is smaller than average, represented by the smaller gap between the two lines as we move to the left along the x-axis.

The second extension to the model links the age profile of the neighbourhood to the size of the gender difference in fear. Like the interaction with the neighbourhood level of socio-economic disadvantage, the extended model reveals that the levels of fear of men are not closely related to the age profile of the local neighbourhood. This means that there is no significant difference in the levels of fear of men living in areas where the surrounding population is generally older than average, when compared with areas characterised by a younger population profile. In contrast, there is a differential effect of being a woman on fear as the age profile of the area changes. This differential relationship is shown graphically below in figure 6.4. In areas which have a younger than average age profile, the gender difference is larger than in areas where there is a much older age

his is represented by the diverging lines as we move towards the left of the graph.

Fear of Personal Crime by Gender and Neighbourhood Age Profile

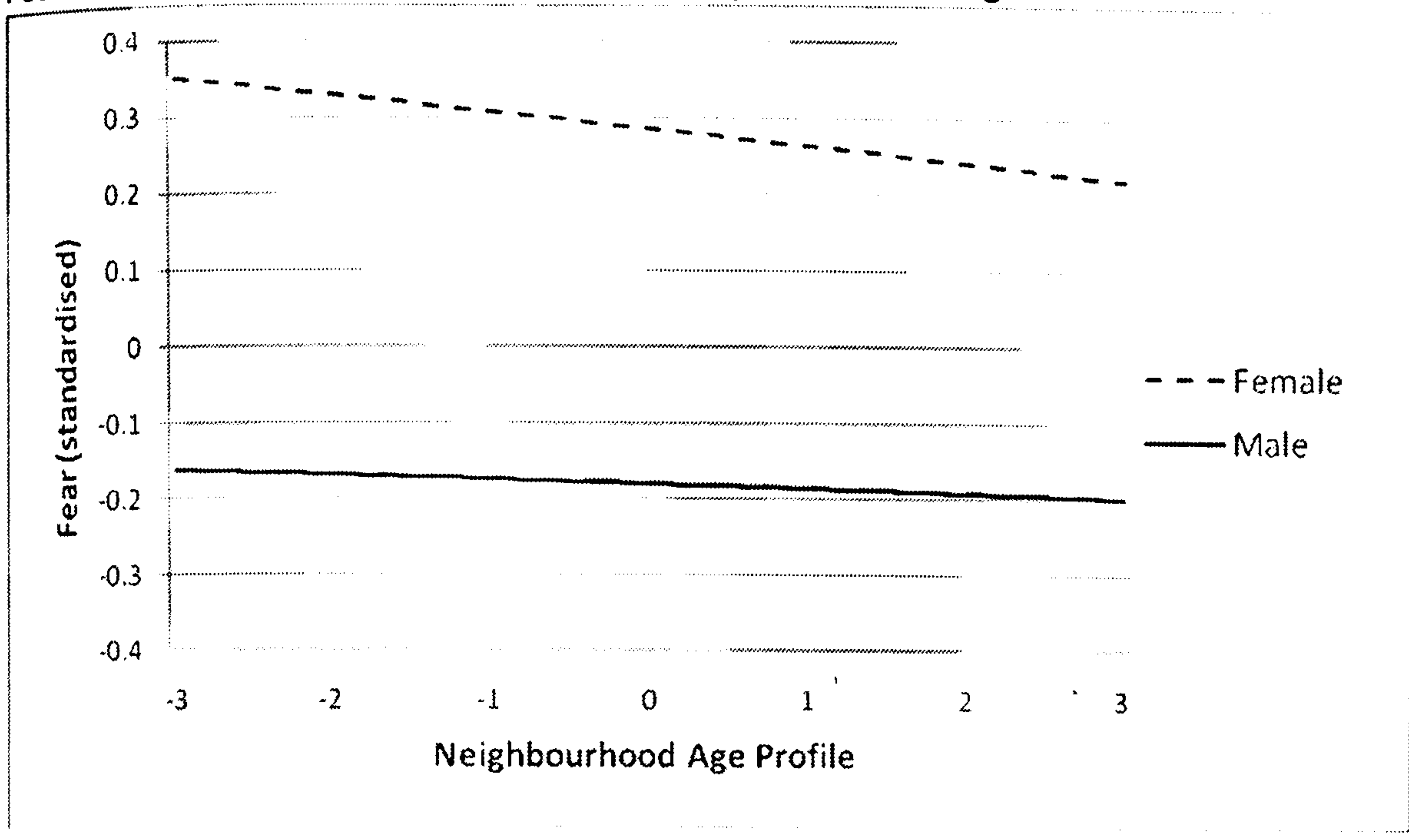

Figure 6.4

The size of the gender gap is also related to the housing structure of the local area. In contrast to the previous interactions, this shows that men's fear of crime differs significantly depending on the housing structure of the local neighbourhood. In areas that are characterised by a higher proportion of terraced accommodation and vacant properties, the levels of fear of men are predicted to be significantly lower than average, and vice versa. In contrast, the levels of fear of women do not differ as the housing profile of the local area changes. The net result is that in areas characterised by higher proportions of terraced and vacant properties, the gender gap will be significantly larger than in areas with a relatively lower proportion of terraced and vacant properties (figure 6.5).

Fear of Personal Crime by Gender and Neighbourhood Housing Profile

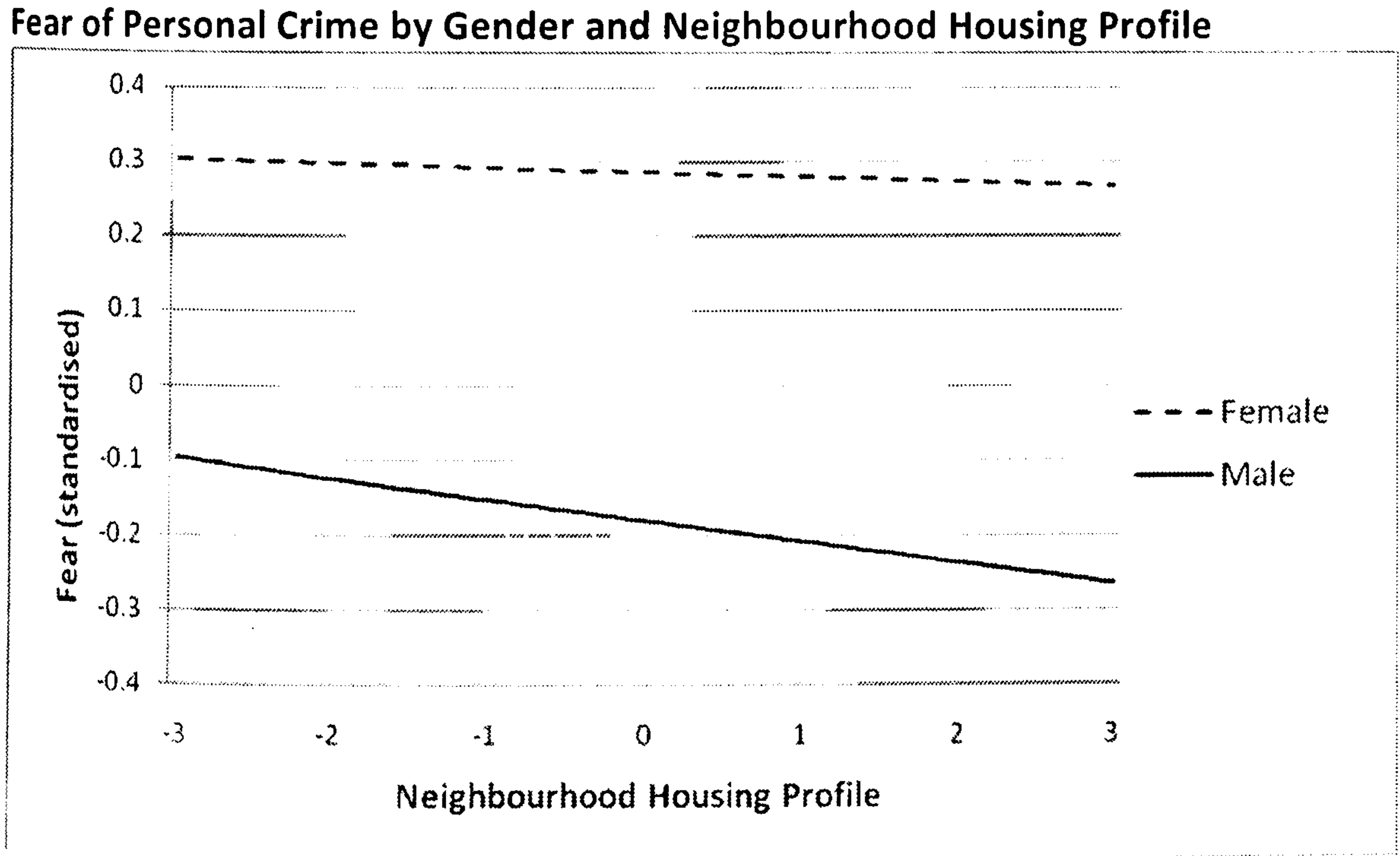

Figure 6.5

Finally, men and women are also differentially affected by the presence of signs of low level disorder in the local surroundings. Both report significantly higher levels of fear as the prevalence of signs of rease, lending support to the claims of the disorder perspective. However, the effect on fear is considerably stronger for women, leading to a significantly larger gender gap in areas characterised by a higher than average prevalence of disorder. This means that women are more likely to associate physical signs of disorder within the neighbourhood with a greater potential threat of crime. Represented graphically (figure 6.6) the strength of this effect is apparent, with a stronger relationship between fear and disorder amongst women.

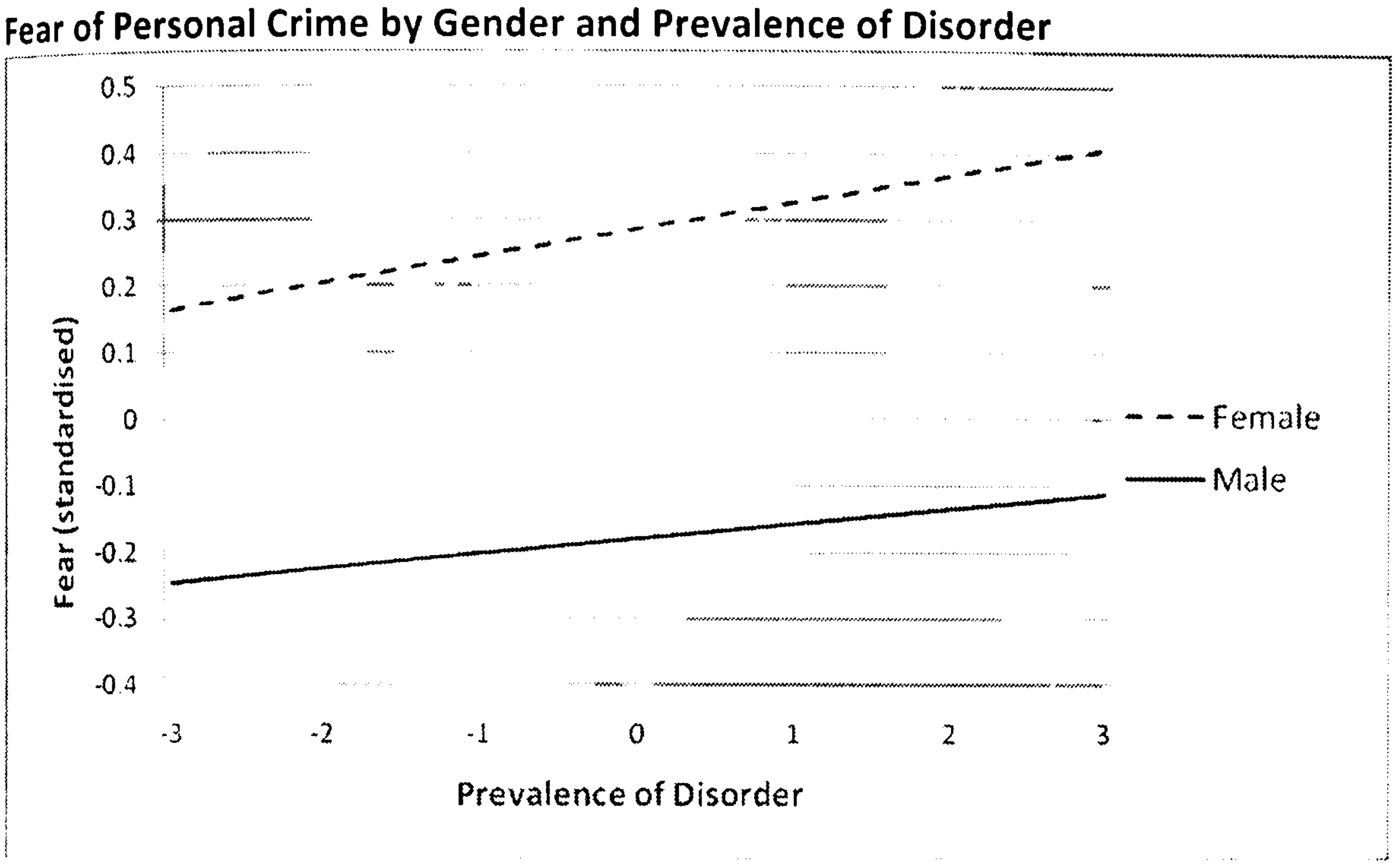

Figure 6.6

The inclusion of these four interaction terms has resulted in a clear drop in the size of the random coefficient associated with gender, with the remaining variance no longer identified as significant. This indicates that the gender differences in fear across neighbourhoods can be reliably predicted by differential effects of the level of disadvantage, the age profile of the local area, its housing structure, and the prevalence of low level disorder. These gender specific effects are a clear demonstration that men's levels of fear of personal crime are more resistant to neighbourhood differences than women's fear, and as such contextual explanations should be adapted to accommodate these differences.

Ethnicity

The extended model also shows an interaction between the effect of belonging to a BME group on fear, and the neighbourhood level of ethnic diversity. This is a complex interaction, indicating that the higher levels of fear which have previously been linked to living in more ethnically mixed neighbourhoods are conditional on individual ethnicity. White people living in more ethnically mixed neighbourhoods will have higher levels of fear than those living in less mixed neighbourhoods. In contrast, when we turn to the experiences of Black residents, living in more diverse local neighbourhoods is actually associated with significantly lower average levels of fear. The effect of this inverse relationship is that in neighbourhoods identified as more ethnically diverse, fear is actually lowest amongst black residents. This is represented below in figure 6.7.

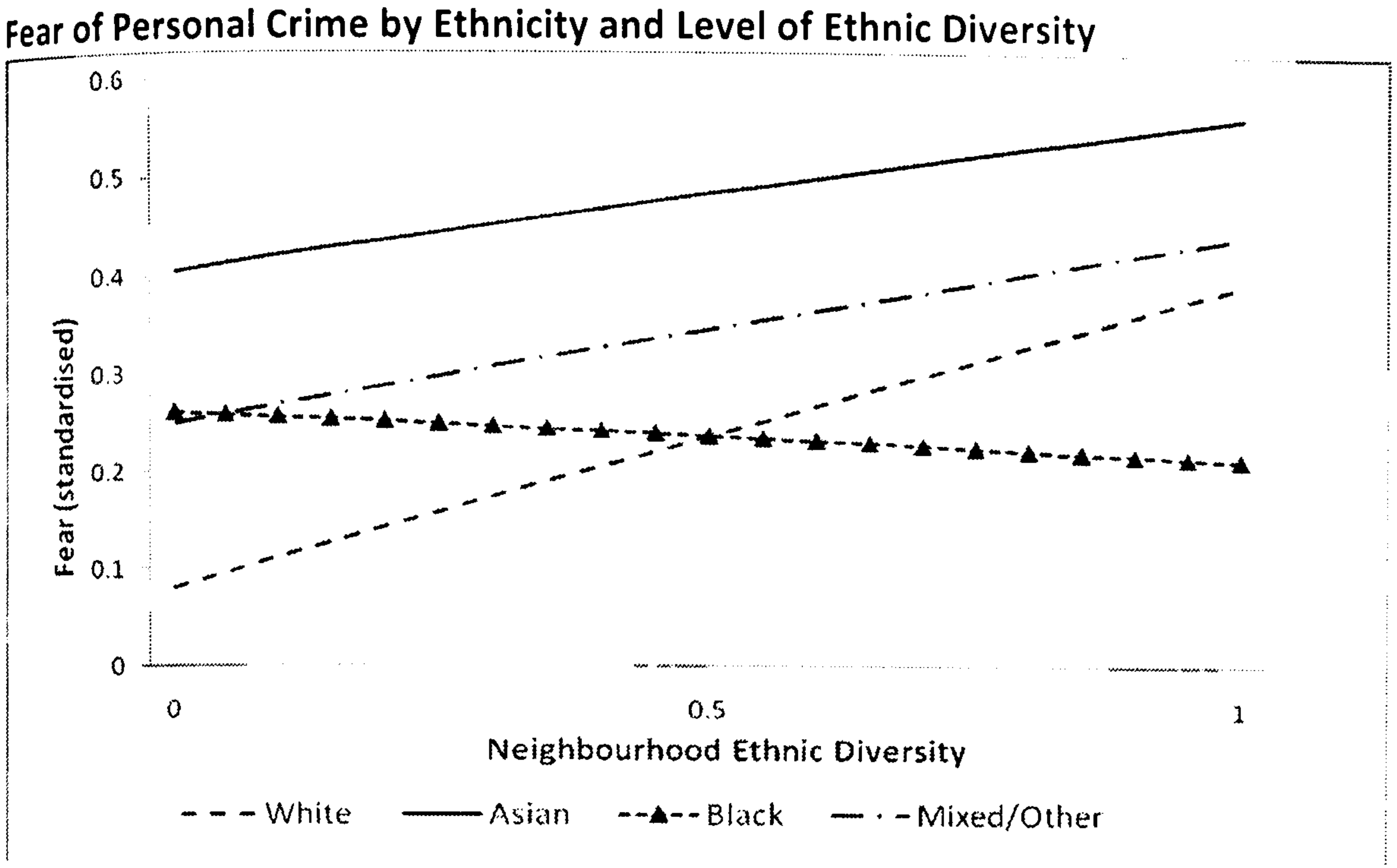

Figure 6.7

The relationship is somewhat less clear when considering Asian residents and those from mixed backgrounds, where the differential effect of ethnic heterogeneity is not identified as statistically significant at conventional levels. Looking at these BME groups it is evident that in more ethnically diverse neighbourhoods levels of fear will still be higher than the equivalent White resident, but that the size of this difference is reduced. This is because the fear amongst White people is significantly higher in more ethnically mixed neighbourhoods, whilst Asian and mixed origin residents are less affected by the surrounding level of diversity. To test whether the effect of heterogeneity on Black residents' fear of crime was simply a reflection of the increased proportion of non-White residents in more heterogeneous neighbourhoods, the proportion of BME residents was also included. This had no substantive effect on results, lending confidence to the assertion that this is a reflection of the effect of diversity, not simply the proportion of non-white neighbours in the area.

This significant cross level interaction results in a small reduction in the remaining unexplained variation in fear across neighbourhoods for black residents (a drop of 3%). This means that the model still exhibits significant variability across neighbourhoods in the effect of belonging to a BME group that has not been successfully explained with the available contextual measures or cross level interactions. This suggests the existence of other important contextual effects that are specific to the experiences of ethnic minority residents.

Victimisation experience

There is also an interesting link between the recorded level of crime in the local neighbourhood, and the effect of previous experience of personal victimisation on people's fear of crime. The extended model clearly shows that in areas where the recorded levels of crime are higher than average, the difference in fear between victims and non-victims is significantly larger than average. This larger difference in fear between victims and non-victims in high crime rate areas can be seen more clearly when represented graphically, (figure 6.8).

Fear of Personal Crime by Victimisation Experience and Neighbourhood Recorded Crime Level

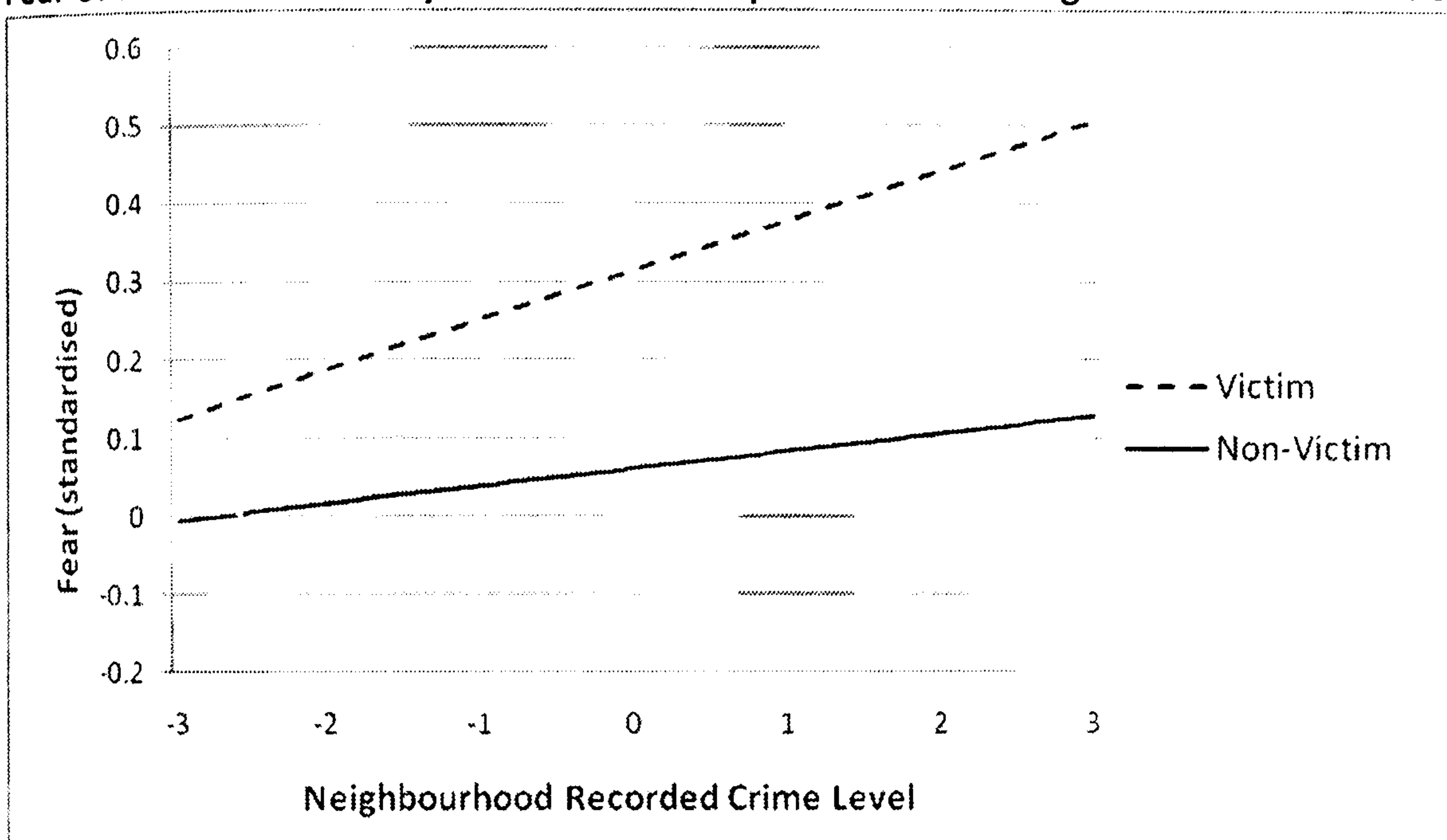

Figure 6.8

This shows that the larger gap in fear between victims and non-victims in high crime rate areas reflects the stronger relationship between the level of crime in the local neighbourhood and fear of crime amongst previous victims of personal crime. In contrast, the levels of fear of non-victims remain relatively stable irrespective of the level of crime in the surrounding area, with only slightly higher levels of fear evident in neighbourhoods that have considerably higher relative levels of crime. This suggests that personal victimisation experience raises people's awareness of the levels of crime in their own neighbourhood, resulting in a closer link between recorded crime and fear. Including this interaction, the variance associated with previous experience of personal victimisation no longer reaches significance.

Health

People with a limiting illness are identified as being significantly more influenced by the presence of low level signs of disorder in their local neighbourhood than people who are not ill or people who are ill but not in a way that limits their daily activity. This suggests a link between physical vulnerability and the importance of disorder, with vulnerable people more likely to associate higher levels of disorder with an increased threat of victimisation (a finding also suggested by the interaction between gender and disorder if we attribute gender differences to vulnerability). Represented graphically, the interaction indicates that there is a significantly larger difference in fear between people with a limiting illness, and those without, when the neighbourhood suffers from a greater prevalence of low level disorder (figure 6.9).

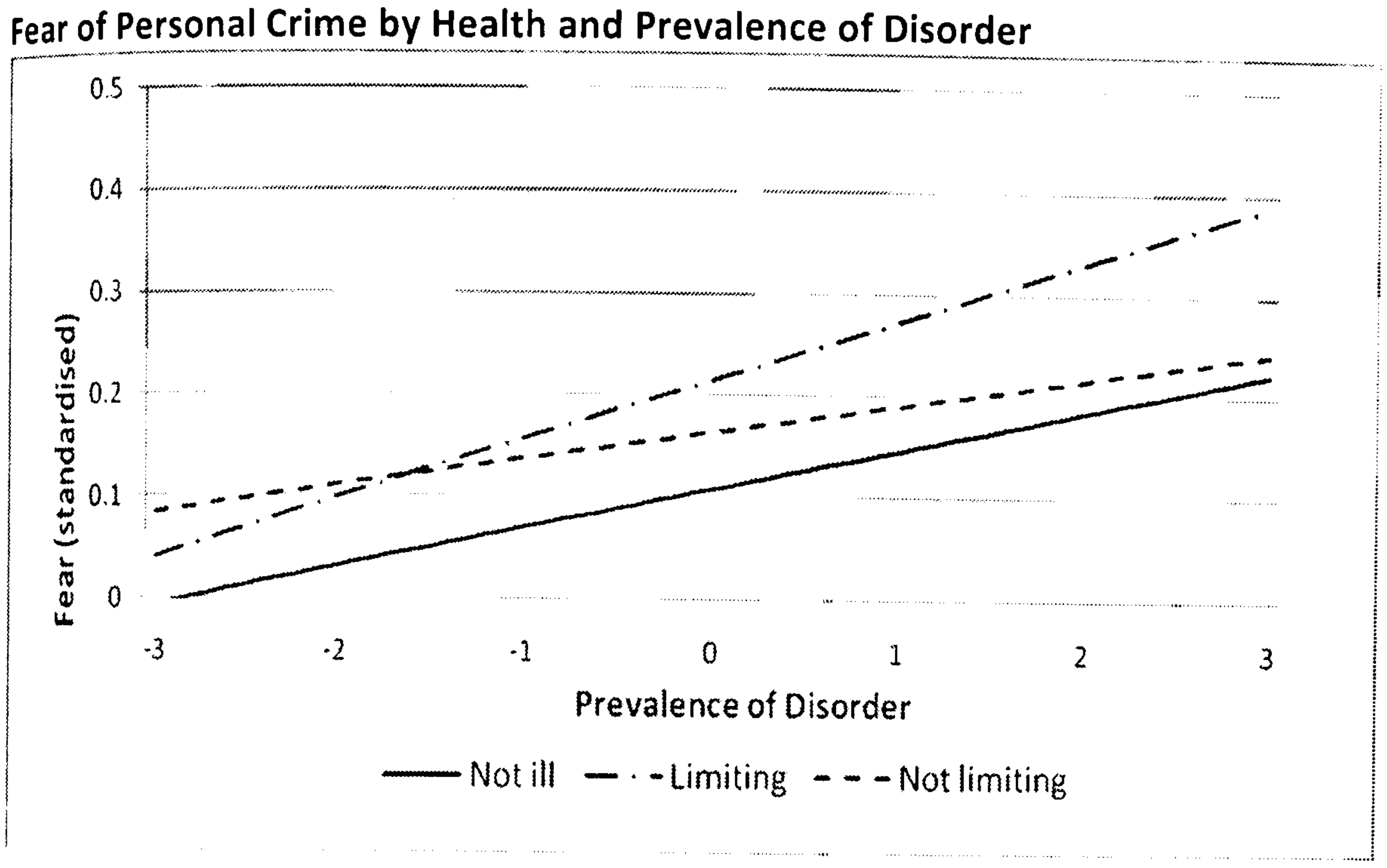

Figure 6.9

Mirroring the failure to identify significant variability in the effect of being ill, but not physically limited by it, the size of the gap in fear between those who have a non-limiting illness and those who have no illness is not significantly altered by the level of disorder. This means that in areas characterised by high levels of disorder, the gap between those with a limiting illness, and those with a non-limiting illness, is also increased.

Length of residence

Finally, a significant interaction is estimated between the effect of the amount of time someone has lived in the area on fear of crime, and the neighbourhood level of urbanisation. In areas that are classified as more urban in structure, the positive effect of length of residence will be stronger than average. This means that fear will be higher in more urban areas amongst those that have lived within the local area for a longer period of time. This can be represented graphically by comparing how the levels of fear of a recently arrived resident (less than 1 year within the area) differ in more urban areas, with the levels of fear of a long term resident (more than 20 years). Looking at the graph (figure 6.10), we see that in more urban areas the gap in levels of fear between recently arrived residents and long term residents is significantly larger than in less urban areas. In contrast, in areas classified as more rural (the left of the graph), levels of fear will actually tend to be higher amongst those that have lived in the area for a shorter length of time.

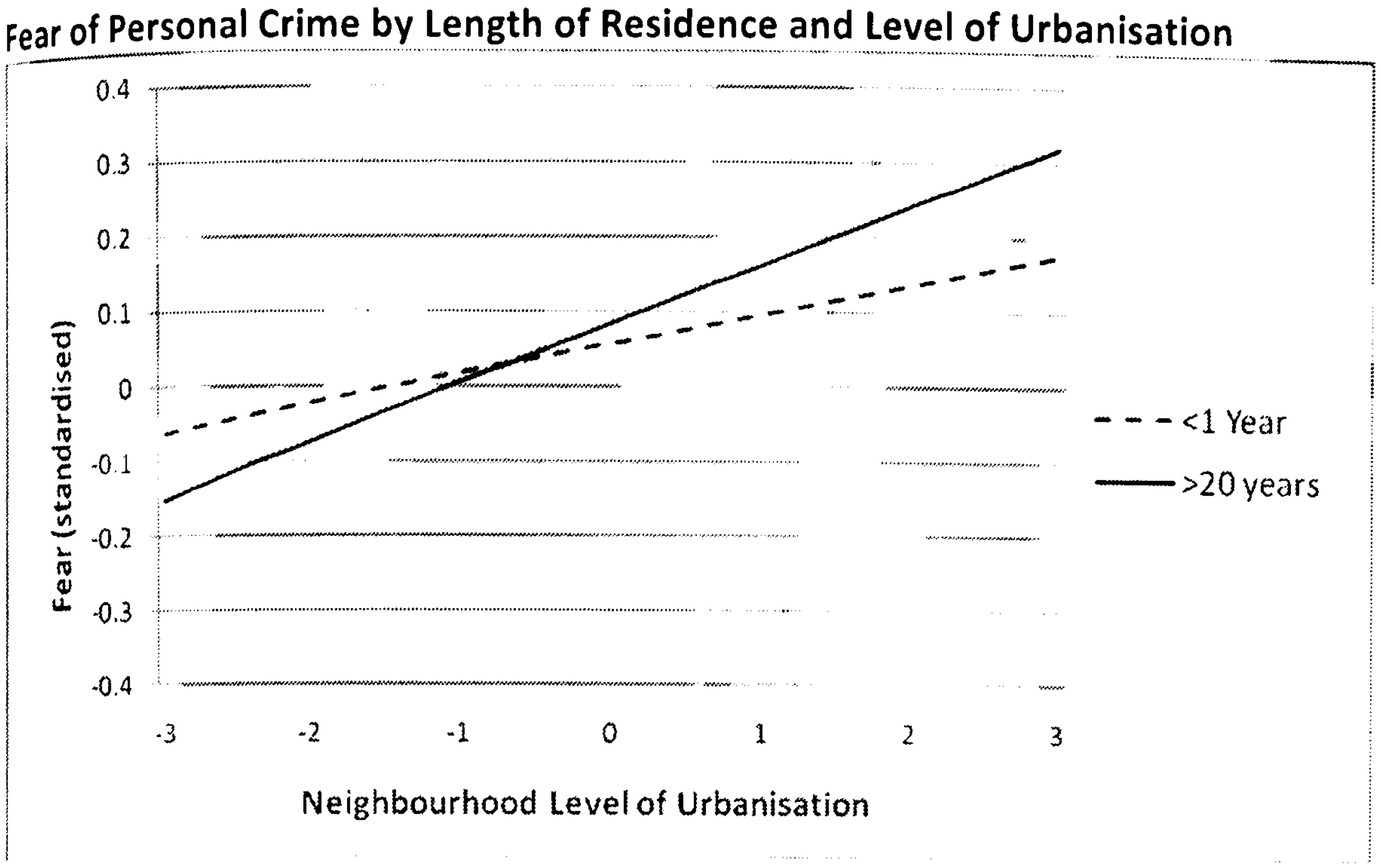

Figure 6.10

The inclusion of these eight interaction terms fits the data significantly better than the random coefficients model, with a drop in the deviance of 168 with 11 degrees of freedom [$p<0.001$]. This confirms the need to examine individual differences within the local context in which they are experienced, providing us with additional detail about how individual relationships with fear are related to contextual differences at the neighbourhood level. Despite representing the data structure significantly better than the previous model, there is still unexplained variability in many of the individual effects that has not been fully accounted for with the inclusion of cross-level interactions. This is an indication of the existence of further differences between neighbourhoods that are experienced differently by the people living in them.

6.5.3 Fear of household crime

Having examined fear of personal victimisation, the same modelling approach is used to integrate individual and contextual explanations for variations in fear of household crime. Table 6.4 contains estimates from the random coefficients model, including columns for the fixed effect estimates, the variances associated with all coefficients that are specified as random, and the covariances between the variance estimates and the random intercept.

Table 6.4: Random Coefficients Model (Household Crime)

		Effect (S.E)	Variance (S.E)	Covariance (S.E)
FIXED EFFECTS				
Constant		.08 (.01)**		
Gender (*Ref: Male*)	Female	.14 (.01)**		
Age	Age	-.004 (.0003)**		
	*Female	-.001 (.003)**		
	Age^2	-.0002 (.00001)**		
Education (*Ref: No qualifications*)	GCSE	-.03 (.01)**		
	A level	-.06 (.01)**		
	Degree	-.13 (.01)**		
	Other (foreign)	-.03 (.01)*		
Ethnicity (*Ref: White*)	Asian	.22 (.02)**	.102 (.023)**	-.003 (.006)
	Black	.14 (.03)**	.111 (.029)**	.010 (.007)
	Mixed/other	.16 (.03)**	.178 (.036)**	.013 (.007)*
Direct Victimisation (*Ref: Non-victim*)	Personal Crime	.14 (.01)**		
	Household Crime	.24 (.01)**	.008 (.004)**	-.007 (.002)**
Newspaper readership (*Ref: No paper*)	Tabloid	.09 (.01)**		
	Broadsheet	.02 (.01)*		
	Local	.08 (.01)**		
NS-SEC (*Ref: Professional/managerial*)	Intermediate Occupation	.02 (.01)		
	Small Employer	.004 (.01)		
	Lower Supervisory Role	.04 (.01)**		
	Routine or Semi Routine	.04 (.01)**		
	Never Worked	.04 (.02)*		
	Student	-.05 (.02)**		
Marital Status (*Ref: Married*)	Separated or Divorced	-.14 (.01)**		
	Single	-.10 (.01)**		
	Widowed	-.10 (.01)**		
Health (*Ref: Not ill*)	Non-Limiting Illness	.08 (.01)**		
	Limiting Illness	.10 (.01)**	.027 (.005)**	.006 (.002)**
Residence	Length of residence	.02 (.002)**	.0004 (.0002)**	.001 (.0004)**
Year	Survey Sweep	-.05 (.004)**		
CONTEXTUAL EFFECTS (Level 2)				
Social disorganisation	Socio-economic disadvantage	.02 (.01)*		
	Urbanisation	.01 (.01)		
	Population mobility	-.03 (.01)**		
	Age Profile	.01 (.005)*		
	Housing Profile	.01 (.01)		
	Ethnic heterogeneity	.15 (.05)**	.066 (.032)**	-.012 (.006)**
Crime	Local Recorded Crime	.05 (.01)**		
Low level disorder	Objective Disorder	.04 (.01)**		
RANDOM EFFECTS				
CDRP level		.012 (.001)**		
Neighbourhood level		.019 (.001)**		
Individual Level		.881 (.004)**		
-2*Loglikelihood		281909.5		
Number of cases		*102,696*		

*** P<(.01)*
**P<(.05)*

As was found for fear of personal crime, significant variability is evident across neighbourhoods in the effects of ethnicity, victimisation experience, and limiting illness on fear of crime. However, there is no significant variation across neighbourhoods in the size of the gender difference, or the length of time that someone has lived in the neighbourhood. Additionally, in this model it is the effect of past household victimisation that varies across neighbourhoods and not personal victimisation, again highlighting the importance of the type of crime that is being examined. All other individual effects are not shown to vary across neighbourhoods, demonstrating considerable consistency across models. Similar to fear of personal crime, there is also significant variation in the effect of ethnic diversity across CDRP, although all other contextual effects remain stable.

Using the variance function, this model provides further evidence that the magnitude of the neighbourhood contribution to the remaining unexplained variance differs significantly depending on the type of individual being considered. For example, the variance attributable to unexplained neighbourhood differences is considerably higher for a BME resident than a White resident, when all other covariates are set at their average. This is estimated at 14.1% for a Black individual, compared to 2% for the equivalent White person (11.3% for an Asian and 19.6% for someone of mixed origin).

Table 6.5 Describes the variance estimates associated with each random coefficient in more detail, showing the range of values that each coefficient takes across the middle 95% of neighbourhoods. This enables us to see how much the estimates differ across neighbourhoods, advancing our understanding of these individual effects by considering them at the local level. This presents a similar picture to the fear of personal crime model, with a comparable range for the individual relationships across neighbourhoods.

Table 6.5: Variance across Middle 95% of Neighbourhoods/CDRP (Household Crime)

		Lower Limit	Effect Size	Upper Limit
FIXED EFFECTS (Across 95% of neighbourhoods)				
Ethnicity *(Ref: White)*	Asian	-0.41	**0.22**	0.85
	Black	-0.51	**0.14**	0.79
	Mixed/other	-0.67	**0.16**	0.99
Direct Victimisation *(ref: Non-victim)*	Household Crime	0.06	**0.24**	0.42
Health *(Ref: Not ill)*	Limiting Illness	-0.22	**0.10**	0.42
Residence	Length of residence	-0.02	**0.02**	0.06
CONTEXTUAL EFFECT (Across 95% of CDRP)				
	Ethnic heterogeneity	-0.61	**0.15**	0.79

Ethnicity

A high degree of variability is again evident in the size of the difference in levels of fear of BME groups compared to White people across neighbourhoods. This means that when examined on average across neighbourhoods, the apparent higher levels of fear amongst BME residents is masking significant variability in the relative levels of fear of BME and White people at the local level. Across the middle 95% of neighbourhoods it is again apparent that BME groups are not always identified as more fearful, with Asian residents identified as less fearful than White people in approximately 25% of neighbourhoods (34% and 35% of neighbourhoods for Black and mixed origin residents respectively). The covariance terms between these variance estimates and the random intercept do not reach conventional levels of significance. This suggests that the remaining unexplained variability in the effect of belonging to a BME group is not directly related to the variability across neighbourhoods for the equivalent White resident.

Household victimisation

The effect of previous household victimisation on fear also varies significantly across neighbourhoods. The significant variability means that estimates of the size of this difference range from .06 to .42 across the middle 95% of neighbourhoods, so in all cases fear is higher amongst victims of household crime. This is equivalent to the fear of personal crime model, albeit specific to victims of household crime, confirming the important part that previous experience of victimisation plays in influencing people's fear of crime. A significant negative covariance is also estimated between the random coefficient and the variability in the intercept across neighbourhoods. This means that in neighbourhoods with higher than average levels of fear, the difference in fear between victims and non-victims tends to be smaller than average. In contrast, in areas where residents report lower than average levels of fear, previous victimisation experience has a comparatively strong effect on fear.

Health

The higher fear amongst people with a limiting illness is again shown to vary considerably across neighbourhoods, ranging from -.22 to .42 across 95% of local neighbourhoods. This is further evidence that the effect of having a limiting illness on fear is dependent on the local neighbourhood, with approximately 27% of neighbourhoods associated with lower fear amongst people with a limiting illness. Like fear of personal crime, there is no corresponding variability in the effect of having a non-limiting illness on levels of fear. This means that the gap in fear between people with a non-limiting illness and those who are not ill remains consistent across neighbourhoods. However, in contrast to fear of personal crime, the variability in the effect of having a limiting illness on fear is not related to the variability in the intercept term, with no significant covariance estimated.

Length of Residence

There is also a small degree of variability in the relationship between the length of time that people have lived in the local area, and fear of crime. The random coefficient reveals that whilst on average living in a neighbourhood longer is associated with a slightly higher fear, In some neighbourhoods this relationship is significantly stronger than the overall average, and in other neighbourhoods the relationship is in the opposite direction.

Along with the small random coefficient, a significant covariance with the random intercept is also estimated. This demonstrates that in areas where the levels of fear tend to be higher than average, the relationship between length of residence and fear will also tend to be stronger. In contrast, in neighbourhoods where levels of fear tend to be lower than average, the relationship with the length of residence will be weaker, or negative.

Ethnic heterogeneity

Like fear of personal crime, there is significant variability in the neighbourhood effect of ethnic diversity across CDRP. Looking at the middle 95% of CDRP, this is estimated to vary between -.61 and .79. This suggests that the structure of the local partnership has important implications for the effect that diversity has on levels of fear, with a considerable proportion of CDRP showing a negative relationship. This means that in these CDRP, neighbourhoods that are identified as more ethnically diverse will actually have lower levels of fear from residents than neighbourhoods that are identified as less diverse. However, the lack of available CDRP data means that it is not possible to examine the reasons for this variability across partnerships.

6.5.4 Introducing cross level interactions (household crime)

Like fear of personal crime, the random coefficients model shows some clear differences in the size of some individual level relationships with fear across neighbourhoods. To get a better understanding of how different people's fear of crime is affected by their local neighbourhood context, cross level interactions are estimated between the contextual effects and the individual effects that varied significantly across neighbourhoods. These are included in table 6.6, along with estimates of the remaining variance partitioned at the individual, neighbourhood and CDRP levels. This table also includes estimates of the remaining unexplained variation across neighbourhoods in the individual effects that were identified in the previous model, along with their covariances with the intercept.

Table 6.6: **Cross Level Interactions Model (Household Crime)**

		Effect (S.E)	Variance (S.E)	Covariance (S.E)
FIXED EFFECTS				
Constant		.08 (.01)**		
Gender (*Ref: Male*)	Female	.14 (.01)**		
Age	Age	-.004 (.0003)**		
	*Female	-.001 (.003)**		
	Age^2	-.0002 (.00001)**		
Education (*Ref: No qualifications*)	GCSE	-.03 (.01)**		
	A level	-.07 (.01)**		
	Degree	-.13 (.01)**		
	Other (foreign)	-.03 (.01)*		
Ethnicity (*Ref: White*)	Asian	.22 (.02)**	.102 (.023)**	-.003 (.006)
	Black	.14 (.03)**	.111 (.029)**	.010 (.007)
	Mixed/other	.16 (.03)**	.178 (.036)**	.013 (.007)*
Direct Victimisation (*Ref: Non-victim*)	Personal Crime	.14 (.01)**		
	Household Crime	.24 (.01)**	.005 (.004)	-.007 (.002)**
Newspaper readership (*Ref: No paper*)	Tabloid	.09 (.01)**		
	Broadsheet	.02 (.01)*		
	Local	.08 (.01)**		
NS-SEC (*Ref: Professional/managerial*)	Intermediate Occupation	.02 (.01)		
	Small Employer	.004 (.01)		
	Lower Supervisory Role	.04 (.01)**		
	Routine or Semi Routine	.04 (.01)**		
	Never Worked	.04 (.02)*		
	Student	-.05 (.02)**		
Marital Status (*Ref: Married*)	Separated or Divorced	-.13 (.01)**		
	Single	-.10 (.01)**		
	Widowed	-.10 (.01)**		
Health (*Ref: Not ill*)	Non-Limiting Illness	.08 (.01)**		
	Limiting Illness	.10 (.01)**	.027 (.005)**	.006 (.002)**
Residence	Length of residence	.02 (.002)**	.0004 (.0002)**	.001 (.0004)**
Year	Survey Sweep	-.05 (.004)**		
CONTEXTUAL EFFECTS AND CROSS LEVEL INTERACTIONS				
Social disorganisation	Socio-economic disadvantage	.01 (.01)*		
	Urbanisation	.01 (.01)		
	Population mobility	-.03 (.01)**		
	Age Profile	.01 (.005)*		
	Housing Profile	.01 (.01)		
	Ethnic heterogeneity	.15 (.05)**	.066 (.033)**	-.013 (.006)**
Crime	Local Recorded Crime	.05 (.01)**		
	*Household Crime	.03 (.01)**		
Low level disorder	Objective Disorder	.04 (.01)**		
	*Household Crime	.03 (.01)**		
RANDOM EFFECTS				
CDRP level		.012 (.001)**		
Neighbourhood level		.019 (.001)**		
Individual Level		.881 (.004)**		
-2*Loglikelihood		281887.8		
Number of cases		*102,696*		

*** P<(.01)*
**P<(.05)*

This is a less complex model than the corresponding fear of personal crime model, reflecting the reduced number of random coefficients that were identified. Two cross level interactions are evident, which help to clarify the variability across neighbourhoods in the effect of previous victimisation. As a result, there is limited evidence in support of a differential impact of social disorganisation on those identified as more fearful in this model.

Victimisation experience

Like fear of personal crime, the effect of previous victimisation experience on fear of household crime is given further detail by linking it directly to the neighbourhood level of recorded crime. Here, the differential effect is evident when considering previous experience of household crime, with the higher levels of fear amongst previous victims identified as significantly larger in areas that have a higher crime rate. Looking at figure 6.11, it is evident that people who have previously been the victim of a household crime are more susceptible to the influence of a changing crime rate than non-victims. This leads to a larger difference in fear between victims and non-victims in higher crime rate areas, and a smaller difference in neighbourhoods with relatively low crime rates.

Fear of Household Crime by Victimisation Experience and Recorded Crime Level

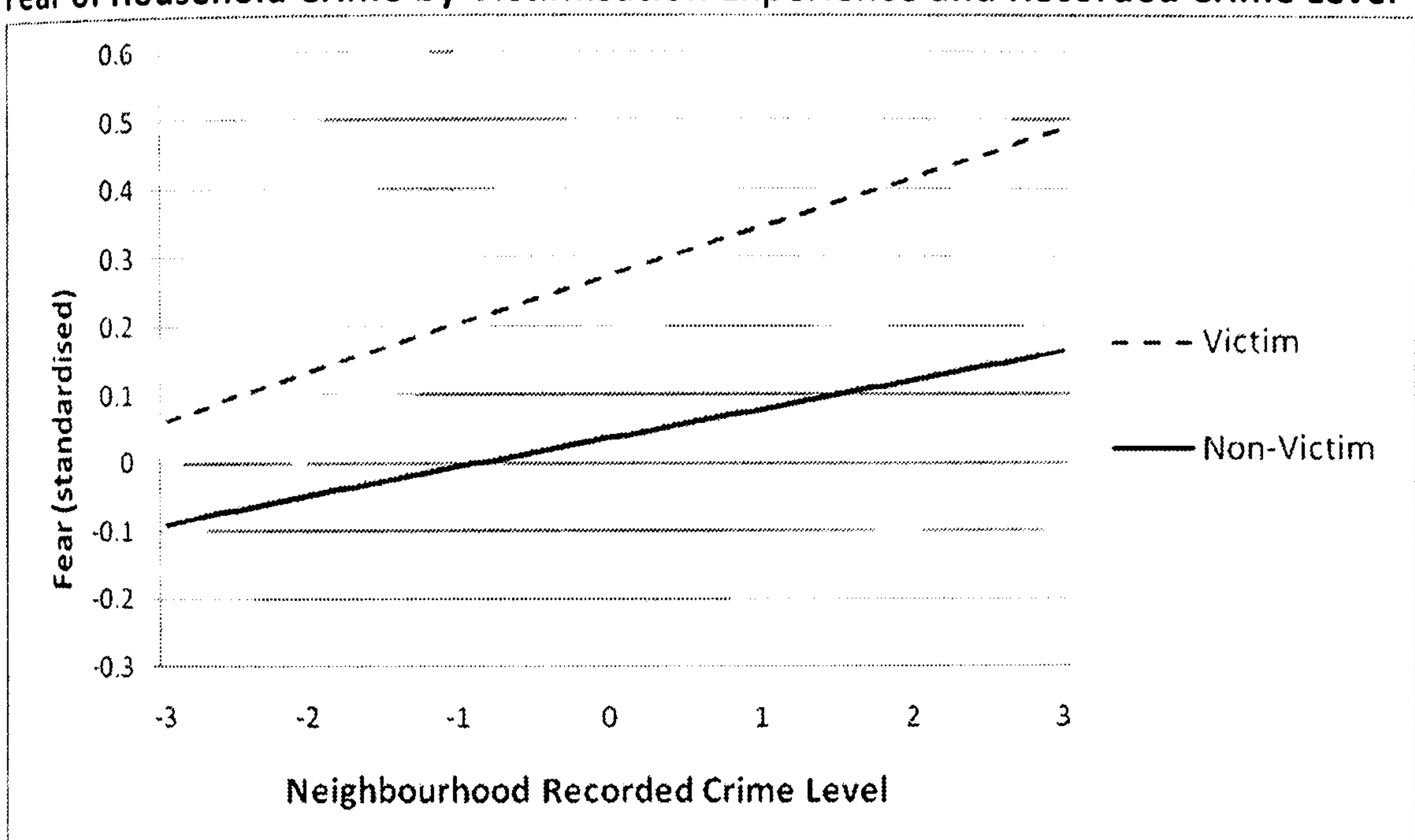

Figure 6.11

A similar effect is evident when the extent of neighbourhood socio-economic disadvantage is considered. Victims of household crime, then, are also identified as more susceptible to the influence of the socio-economic character of their local neighbourhood, with a larger difference in fear between victims and non-victims in areas characterised by more disadvantage. Represented graphically, the effect is the same as the differential effect of recorded crime (figure 6.12). It therefore appears that people who have previously been the victim of household crime are more likely to be influenced by the relative level of disadvantage in the neighbourhood, perhaps because they are linking this to increased risks of future victimisation.

Fear of Household Crime by Victimisation Experience and Neighbourhood Socio-economic Disadvantage

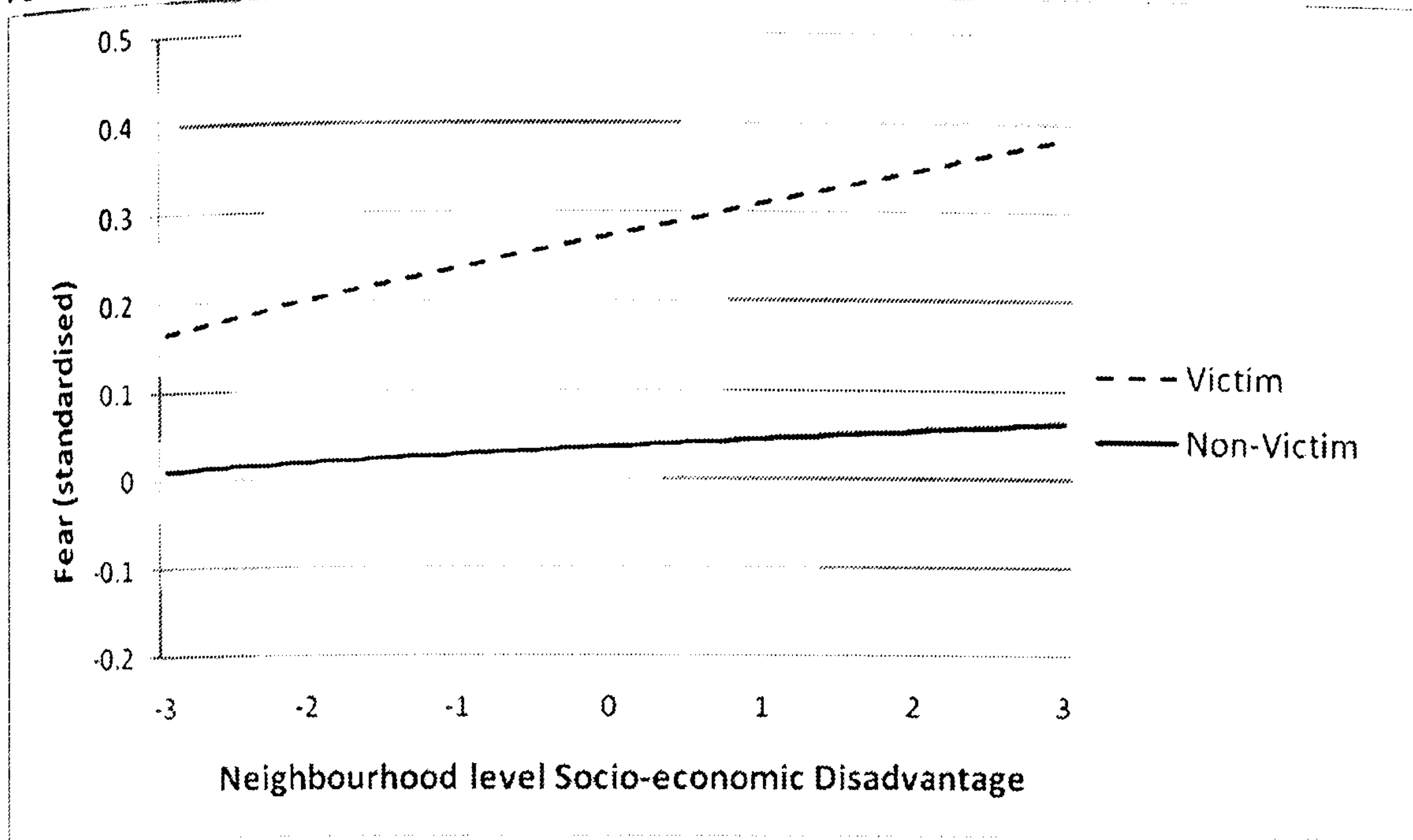

Figure 6.12

6.6 Discussion III: Contextualising individual effects

Existing research has provided us with a number of explanations for variations in fear of crime, focusing on both individual and contextual differences. In chapters 4 and 5, I presented a series of models that tested these theories within an integrated framework, finding some support for the importance of social disorganisation, disorder, and recorded crime when assessed alongside individual differences in fear. In this chapter, I have extended this assessment of the contextual explanations for variations in fear to allow individual differences in fear to vary across neighbourhoods. This is a direct test of the assumption that individual differences in fear are uniform across neighbourhood contexts, allowing a more nuanced assessment of how people's fear of crime is affected by where they live. I then linked these individual variations across neighbourhood context directly to the contextual theories, testing the applicability of these more general explanations to the experiences of local residents.

When examined at the local level, clear differences in individual experiences of fear of crime across neighbourhoods are evident that were not found when relying on national aggregates. For both fear of personal crime and fear of property crime, the individual level explanations for differences in fear have been given additional detail by being specified as random coefficients that are allowed to vary across neighbourhoods. These suggest that individual differences in fear are not uniform across all neighbourhoods, instead the characteristics of the neighbourhood play an important role in determining how much of an impact individual characteristics have.

Including cross-level interactions between individual level relationships with fear and neighbourhood effects has then demonstrated how the contextual explanations for differences in fear are directly related to the types of individual that are resident in the neighbourhood. This has provided us with further detail about the complex relationship between individuals and the local context in which they live their daily lives. This represents an important extension to current analyses of the structural determinants of fear, which have generally been limited by assuming that local context affects all types of individual in the same way. Additionally, this comes closer to the detailed conceptualisation of neighbourhood put forward by qualitative community studies, placing individuals centrally to the impact of neighbourhood effects.

In general, this shows that it is the most fearful groups in society that are the most influenced by the local environment. This is demonstrated by the stronger relationships between fear and neighbourhood measures amongst women, victims, and those with limiting illnesses, all groups that have been identified as significantly more fearful. These groups seem to be more aware of their local environment, with stronger relationships evident with the prevalence of disorder and the level of crime in the local neighbourhood. The structure of the local community is also shown to be more important to these fearful groups, with many of the characteristics that have been linked with more socially disorganised communities having a stronger effect on those that are identified as the most fearful.

Just as the influence of neighbourhood differences was larger when considering fear of personal crime, individual differences in fear of personal crime are found to be more susceptible to the influence of contextual effects. This implies that individual level differences in fear of burglary are more stable across neighbourhoods, with different types of individual less likely to be differentially influenced by local neighbourhood cues. This is a plausible conclusion given the reduced contribution that neighbourhood differences appeared to make to unexplained variability in the simplified random intercept model describing fear of household crime.

The differential variability across neighbourhoods may also reflect qualitative differences between fear of personal crime and fear of household crime, with the sphere of personal crime extending into the local environment whilst the potential risk of household crime is restricted to an individual's home. The reduced complexity of the household model may additionally reflect the differing nature of the measurement instrument used, with the assumption of a linear model failing to adequately reflect the nature of the 4-point likert scale. A logit model was also specified to test this proposition, demonstrating similar results to the current models. This provides us with some reassurance that the assumption of linearity is not leading to erroneous conclusions. An ordinal logit model would have been preferable to accurately capture the variability in fear of property crime, but the complexity of the three level random coefficients model and the size of the current data set meant that this was not possible. As a result, there is still some question over the extent that the failure to identify and explain additional variability across neighbourhoods is a reflection of modelling limitations.

The identified random coefficients and cross-level interactions demonstrate the importance of incorporating the hierarchical structure of survey data in individual level fear of crime models. The extended models indicate that when taken in isolation from individual differences, social disorganisation and the impact of disorder provide an overly simplistic appraisal of the impact of contextual effects on fear. The original theories fail to adequately consider how different types of people might be affected by the breakdown of informal social control mechanisms that are synonymous with social disorganisation, or how the presence of 'outsider' groups might lead to different reactions depending on how people are themselves characterised. Similarly, the presence of signs of low level disorder, or high levels of crime have not been examined as they relate to particular types of people, with different people paying more or less attention to the state of their surroundings, or feeling differentially threatened, depending on their own personal situation.

Across crime type a positive interaction between victimisation experience and levels of crime in an area was observed. This informs us that previous victimisation experience has a strong impact on levels of fear amongst residents of neighbourhoods that are characterised by higher relative levels of crime, and a relatively weak effect in low crime rate neighbourhoods. In contrast, the levels of fear of non-victims have a weak relationship with the level of recorded crime when dealing with fear of household crime, and are unrelated to the recorded crime rate when considering fear of personal crime.

Like the main effect of victimisation shown in chapter 4, the relationship between the effect of victimisation experience on fear and recorded levels of crime is shown to be crime specific. The interaction is between the effect of personal victimisation experience and crime rates when considering fear of personal crime, and household victimisation experience when looking at fear of household crime. This highlights the importance of treating the two crime types separately when examining variations in fear. The close ties between victimisation experience and the recorded crime rate in the neighbourhood help to extend our understanding of the link between official risks of crime and the levels of fear. Previous research has attempted to explain differences in fear based on the victimisation histories of individuals, or looked at the overall relationship between objective risk and levels of fear (Vanderveen, 2006). Other research has argued that levels of crime at the local level are the driving force behind differences in fear, with fear more closely matching risks when examined at a smaller spatial scale (Young, 1996). The current models demonstrate support for the contention that fear more closely matches risk when it is measured at the very local level, but also show the relationship to be more complex and tied to individual victimisation histories.

This suggests that the levels of crime in the area have a greater salience for those that have themselves been a recent victim, leading to an increased awareness of the extent of criminal activity in the neighbourhood, and higher levels of worry based on the impact this has on their perceived risks. Having to directly confront their own risks of crime leads people to pay closer attention to their future risks, based on the prevalence of criminal activity. Alternatively, this might represent an increased likelihood that the crimes experienced by someone living in a higher crime rate area will be more serious, and hence more likely to have a stronger impact on levels of fear. Whilst it is not possible to definitively identify the root explanation for this differential relationship, what is clear is that the significant effect of objective crime risks is not a global effect on all types of individual, even when measured at such a small spatial scale.

This analysis has also demonstrated that when considering fear of household crime, victims are more affected by the level of neighbourhood disadvantage than non-victims. The result of this is a larger gap between the fear of victims and non-victims in neighbourhoods that are more economically disadvantaged, suggesting that recent victims are more susceptible to the influence of the state of the neighbourhood than non-victims. The importance of disadvantage amongst victims again points to a heightened awareness of the environmental cues that signal a higher risk of crime amongst victims, whereas non-victims are less influenced by these environmental cues.

Across all neighbourhood types, women are identified as significantly more fearful than men, a difference that has previously been explained with reference to the contribution of influences like increased physical vulnerability (Killias, 1990), greater risks associated with 'hidden crimes' (Stanko, 1988), and the shadow of sexual assault (Ferraro, 1996). However, this analysis shows that contextual differences also contribute to women's higher levels of fear of personal crime. The neighbourhood level of socio-economic disadvantage and the age structure of the local area both exhibit significant interactions with gender. This leads to larger gender gaps in neighbourhoods identified as more disadvantaged or with a larger youth population. In contrast, men's fear of crime remains relatively stable across neighbourhoods irrespective of disadvantage or the neighbourhood age structure. Returning to social disorganisation, this additional evidence questions the earlier support for a global influence on fear, indicating that some of the structural determinants of disorganisation are only influential for women. The disorder perspective is also extended, with a significantly weaker relationship between the prevalence of disorder and fear of crime amongst men. This indicates that women place a greater emphasis on the prevalence of signs of disorder, which translates into increased fear of crime in areas where disorder is higher. This significantly advances existing treatments of the higher levels of fear amongst women, demonstrating how contextual differences can help to explain why women are more fearful than men.

The impact of vulnerability on fear is extended by considering how the effect of physical vulnerability varies across neighbourhoods. Looking at fear of both household and personal crime, people with a limiting illness are identified as significantly more fearful than those who are not ill, or who have a non-limiting illness. The extended models reveal that this overall higher level of fear masks significant variability across neighbourhoods, with the residents of as many as 27% of neighbourhoods having lower levels of fear if they have a limiting illness (9% of neighbourhoods when considering fear of personal crime). Considering fear of personal crime, part of this variability across neighbourhoods was accounted for by incorporating the prevalence of signs of disorder in the neighbourhood. In neighbourhoods where disorder is relatively high, fear is significantly higher amongst residents with a limiting illness. In contrast, when disorder is relatively low, the gap between those with a limiting illness and those without is significantly reduced. This again suggests that more vulnerable people are more susceptible to the effect of environmental cues that signal that the neighbourhood is disorderly.

Another striking interaction specific to personal crime is the changing difference in fear between BME groups and White people as the level of ethnic diversity in the neighbourhood changes. In particular, lower levels of fear are reported from Black people living in more mixed areas. Therefore the common finding in much research that the levels of fear of BME groups are higher than the fear of White people is shown to be conditional on the ethnic structure of the surrounding area. In areas that are characterised by higher levels of heterogeneity the predicted higher level of fear reported by Black residents does not hold. This fits with the suggestions of Putnam (2007) that outsiders feel less integrated within their community, and hence feel more fearful. In more diverse neighbourhoods, White people are more of a minority group, and hence are more fearful. In contrast BME groups are increasingly represented within the community, so the gap in fear between them and White residents is reduced. For Black people, the presence of 'outsider' groups may actually reduce fear, perhaps fostering a greater degree of tolerance towards others.

However, a plausible alternative explanation is that Black people simply feel more comfortable in areas that are less dominated by White people, and hence it is less about heterogeneity and more about their increased representation within the area. To test this proposition, the proportion of residents from BME groups was included in the analysis. This had no substantive impact on results, suggesting it is the degree of diversity that is important to Black residents, not the size of the White population. This has important implications for interpretations of the influence that diversity has on levels of fear, linking it directly to the ethnicity of the individual.

Research has often highlighted higher levels of fear amongst residents of more urban neighbourhoods when compared against their rural counterparts (Hale, 1996), but less consideration has been given to whether the fear enhancing effect of urbanisation takes time to foster. This analysis reveals that the length of time people have been living in the neighbourhood is important, showing that fear is only higher in more urban areas when considering longer term residents. In more rural areas, local ties between residents have been shown to be stronger, leading to lower levels of fear (Krannich et al., 1989). This analysis indicates that these ties actually take time to develop, resulting in higher fear from short term residents who have not yet integrated within the social fabric of the neighbourhood. In contrast, in more urban areas, ties between residents have been described as weaker and more diffuse (Jones et al., 1986; Merry, 1981b). As a result, the longer people live within the area, the more isolated they come to feel as they are unable to develop strong networks of association. Consequently, fear is higher amongst those who have lived in urban areas for longer.

The extended models that I have presented offer more detail about the differential relationship between individual level characteristics and fear based on local context, yet they also demonstrate that there are other differences that have not been explained. Notably, there is still significant variability in the effect of ethnicity across neighbourhoods. Whilst the national picture indicates that BME residents have higher average levels of fear than White people, this effect is shown to be inconsistent across neighbourhoods. As a result, in some neighbourhoods there will be no difference in the levels of fear of White and BME residents, and in others the levels of fear from BME groups will be significantly less than the levels of fear of White people. This is a very different picture of the effect of ethnicity than has been presented in existing research, suggesting that characteristics of the local neighbourhood play an important role in how BME residents differ in their experiences of fear.

Reflecting this, unexplained neighbourhood differences are found to make a considerably larger contribution to the remaining variability in levels of fear of BME groups than of White residents. This means that whilst the included contextual measures go some way towards explaining differences in fear between neighbourhoods, there is still considerable neighbourhood variation that has not been explained when considering BME groups. When taken in conjunction with the lack of significant covariances, this suggests that the neighbourhood influences on the fear of BME residents operate differently from those influencing White people, indicating the existence of differential neighbourhood effects.

Part of this remaining variability in the size of the difference in fear between BME residents across neighbourhoods might reflect the broad classifications adopted in this analysis. Distinguishing only between the levels of fear of Asian, Black, mixed or other origin and White people is likely to result in important variations in the levels of fear within these groups being missed. For example, the levels of fear of Asian Indians may be significantly different from the fear of Asian Pakistanis, which in turn may be different from the levels of fear reported by mixed origin Asians.

There is also considerable unexplained variation in the effect of having a limiting illness on levels of fear across neighbourhoods, with the included interactions failing to fully explain why people with a limiting illness are less fearful in some neighbourhoods, yet more fearful in others. This may again reflect limitations with the survey instrument, with the broad definition of limiting illness masking considerable variation in the nature of the illness experienced, and the extent that they may infringe on people's daily activities. Additionally, no details of the amount of care and support that people with a limiting illness receive were given in the current analysis, with this expected to influence the extent that people experience higher levels of fear.

The effect of ethnic diversity was shown to vary significantly across CDRP when considering both fear of household victimisation and fear of personal victimisation. The result of this variability is that the positive relationship identified across all neighbourhoods does not hold within all CDRP, with a negative relationship identified in some partnerships. This is a potentially revealing finding, pointing to the existence of important processes at the partnership level that moderate the effect of diversity. However, the lack of available CDRP data means it has not been possible to expand on this in the current analysis. This is further evidence of the importance of differences between CDRP, and the need for complete data at the partnership level to augment data at the individual and neighbourhood levels.

In this chapter, the fear of crime model has been significantly expanded to incorporate a more local assessment of differences in fear within the national framework of the BCS. This has revealed that many of the observed differences in fear between individuals vary significantly across neighbourhood contexts. This has also demonstrated that the contextual explanations used to explain variations in fear across neighbourhoods are directly tied to the individuals that live within them. Despite representing a significant advance over existing treatments of fear of crime by integrating individual and contextual explanations, there is still considerable variability at the area level that has not been explained.

In chapter 7, I argue that the remaining higher level variation in fear of crime may actually represent the impact of survey interviewers. Here the focus is on the potential influence of the fact that respondents from the same local area will also share the same interviewer, and hence unexplained higher level variability also incorporates the effect of differences between interviewers. Typically it has not been possible to partition these competing sources of dependency because interviewers are generally assigned to specific locations. This means that the two sources of clustering are regularly confounded. However, the re-design of the BCS sample in 2001 has made a more complex examination possible within the multilevel framework. This will be examined in detail in the next empirical chapter, where I will extend the random coefficients model to allow for the accurate incorporation of a non-nested data structure resulting from the combined influence of area and interviewer variations.

CHAPTER 7: INTRODUCING THE COMPETING INFLUENCE OF INTERVIEWER EFFECTS

7.1 Introduction

In the previous three chapters I have argued for the importance of incorporating local neighbourhood characteristics to better understand the fear of crime of the people living within them. Using multilevel modelling techniques I identified a significant degree of neighbourhood level variation in individuals' fear or crime, and in the relationships between individual characteristics and fear. I further explored this contextual source of variability in fear using an ecological data set constructed from a combination of census items characterising the relative differences between local neighbourhoods. These were integrated within individual level fear of crime models, providing a more locally focused assessment than the national picture typically provided by the BCS.

These models demonstrated some clear relationships with the included contextual measures, along with some important interactions between many of the individual level relationships with fear and neighbourhood level characteristics. In particular, the link between victimisation experience and fear of crime was shown to be directly tied to the crime rate of the local neighbourhood. This leads to a larger gap between victims and non-victims in areas with a higher than average crime rate. Women were also shown to be more influenced by the character of the neighbourhood than men, with differences in the size of the gender gap depending on the neighbourhood structure. Additionally, levels of fear were closely related to the degree of ethnic heterogeneity, which varied as a function of individual level ethnicity. This meant that the levels of fear of White residents were higher in more diverse areas, whilst in contrast the levels of fear of Black people tended to be lower in areas characterised by greater ethnic diversity. However, despite identifying some important differences relating to the structural characteristics of the neighbourhood, these models did not successfully account for all of the variance that was partitioned at the area level. Thus, whilst they provide strong evidence of differential effects of individual characteristics on fear of crime in different neighbourhoods, there are still significant unexplained contextual differences contributing to the variability in levels of individual fear.

In this chapter I pursue an alternative explanation to account for the remaining unexplained contextual variation in levels of fear. This focuses on the potential contribution of interviewer differences to variability in the levels of fear reported by individuals. To do this, the clustering of individuals within interviewers is incorporated within the fear of crime model, in the same way that the clustering of individuals within local neighbourhoods has been included. Just as the clustering of individuals within neighbourhoods can result in higher levels of within cluster dependency due to shared characteristics and similarities in social situation, I demonstrate that the clustering of individuals within interviewers also leads to higher levels of dependency resulting from characteristics of the interviewer.

As a result of the sample structure of most large scale surveys, with interviewers assigned to specific geographic locations that are coterminous with sampling points, it has traditionally been difficult to separate the influence of interviewers from the influence of neighbourhood differences. This is because the two sources of clustering are confounded, with no way to separate interviewer from neighbourhood differences (O'Muircheartaigh & Campanelli, 1998). This has typically led researchers either to focus on the influence of neighbourhoods, or on the influence of interviewers, essentially ignoring the contribution that the other might make. This is a largely artificial distinction, with the clustering mechanism incorporating both sources of variance, but labelled as the effect of neighbourhood differences or interviewer differences depending on the interests of the researcher.

To provide a clearer assessment of the influence of interviewers, I incorporate interviewer effects as an additional source of 'non-nested' variation in the models estimated in chapters 4 and 5. This capitalises on the complex sample design of the BCS, which enables the identification an additional source of clustering attributable to interviewers which is not directly nested within the other sources of clustering. The identification of interviewer influences is possible because some neighbourhoods have more than one interviewer collecting data in them, and some interviewers cover more than one neighbourhood. This is a considerably more complex multilevel structure than the previous 'nested structure', where individuals were clustered within neighbourhoods which were in turn clustered within CDRP. As a result of the more complex data structure, a more complex modelling approach is required, referred to in the methodological literature as a cross classified multilevel model (Goldstein, 2003).

Using this cross-classified model structure allows the relative contribution that interviewer differences have on fear of crime to be accurately assessed, controlling for the contribution of neighbourhood and CDRP differences. Additionally, it makes possible an assessment of the impact of including interviewer differences on the results of the existing contextual models. Finally, by extending the interviewer model to include interviewer characteristics and cross-level interactions between these characteristics and individual relationships with fear, it provides an assessment of how specific individuals are influenced by the type of person conducting the interview.

7.2 Modelling interviewer differences

The interviewer plays a central role in survey research, often taking responsibility for a number of tasks during the data collection process including; locating and contacting sample households; persuading respondents to co-operate; delivering questions; providing clarifications and answering respondent queries (Groves, 1989). However, this central role also means that interviewers are one of the main sources of measurement error in survey research, directly influencing levels of non-response (both to individual questions, and to surveys in general), and potentially biasing the answers given by respondents (Pickery & Loosveldt, 2001). This might result from different interviewers using particular question wordings, or deviating from the survey script to encourage answers from respondents. As a result, the effect of interviewer variability on survey estimates has become a well established area of survey methodology, with an increasing body of evidence focusing on the effects of differences between interviewers on survey estimates (Groves, 1989; Groves et al., 2004; Groves & Couper, 1998; O'Muircheartaigh & Campanelli, 1998).

Research on interviewer variance has primarily been focused on assessments of the ICC associated with individuals interviewed by the same interviewer. This involves the estimation of the extent that the response errors from people interviewed by the same interviewer are correlated, or to put it more simply, the likelihood that different interviewers would obtain different answers from the same respondent (Groves, 1989). The ICC, also referred to as ρ, can then be used to calculate the effect that interviewer clustering has on variance estimates, commonly referred to as the Variance Inflation Function (VIF), or design effect (equation [7.1]). The VIF shows the effect of interviewer variability on the precision of survey estimates, and is a function of the ICC and the average cluster size, n (Kish, 1967).

$$V.I.F = 1 + \rho(n-1) \qquad [7.1]$$

The accurate estimation of the ICC is made possible with the use of an interpenetrated sample design, first outlined in the work of Mehalanobis (1946). This involves the random allocation of individuals to interviewers, thus ensuring that each interviewer is assigned an 'equivalent' respondent group (Groves & Magilavy, 1986). The interpenetrated sample design is relatively straightforward to incorporate when using computer assisted telephone interviewing (CATI) techniques, with no geographic clustering meaning that interviewer nesting is the only source of clustering from which group dependency can occur. As a result, many studies have successfully examined interviewer effects using the CATI design, with much existing knowledge based on these findings. However, the interpenetrated design is considerably more difficult to incorporate within computer assisted personal interviews (CAPI), as this involves the random allocation of individuals to interviewers, irrespective of the geographic clustering that is employed (Groves et al., 2004). This is rarely carried out because of the high costs involved in randomly allocating people to interviewers within a CAPI design, removing the savings resulting from adopting a geographically clustered design. As a result, there is considerably less evidence about the effect of interviewers in CAPI designs.

This focus on the calculation of the ICC means that we can also treat the examination of interviewer effects as another example of a multilevel structure, with respondents nested within interviewers in the same way that individuals have been treated as nested within areas (Hox et al., 1991; Hox, 1994; O'Muircheartaigh & Campanelli, 1998; Olson & Peytchev, 2007; Pickery et al., 2001). The use of multilevel methods in interviewer effects research has enabled researchers to better incorporate the impact of dependency resulting from individuals sharing the same interviewer, leading to improved estimates of effect sizes that accurately reflect the number of interviewers in the sample. This has also made it easier to incorporate interviewer characteristics within analyses, allowing researchers to provide more detailed accounts of how interviewers influence the responses of the people they interview (Hox, 1994).

In general, studies focusing on the impact of interviewers have found that interviewer differences can have a considerable impact on variance estimates (Bailey et al., 1978; Collins & Butcher, 1982; Fellegi, 1964; Groves & Magilavy, 1986). Studies have also demonstrated that interviewers do not have a uniform influence on all question types, with factual questions less affected by interviewer variance, and attitudinal questions generally more affected (Collins & Butcher, 1982; Kish, 1962; Schnell & Kreuter, 2006). Questions that are harder to answer have also been associated with larger interviewer variance estimates (Schnell & Kreuter, 2006), as have open ended questions (O'Muircheartaigh, 1976), and questions about topics unfamiliar to respondents (Schnell & Kreuter, 2006). Additionally, Bailar et al., (1977) demonstrated that survey items that evoke emotional reactions from respondents were likely to produce larger interviewer effects than questions about less emotional topics.

These differences in the size of the interviewer effect based on question type have led researchers to posit various mechanisms to explain why answers to some types of question are more influenced by interviewer differences. These are generally based on the assumption that despite guidelines to the contrary, different interviewers administer questionnaires in different ways, and hence the stimuli that respondents receive are not uniform (Groves, 1989). Researchers have therefore focused on the differing communication tasks that are required by different question types, with some questions requiring more interviewer input than others. Thus questions which are familiar to respondents will require less clarification by interviewers, and hence will be less susceptible to the influence of interviewer prompts, whereas difficult or unfamiliar questions may require additional interviewer probing which may not be standard across interviewers (Fowler & Mangione, 1985). Similarly they suggest that interviewer variations can be explained by the different emphasis that interviewers place on different words, or the different intonations that might be used when asking questions. Additionally, a failure to read questions directly as printed, or reading questions too fast or slow is highlighted by Marquis and Cannell (1969). The influence of interviewer expectations has also been raised by researchers, with Sudman (1977) suggesting that interviewers may change the wording and manner in which they present questions, based on the answer they are expecting to hear from the respondent. However there is currently little empirical evidence to support this claim (Groves, 1989; 2004).

O'Muircheartaigh (1976) places emphasis on the impact of active interviewer involvement to explain different variance estimates for different types of question. He links the higher interviewer variances observed when considering unfamiliar, difficult, or open ended questions to the higher levels of interviewer input that are often required to help respondents understand and answer these types of question. O'muircheartaigh goes on to argue that the more involvement there is from the interviewer, the greater the likelihood of the interviewer influencing responses, and hence the larger the interviewer effect. A similar effect was also found in the work of Cannell et al., (1981), who demonstrated that less feedback and interaction from interviewers reduces the size of the interviewer variance.

In addition to methodological explanations for interviewer variance that focus on differences based on question types and the level of interviewer involvement, a number of studies have examined the impact of interviewer and respondent characteristics. These have highlighted a range of interviewer characteristics that are potentially helpful for explaining differences between interviewers, with the majority focusing on the impact of interviewer gender and ethnicity (Groves, 1989). Along with gender and ethnicity, researchers have examined the impact of age and level of experience (Olson & Peytchev, 2007), level of interviewer effort (Bitler & Wolken, 2007), and socio-economic status (Dohrenwend et al., 1968). These studies have also highlighted the effect of the interaction of particular interviewer characteristics with particular types of respondent (Schaeffer, 1980). They focus on interviews as a 'communicative process', proposing a number of explanations for interviewer effects that move away from the methodological explanations which focus on general estimates of interviewer variance across different question types (Schwarz & Sudman, 1995). For example, Dohrenwend et al., (1968) explain observed interviewer effects in relation to the degree of social distance between the interviewer and the respondent, suggesting that too little or too much social distance has a negative effect on responses.

Other researchers have highlighted the importance of social desirability, with respondents altering their responses to present themselves in a more favourable light to interviewers based on what they think the interviewer wants to hear (Schnell & Kreuter, 2006). This has also been described as an 'acquiesance effect' (Finkel et al., 1991), whereby respondents are thought to infer interviewer attitudes and behaviours based on the observable characteristics of interviewers such as their age, race and gender. Respondents then adjust their responses accordingly. These mechanisms have then been used as justifications for employing interviewer matching procedures, which some have argued can be used to improve the accuracy of responses (Groves, 1989). In contrast, other studies have focused on the importance of the level of interviewer experience, with more experienced interviewers associated with smaller interviewer variance because they are more familiar with question wordings and are better at eliciting accurate responses (Olson & Peytchev, 2007). However, the empirical evidence to support these explanations based on interviewer characteristics is inconsistent at best, with many studies finding no observable effects of specific interviewer measures. Additionally, when studies have found relationships with interviewer characteristics, their impact on variance estimates has typically been small (Groves, 1989), particularly when interviewer characteristics have been modelled in a multilevel framework to incorporate within interviewer dependency (Hox, 1994).

Studies assessing the influence of interviewer differences have provided us with some useful evidence about how this source of dependency can affect the accuracy of survey estimates.

However, these have been almost exclusively within survey methodology research, with researchers studying area effects seemingly unaware of this alternative source of variation. As a result, there have been very few studies conducted that combine an examination of interviewer effects with area effects, meaning there is very little information about how this source of variability relates to the effect of sample clustering (O'Muircheartaigh & Campanelli, 1998). This is largely the result of sample design limitations, with sample point workloads typically assigned to a single interviewer, and interviewers usually only working in a single sample point. Whilst this is essential to minimise the costs associated with data collection, it also means that the two competing sources of variance are regularly confounded in surveys, with no way to identify what proportion of the variance is the result of interviewer differences, and what is the result of the clustered sample design (Ganninger et al., 2007; Pickery et al., 2001). This clearly has implications for neighbourhood studies that capitalise on sample designs to generate estimates of the magnitude of area variances, with the inability to separate the influence of interviewers potentially leading researchers to erroneously label interviewer differences as the result of unexplained neighbourhood effects.

There are, however, a few notable exceptions that have been able to provide a detailed assessment of the relative influence of the two confounding sources of variance (O'Muircheartaigh & Campanelli, 1998; Schnell & Kreuter, 2006). These have employed a sampling procedure that adopts an altered version of the interpenetrated methodology outlined by Mahalanobis (1946). This is premised on the random allocation of individuals to interviewers, although achieves this goal within the constraints of a standard clustered sample design. O'Muircheartaigh and Campanelli (1998) implement this by randomly allocating interviewers to individuals within geographic pools made up of groups of three sample clusters. They then use a cross-classified multilevel model to incorporate both sources of non-nested clustering within a single analysis. This enables them to partition the cluster and interviewer sources of variance (see also Campanelli et al., (1997)). In contrast, Schnell and Kreuter (2006) achieve a similar result by assigning up to three interviewers to the same geographic cluster, and randomly allocating respondents across the interviewers assigned to the same area. They then use a three level multilevel model with individuals nested within interviewers, and interviewers clustered within areas, to assess the relative contribution of interviewers and areas.

Both of these approaches have extended our understanding of the relative importance of geographic clustering and interviewer effects across a range of different question types. They both find that the proportion of variance attributable to interviewers is generally larger than the variance associated with geographic clustering, and hence that interviewers have a larger effect on estimates than geographic areas. O'Muircheartaigh and Campanelli (1998) also find a strong correlation between the two sources of variance, indicating that the types of question which have higher than average interviewer variances will also have higher than average area variances. These studies have provided us, then, with the important caveat that area effects may oftentimes be overestimated because of their confounding with the effects of interviewers (Schnell & Kreuter, 2006).

Because of their reliance on alterations to standard data collection procedures the scope of these studies has been necessarily limited. The analysis of O'Muircheartaigh and Campanelli (1998) for instance, was restricted to a sample of 1,493 households from 30 areas that were interviewed by a total of 60 interviewers. This meant that despite indicating that interviewer variances appeared to be higher than area variances, only 4 in 10 of the area variance estimates, and 3 in 10 of the interviewer estimates reached conventional levels of significance. This design also restricted the scope of their assessment of the effect of incorporating interviewer characteristics, with no interviewer effects reaching significance on any of the items examined.

The study of Schnell and Kreuter (2006) was broader in scope, utilising data in 160 local areas from 420 interviewers. However the different interviewers used in each area were from different data collection agencies, meaning that some of the differences between interviewers may actually reflect differences between the practices of the data collection agencies. Additionally, this study restricted its focus to an assessment of variance estimates across a range of different question types, making no attempt to include interviewer characteristics to examine the reasons for interviewer variances. This also meant that no individual level controls were incorporated to account for the potential uneven sample composition within each area and interviewer.

In this analysis I present an extended analysis of the relative importance of interviewer and area differences for variations in fear of crime. This incorporates a detailed individual level model along with neighbourhood effect measures and some basic interviewer characteristics. As a result, it extends the focus of this thesis beyond neighbourhood effects to examine the competing influence of interviewers. Individual levels of fear of crime are particularly suitable for this analysis, with clear theoretical justifications for expecting local neighbourhood context to play a role in shaping the levels of fear of local residents, but reason to believe that these question types will also have an interviewer component (Schnell & Kreuter, 2006).

There are a number of reasons to expect interviewer differences to influence the levels of fear of crime reported by individuals. Firstly, non-factual questions have typically been associated with significant interviewer variance, often open to more interviewer involvement than factual questions (Schnell & Kreuter, 2006). Moreover, these questions require respondents to provide 'hypothetical' answers about something they may not often think about in their daily lives, making them more susceptible to interviewer influence (Farrall et al., 1997). These questions also require respondents to provide a summary measure of their overall levels of worry about different crimes, so they might also be characterised as relatively difficult to answer, making them susceptible to further interviewer variance (Jackson, 2005). This makes it likely that, along with the influence of neighbourhoods, individuals' reported levels of fear will also be strongly influenced by interviewers.

7.3 Data

To enable a separation of interviewer and neighbourhood clustering, this analysis capitalises on the recently expanded BCS sample design and the newly introduced SOA geography to fashion a quasi-interpenetrated design. This approach draws heavily on the modelling procedures adopted by O'Muircheartaigh and Campanelli (1998), and Schnell and Kreuter (2006), but utilises the existing sample structure of the BCS rather than implementing a costly bespoke design.

As I outlined in chapter 4, the BCS is a national survey with a complex sample design and a data collection process that was significantly extended in 2001 (Lynn & Elliot, 2000). In 2001 the survey moved to a rolling design whereby interviews are conducted all year round in a large number of sampling points. This increased scope means that interviewer assignments are no longer restricted to a single PSU, with interviewers conducting interviews in a number of geographic areas over the course of a year. Additionally, approximately 15,000 initially non-responding addresses are re-issued throughout the year to reduce the effects of non-response (Grant et al., 2006) meaning that a number of sample points will also be covered by more than one interviewer each year. Finally, using MSOA boundaries to represent local neighbourhoods and control for area dependency results in a further degree of crossing of interviewers over area boundaries. This is because MSOA boundaries were constructed independently of postcode sector boundaries, with the result that they are not coterminous with PSU. This yields a suitable data structure to conduct a cross-classified modelling procedure, enabling a decomposition of the higher level variance between interviewers and areas.

The analysis in this chapter is restricted to a sample of 37,779 respondents who were interviewed in the 2004/05 sweep of the BCS, for whom details of the interviewer that conducted the survey were made available by the Home Office. The incorporation of interviewer data is a time consuming and costly process. Therefore, interviewer information was only made available for a single year. In addition to the individual level BCS data, the code of the interviewer that completed the interview has been included to enable the clustering of respondents within interviewers. Some basic interviewer characteristics have also been included. As with the previous models, the neighbourhood and CDRP that each respondent is resident in is also included, along with the contextual effects which were constructed in chapter 5. This results in two distinct, but overlapping levels of clustering relating to area and interviewer level variations.

In the sample, 37,779 respondents are nested within 439 Interviewers and 3,750 areas (themselves clustered in 350 CDRP), with 10 interviewers covering only one neighbourhood, and 56.4% of areas covered by more than one interviewer. This is a high degree of cross-classification (Browne, 2005), enabling the unexplained higher level variation to be accurately partitioned between interviewers and areas to uncover the relative influence of each source of variability. However, the reduced sample size does result in fewer people nested within each area, with an average of 10 respondents per area and 86 per interviewer. This limits the potential complexity of the area level models estimated in this chapter.

In addition to the interviewer codes used to identify which interviewer collected data from which respondents, the gender, ethnicity, age and experience levels of the interviewers was made available for analysis. Table 7.1 includes some basic descriptive details about interviewers used to collect data for the BCS. This reveals fewer male than female interviewers (59% and 41% respectively), and only a small number of interviewers are from BME groups (6% in total, with a similar proportion Asian and Black). Additionally, the sample of interviewers is predominantly older, with at least 2 years experience (only 14% are younger than 45, and 17% have less than 2 years experience).

Table 7.1: Basic Interviewer Details

		Percentage
INTERVIEWER CHARACTERISTIC		
Gender	Male	58.7
	Female	41.3
Ethnicity	White	93.9
	Black	3.5
	Asian	2.5
Age	16-34	5.8
	35-54	27.5
	55-64	46.6
	65+	20
Experience Level	Less than 12 months	7.1
	12 months - 2 years	10.2
	2 years - 5 years	40.9
	5 years - 10 years	27.6
	More than 10 years	14.2
Number of Interviewers		439

7.4 The Cross classified multilevel model

In the multilevel models that have been described so far, the data structure has been strictly hierarchical, with observations clustered within areas, and these areas clustered into larger administrative areas. However, in this chapter, the data structure is more complex, with separate sources of clustering that are not directly linked to one another. For example, considering the clustering of individuals within local areas and interviewers, there is no requirement that individuals from the same neighbourhood are also clustered within the same interviewer. This change in data structure can be shown diagrammatically, comparing the hierarchical clustering of individuals within local areas that are themselves clustered within regions (figure 7.1), with the complex clustering of individuals within local areas and interviewers (figure 7.2).

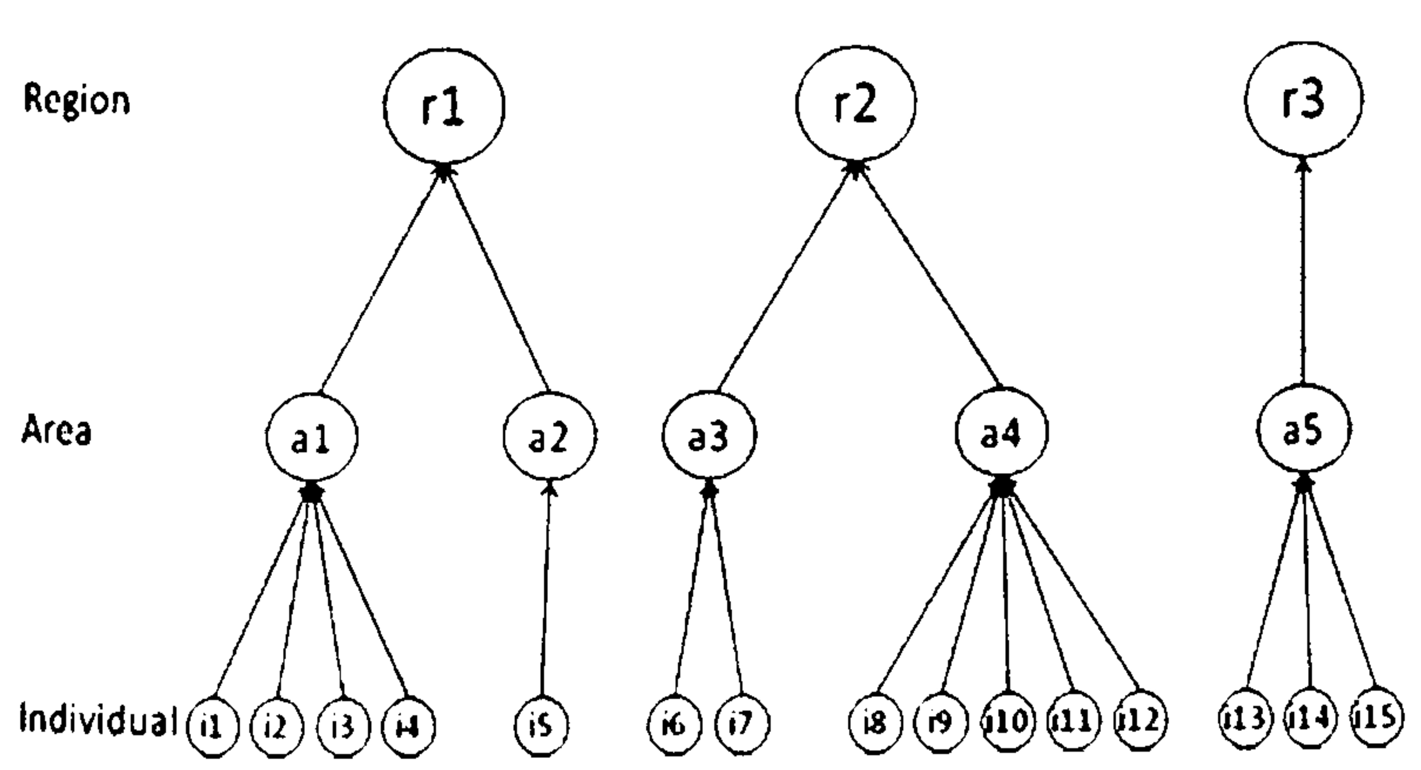

Figure 7.1: Multilevel Data Structure

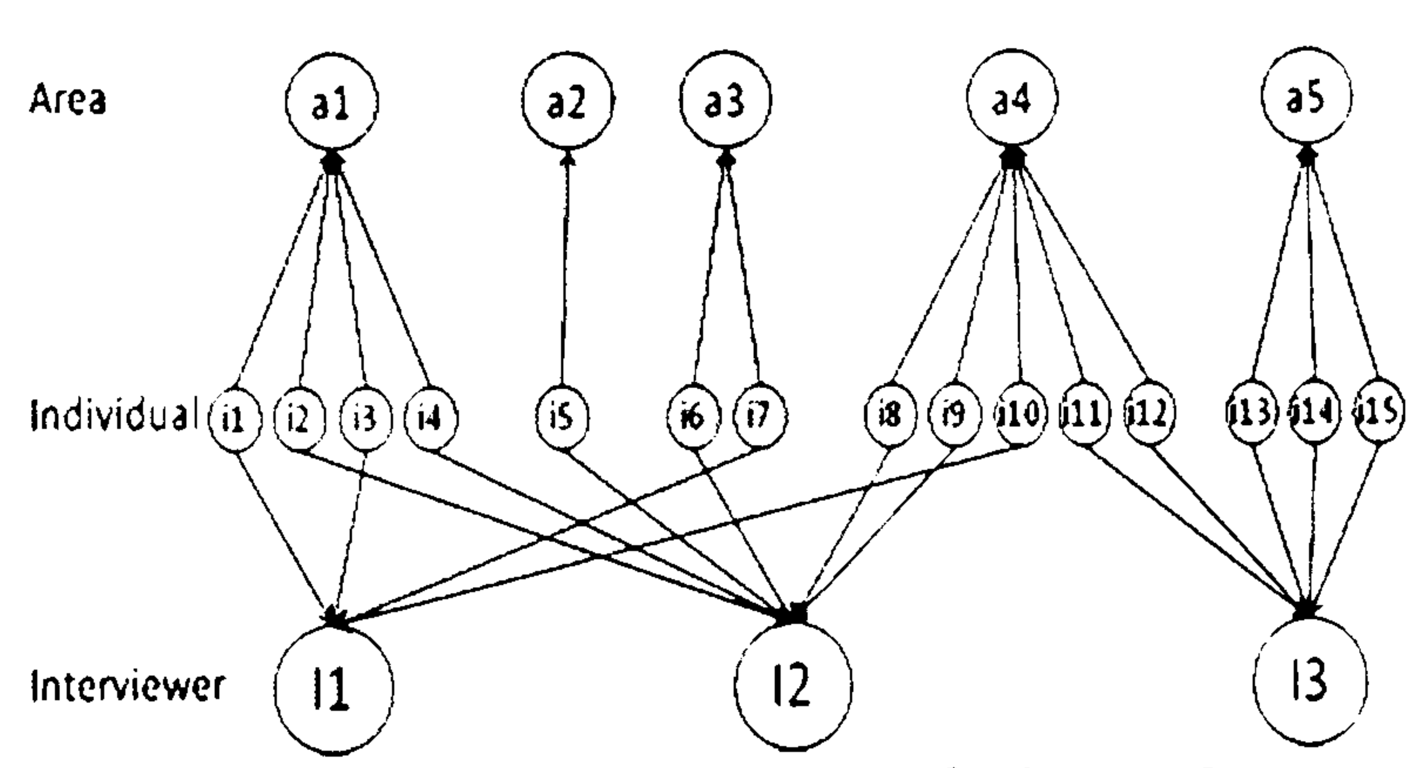

Figure 7.2: Cross Classified Data Structure

Figure 7.1 was first outlined in chapter 4, with 15 individuals (i1-i15) clustered within 5 local areas (a1-a5) that are themselves clustered within 3 regions (r1-r3). It is clear from this structure that all individuals clustered within areas 1 and 2 are also clustered within region 1, with none of these individuals belonging in region 2 or 3. Equally, all individuals from areas 3 and 4 are clustered in region 2, and all individuals from area 5 are clustered in region 3. In contrast, looking at figure 7.2, the structure is quite different. Here, individuals are still clustered within the same 5 areas, but now they are clustered within 3 interviewers (I1-I3), with no requirement that all individuals from the same area be within the same interviewer. Instead of having a 3 level data structure, then, we have a data structure that has two distinct sources of level 2 clustering.

This means that the modelling approach must be adapted to incorporate multiple sources of random variation that are not directly nested within one another. To do this, we extend the random intercept model by identifying all of the different combinations of higher level clusters which individuals are nested within (i.e. pairs of interviewers and areas), and then incorporate the estimated residuals from this extended assessment as two separate variances in the model (Goldstein, 2003). This is referred to as the cross-classified multilevel model, which uses multiple clustering classifications to identify the clusters which each individual is nested within. This is a relatively new development in multilevel modelling that has only recently become computationally feasible.

To incorporate multiple sources of non-nested clustering within our multilevel equation, we again begin with the two level random intercept model from chapter 4, composed of an individual level model (equation [4.3]), and an area level model (equation [4.4]). In the cross-classified model specification, we now have two separate sources of clustering, one referring to the area clusters and one to the interviewer clusters. To incorporate these in the model, we first extend the notation of the individual level model, forming equation [7.1] (Rasbash et al., 2004).

$$y_{i(jk)} = \beta_{0(jk)}x_0 + \beta_1 x_{1i(jk)} + e_{0i(jk)}x_0 \qquad [7.1]$$

The model therefore refers to the i^{th} individual from the cluster defined by the j^{th} neighbourhood and the k^{th} interviewer, also referred to as the $(jk)^{th}$ neighbourhood/interviewer cluster. As before, there is a fixed effect $x_{1i(jk)}$ that is measured at the individual level, along with an individual level variance term $e_{0i(jk)}$. However, now the intercept term β_0 has been subscripted *jk*, indicating that it now refers to the overall intercept across all combinations of neighbourhood and interviewer clusters.

Equation [7.2] is the accompanying higher level model, which is now used to describe the variations in the intercept between each neighbourhood/interviewer cluster. In equation [7.2] the overall intercept $\beta_{0(jk)}$, is composed of the average intercept across all neighbourhood and interviewer clusters β_0, and the residual difference from the average intercept for each neighbourhood and interviewer cluster, represented by the error terms u_{0j} and u_{0k} respectively. These residuals are assumed to be normal, independently and identically distributed with variances σ^2_{uj0} and σ^2_{uk0}. Contextual variables describing characteristics of neighbourhoods and interviewers can then be included within this neighbourhood/interviewer model.

$$\beta_{0(jk)} = \beta_0 + u_{0j} + u_{0k} \qquad [7.2]$$

When the neighbourhood/interviewer equation is substituted back into the individual level model, we form the cross-classified multilevel model, equation [7.3]. As with the previous multilevel models, the x_0's have been omitted for clarity.

$$y_{i(jk)} = \beta_0 + \beta_1 x_{1i(jk)} + \left(u_{0j} + u_{0k} + e_{0i(jk)}\right) \qquad [7.3]$$

Specification of a cross-classified multilevel model within the IGLS estimation framework used by Mlwin is a complex and computationally intensive procedure (Goldstein, 2003). Using the current example of individuals grouped within neighbourhood/interviewer clusters, this begins with the specification of a two level model with individuals nested within neighbourhoods. The model is then extended to three levels, with the third level defined by a single cluster that spans the entire dataset. Dummy variables then need to be included for each interviewer cluster in the model. These are incorporated with no fixed component, but specified as random at the third level, with variances constrained to be equal. Thus, although the model is set up as a three level random intercept model, the third level is really being used to specify the second source of clustering at level 2.

The need to include dummy variables for each higher level cluster in the model means that these models can quickly become restricted by memory limitations and convergence problems (Goldstein, 2003). In practice then, the IGLS procedure is generally only suitable when there are a limited number of clusters to be specified, and two separate sources of clustering are identified. As a further limitation, to extend the model to include fixed effects at the interviewer level, product terms must then be calculated between each interviewer dummy and the interviewer variable, which would be included in the model with coefficient estimates constrained to equality. This means that these models are restricted in their focus to a small number of fixed effects when contextual variables are included.

As a result of the limitations associated with the IGLS approach to the estimation of cross-classified models, and the large number of clusters and individuals available for the current analysis, a Markov-Chain Monte Carlo (MCMC) estimator will be used. The model is algebraically equivalent to the IGLS model, but, rather than using dummy variables at the third level, each combination of interviewer and neighbourhood clusters is specified in the data structure. These are then estimated as residuals directly within the model. This is done as a single extra step in the MCMC algorithm, permitting analyses of significantly larger datasets that contain many more higher level units (Browne, 2005).

MCMC is a simulation based procedure that generates many estimates of each parameter, with each successive estimate generated using information from the previous estimate. This is done by taking a large number of simulated random draws from the joint posterior distribution of all of the parameters included in the model, and using these to summarise the underlying distribution of each parameter. This means that rather than producing a single point estimate for each parameter included in the model, MCMC methods produce summary statistics of all of the estimates for each parameter; the mean of each parameter and its standard deviation (for a detailed explanation of the MCMC framework see Browne, (2005)).

The cross classified model estimated via MCMC can therefore be used to provide additional detail about the complex influences on individual levels of fear of crime. This will enable us to unpick the often confounding impact of area and interviewer differences. However, MCMC methods require the estimation of all random covariances associated with any random coefficients that are specified in the model (Browne, 2005). This means it is not possible to restrict covariances to 0 to reflect a lack of theoretical justification for a covariance between two random slopes. This quickly increases model complexity, with considerably more parameters estimated. This means that these models are often restricted to the estimation of fixed effects, with the random component limited to residual variances at the individual and clustering levels.

7.5 Results V: Introducing the contrasting influence of interviewer clustering

To assess the impact of interviewer variations on individuals' reported levels of fear, I begin by examining whether interviewer variations make a significant contribution to the variance in fear of crime beyond the variations attributable to local neighbourhood and CDRP differences. This is done using the unconditional formulation of the random intercept model that was first introduced in chapter 4. To enable a clear examination of the impact of interviewers and maintain consistency with the cross-classified models, I first repeat the unconditional random intercept model from chapter 4, treating individuals as nested within neighbourhoods and CDRP using data from 2004/05 only. The model refers to the level of fear of the i^{th} individual living within the j^{th} neighbourhood cluster within the k^{th} CDRP. To include the impact of interviewers, the model is then extended with the addition of an extra residual u_{0l} referring to interviewer differences.

The models are estimated with the MCMC algorithm implemented in Mlwin, using a 'burn in' length of 500 and a run of 5,000 simulated random draws from the joint posterior distribution, following the methodology of Browne, (2005). The 'burn in' is a series of random draws that are discarded, ensuring that the MCMC algorithm has settled and is sampling from the true posterior distribution of the parameters. Using 5,000 simulated random draws from this distribution was sufficient to ensure that the distribution of each parameter in the model is summarised correctly.

7.5.1 Fear of personal and household victimisation

Table 7.2 includes estimates of how the variation in fear of personal and household victimisation is partitioned between individual differences, area differences, and interviewer differences. Model 1 contains the estimates from the unconditional random intercept model, showing the proportion of variance partitioned as a result of neighbourhood, CDRP and individual differences. Model 2 extends this specification, contrasting the influence of interviewer variations with neighbourhood and CDRP variations.

Table 7.2: Unconditional Cross Classified Models

	Personal Crime		**Household crime**	
	Model 1 Effect (S.E)	**Model 2 Effect (S.E)**	**Model 1 Effect (S.E)**	**Model 2 Effect (S.E)**
RANDOM EFFECTS				
CDRP level	.066 (.007)**	.020 (.003)**	.038 (.004)**	.015 (.002) **
Neighbourhood level	.074 (.004)**	.024 (.003)**	.046 (.004)**	.018 (.003)**
Individual level	.862 (.007)**	.837 (.006)**	.909 (.007) **	.892 (.007)**
Interviewer level		.114 (.010)**		.068 (.006)**
Deviance (DIC)	102689.7	101133.9	104782.5	103808.6
Number of cases	*37,779*	*37,779*	*37,779*	*37,779*

*** P<(.01)*
**P<(.05)*

Looking first at personal crime, in the unconditional random intercept model (model 1), approximately 14% of the variance in fear of crime is partitioned at the area level, split fairly evenly between neighbourhood and CDRP variations, with the remaining variance attributable to individual differences. This is a larger contribution than was found in the three year dataset, where approximately 10% of the variation in fear of crime was attributable to neighbourhood and CDRP differences. This suggests a reasonable degree of variability in the size of the area level component across the three years of data used in the previous chapters, justifying the incorporation of survey year as a control variable. To test whether the difference in variance estimates was the result of the use of an MCMC estimation procedure, the three year models were re-estimated within the MCMC framework. The estimates from this model were no different from the estimates from the IGLS models.

When the model is extended to incorporate the contrasting influence of interviewer differences (model 2), there is a substantial re-partitioning of the higher level unexplained variation in fear. This shows that 69% of the unexplained variation that had previously been attributed to contextual differences is better characterised as the result of interviewer effects. In this model, neighbourhood and CDRP differences account for 4% of the remaining unexplained variation in fear of crime, whereas 11% is identified as the result of interviewer differences. This is also associated with an improvement in model fit of 1556 with 1 degree of freedom [$p<0.001$], based on an assessment of the difference in the Deviance Information Criterion (DIC - the equivalent of the -2*loglikelihood in the MCMC framework).

Turning to fear of household crime, it is again evident that when the influence of interviewers is included in the model, the majority of the variance previously attributed to areas is re-partitioned as the result of interviewers. In the unconditional random intercept model, 8% of the total variance in fear is partitioned at the area levels, dropping to 3% when interviewers are included. As a result, interviewers are again identified as an important source of variability in fear, accounting for 67% of the higher level variance, and 7% of the total variance in fear.

The unconditional cross-classified model that includes the effect of interviewer clustering presents us with a significantly different picture to the model restricted to the influence of area differences. Including the influence of interviewers has shifted the focus away from the effect of local context, towards the impact of interviewer differences. This has provided us with an initial indication that the impact of interviewers might provide us with a better explanation for differences in reported levels of fear than local area differences. The importance of interviewer clustering is in line with the findings of Schnell and Kreuter (2006), and O'Muircheartaigh and Campanelli (1998; 1999), which have shown that interviewers account for a greater proportion of variance in many survey items than sample points.

One important consideration when examining the competing influence of multiple sources of clustering in a cross-classified design is the impact of cluster sizes. Goldstein (2003: 191) indicates that this can provide a potential explanation for the different sized contributions to unexplained variance from different sources of clustering, with larger clusters having a smaller degree of sampling variance and hence making a smaller contribution to the final model. To examine this potential influence on variance estimates, measures of the cluster sizes for each source of clustering (interviewer, neighbourhood and CDRP) were included in the model as random coefficients, producing an estimate of how the variance contribution from each cluster level varies as a function of cluster size. This revealed no significant influence of cluster size on variance estimates, indicating that it is not necessary to incorporate this additional source of model complexity in future models examining the potential influence of interviewers.

7.6 Results VI: Incorporating the impact of uneven cluster composition, selection bias, and contextual effects

The unconditional cross-classified models have demonstrated that interviewer differences appear to make a significantly larger contribution to the unexplained variation in fear of crime than local neighbourhoods and CDRP. However, so far this only provides an initial assessment of the contrasting influence of interviewers, restricted to an examination of how the variance associated with fear of crime is partitioned. To enable a more detailed assessment of the relative importance of interviewer differences to the unexplained variations in fear of crime, it is necessary to control for the impact of uneven sample composition, and potential selection effects. This is important because it was clearly demonstrated in chapter 4 that a significant proportion of the variance initially identified as the result of areas was actually the result of individual differences. The same may also be true of the estimated interviewer variance. Additionally, since one of the key assumptions of models adopting an interpenetrated design is that each interviewer assignment is equivalent, it is important to include controls for the potential uneven sample composition within each interviewer assignment (Groves, 1989). To do this, the existing random intercept model with individual level covariates from chapter 4 will be re-estimated within the cross-classified modelling framework using 2004/05 data (for details of the included individual level covariates see section 4.12).

Having incorporated individual level covariates within the cross-classified model, the additional effects of contextual differences between local neighbourhoods will be included in the model. This uses the same contextual measures that were originally included in chapter 5, ensuring that estimates of interviewer variability have been controlled for the potential impact of geographic dependency (the contextual effects are outlined in detail in section 5.4). This also enables an assessment of the effect of the apparent shift in emphasis away from area differences towards the effect of interviewers. Like the previous random intercept models, the higher level variance is partitioned between the area and the interviewer components, providing a more accurate assessment of the influence of clustering effects.

In Chapter 6 it was demonstrated using cross level interactions that many of these contextual measures relate differently to the levels of fear of different types of individuals, reflecting differential perceptions of the local neighbourhood. However, the full random coefficients model with cross level interactions will not be presented. This is because, within the cross classified framework, the inclusion of as many as 8 random coefficients (the number of random coefficients in the full personal crime model) would require the estimation of an additional 36 unknown parameters (8 variances and 28 covariances), leading to convergence failure. Additionally, the smaller sample size within each neighbourhood restricts the precision of estimates of cross-level interactions.

7.6.1 Fear of personal Crime

Looking first at fear of personal crime, table 7.3 includes estimates from both the cross-classified model including fixed effects at the individual level (model 3), and the extended model that introduces contextual effects measured at the neighbourhood level (model 4). These models also include estimates of the unexplained variation partitioned between individuals, areas, and interviewers. Examination of the model diagnostics suggests that the initial run of 5,000 iterations was sufficient for estimates to converge on their true values.

Table 7.3: Individual and Contextual Cross Classified Models (Personal Crime)

		Model 3: Individual Effect (S.E)	Model 4: Contextual Effect (S.E)
FIXED EFFECTS			
Constant		.10 (.02)**	.10 (.02)**
Gender (*Ref: Male*)	Female	.44 (.01)**	.44 (.01)**
Age	Age	-.005 (.0003)**	-.004 (.0003)**
	*Female	-.01 (.001)**	-.01 (.001)**
	Age^2	-.0002 (.00002)**	-.0002 (.00001)**
Education (*Ref: No qualifications*)	GCSE	-.06 (.01)**	-.05 (.01)**
	A level	-.09 (.02)**	-.07 (.02)**
	Degree	-.19 (.02)**	-.17 (.02)**
	Other (foreign)	-.05 (.02)**	-.04 (.02)**
Ethnicity (*Ref: White*)	Asian	.36 (.03)**	.29 (.03)**
	Black	.19 (.04)**	.11 (.04)**
	Mixed/other	.20 (.04)**	.16 (.04)**
Direct Victimisation (*Ref: Non-victim*)	Personal Crime	.26 (.02)**	.26 (.02)**
	Household Crime	.15 (.01)**	.13 (.01)**
Newspaper readership (*Ref: No paper*)	Tabloid	.11 (.01)**	.11 (.01)**
	Broadsheet	-.02 (.02)	-.02 (.02)
	Local	.10 (.02)**	.09 (.02)**
NS-SEC (*Ref: Professional/managerial*)	Intermediate Occupation	.03 (.02)*	.03 (.02)*
	Small Employer	-.06 (.02)**	-.06 (.02)**
	Lower Supervisory Role	.01 (.02)	.001 (.02)
	Routine or Semi Routine	.06 (.01)**	.05 (.01)**
	Never Worked	.04 (.02)	.02 (.03)
	Student	.16 (.03)**	.16 (.03)**
Marital Status (*Ref: Married*)	Separated or Divorced	-.03 (.01)*	-.05 (.01)**
	Single	-.01 (.01)	-.02 (.01)
	Widowed	-.03 (.02)	-.04 (.02)*
Health (*Ref: Not ill*)	Non-Limiting Illness	.07 (.02)**	.07 (.02)**
	Limiting Illness	.15 (.01)**	.15 (.01)**
Residence	Length of residence	.007 (.003)*	.006 (.003)*
FIXED EFFECTS (Level 2)			
Social disorganisation	Socio-economic disadvantage		.03 (.01)**
	Urbanisation		.08 (.01)**
	Population mobility		-.0002 (.01)
	Age Profile		.01 (.01)
	Housing Profile		-.01 (.01)
	Ethnic heterogeneity		.29 (.06)**
Crime	Local Recorded Crime		.05 (.01)**
Low level disorder	Objective Disorder		.02 (.01)**
RANDOM EFFECTS			
CDRP level		.009 (.002)**	.001 (.001)**
Neighbourhood level		.016 (.002)**	.011 (.008)**
Individual level		.759 (.006)**	.759 (.006)**
Interviewer level		.108 (.009)**	.099 (.008)**
Deviance (DIC)		95866.3	95658.7
Number of cases		*37,017*	*37,017*

*** P<(.01)*
**P<(.05)*

.ooking first at the cross classified model with fixed effects measured at the individual level, the najority of the area level variance is again re-partitioned as the result of interviewer differences. In this extended model area differences account for approximately 3% of the remaining unexplained variation in fear of crime, with 12% identified as the result of interviewers. This demonstrates that when the uneven composition of each interviewer assignment and neighbourhood sample is controlled, interviewers are still identified as the dominant source of higher level variability in fear of personal crime. Additionally, the variance at the interviewer level is less affected by the sample composition within each interviewer assignment, likely reflecting the larger clusters sizes at the interviewer level.

However, despite significantly reducing the estimated contribution of unexplained neighbourhood differences to variations in fear, the cross classified model does not completely remove the importance of local context. There is still significant variability partitioned at the local neighbourhood and CDRP levels, albeit less than was previously suggested. This is clearly demonstrated by the increase in the DIC of 331 with 2 degrees of freedom [p<0.001] when the neighbourhood and CDRP levels are omitted. Consequently, rather than suggesting that a focus on area effects should be dropped in favour of interviewer effects, the claims of this model are more modest, indicating that the influence of neighbourhoods and CDRP make a smaller contribution than previously estimated, and a significantly smaller contribution than the influence of interviewers.

Importantly, extending the model to include the influence of clustering within interviewers does not result in any substantive differences in the estimates of the individual level relationships with fear. Therefore all coefficients are estimated in the same direction and are of a similar magnitude to the model estimated in chapter 4 (table 4.5). Fear is consistently higher amongst women and BME groups, as well as people who have recently been the victim of a personal or household crime. Fear is also higher amongst people who are identified as more physically and socially vulnerable, and those who are exposed to tabloid media sources.

When the neighbourhood model is extended to include contextual measures, the large contribution of interviewer clustering has no substantive effect on the estimated effect of the structural determinants of social disorganisation, low level disorder, or the impact of recorded crime rates. However, the modest effects of the neighbourhood age structure and the local housing profile fail to reach significance, likely reflecting the smaller sample size on which these estimates are based. This demonstrates that whilst it has clearly been shown that interviewer differences account for the majority of higher level variance in fear of crime, fixed effect estimates at the neighbourhood level are consistently estimated. As such, fear is still higher amongst residents of more socio-economically disadvantaged neighbourhoods, and neighbourhoods that are identified as more urban. Additionally, fear is highest amongst residents of ethnically diverse areas, and areas that have more signs of low level disorder and a higher crime rate.

7.6.2 Fear of household crime

Turning to fear of household crime, table 7.4 presents estimates from the equivalent cross-classified models. Model 3 again includes the set of individual level covariates characterising differences in fear and controlling for selection bias. This also includes estimates of the remaining unexplained variance partitioned between individuals, neighbourhoods, CDRP, and interviewers. Model 4 extends this with the inclusion of contextual data measured at the neighbourhood level.

Table 7.4: Individual and Contextual Cross Classified Models (Household Crime)

		Model 3: Individual Effect (S.E)	Model 4: Contextual Effect (S.E)
FIXED EFFECTS			
Constant		.10 (.02)**	.10 (.02)**
Gender (*Ref: Male*)	Female	.16 (.01)**	.16 (.01)**
Age	Age	-.004 (.0004)**	-.004 (.0003)**
	*Female	-.001 (.001)**	-.001 (.0003)**
	Age^2	-.0002 (.00002)**	-.0002 (.00002)**
Education (*Ref: No qualifications*)	GCSE	-.04 (.01)**	-.03 (.01)*
	A level	-.08 (.02)**	-.06 (.02)**
	Degree	-.16 (.02)**	-.14 (.02)**
	Other (foreign)	-.01 (.03)	-.001 (.03)
Ethnicity (*Ref: White*)	Asian	.27 (.03)**	.22 (.03)**
	Black	.17 (.04)**	.12 (.04)**
	Mixed/other	.17 (.04)**	.15 (.04)**
Direct Victimisation (*Ref: Non-victim*)	Personal Crime	.16 (.02)**	.16 (.02)**
	Household Crime	.26 (.01)**	.24 (.01)**
Newspaper readership (*Ref: No paper*)	Tabloid	.09 (.01)**	.09 (.01)**
	Broadsheet	.01 (.02)	.02 (.02)
	Local	.08 (.02)**	.08 (.02)**
NS-SEC (*Ref: Professional/managerial*)	Intermediate Occupation	.01 (.02)	.01 (.02)
	Small Employer	.004 (.02)	.002 (.02)
	Lower Supervisory Role	.01 (.02)	.001 (.02)
	Routine or Semi Routine	.04 (.01)**	.02 (.01)*
	Never Worked	.09 (.03)**	.08 (.03)**
	Student	-.07 (.03)*	-.06 (.03)**
Marital Status (*Ref: Married*)	Separated or Divorced	-.12 (.02)**	-.14 (.02)**
	Single	-.08 (.02)**	-.09 (.01)**
	Widowed	-.08 (.02)**	-.09 (.02)**
Health (*Ref: Not ill*)	Non-Limiting Illness	.06 (.02)**	.05 (.02)**
	Limiting Illness	.10 (.01)**	.09 (.01)**
Residence	Length of residence	.02 (.003)**	.02 (.003)**
FIXED EFFECTS (Level 2)			
Social disorganisation	Socio-economic disadvantage		.02 (.01)*
	Urbanisation		.02 (.01)**
	Population mobility		-.03 (.01)**
	Age Profile		.02 (.01)*
	Housing Profile		.02 (.01)*
	Ethnic heterogeneity		.18 (.07)**
Crime	Local Recorded Crime		.06 (.01)**
Low level disorder	Objective Disorder		.02 (.01)**
RANDOM EFFECTS			
CDRP level		.009 (.002)**	.003 (.001)**
Neighbourhood level		.012 (.002)**	.008 (.003)**
Individual level		.859 (.007)**	.859 (.007)**
Interviewer level		.062 (.006)**	.058 (.005)**
Deviance (DIC)		100733.4	100595.4
Number of cases		*37,187*	*37,187*

*** P<(.01)*
**P<(.05)*

Looking at the model including individual level fixed effects (model 3), the size of the area level contribution is again substantially reduced when interviewer clustering is included, with interviewers accounting for 75% of the higher level variance. As a result, just 2% of the total variance in fear of household crime is the result of areas (43% of this variance at CDRP level and 57% at the local neighbourhood level), with 7% attributable to interviewers. The individual level covariates included in this model are all estimated in the same direction, and of similar magnitude, to the estimates from the model which did not include the contribution of interviewers (table 4.6). Once again, this extended model does not remove the influence of areas, with the omission of neighbourhood and CDRP variance resulting in an increase in the DIC of 225 with 2 degrees of freedom [$p<0.001$]. However, it does place greater emphasis on the influence of interviewer variability.

Turning to the extended model with contextual effects again reveals that the included neighbourhood level effects appear to be reasonably robust to the omission of interviewer variability, with similar sized effect estimates. Additionally, all effects are estimated in the same direction, so the substantive interpretation has not been altered by the extended model.

7.7 Results VII: A closer examination of the interviewer model

The previous models have demonstrated that interviewers play an important role in shaping individuals' responses to questions about their levels of fear. Additionally, interviewers have been shown to make a significantly larger contribution than the effect of neighbourhoods, although on the whole neighbourhood level fixed effects remain consistently estimated. To provide a more detailed examination of the effect of these interviewer differences on estimates of fear, I now extend the interviewer model to include a number of interviewer characteristics. These will be incorporated as contextual measures at the level of the interviewer, in the same way that neighbourhood effects were included in the neighbourhood model.

The available data provide us with details of interviewer gender, age, and ethnicity. In addition to these demographic characteristics, a measure of the interviewer's level of experience is also included in the model. These four characteristics have featured prominently in existing interviewer effects research, where they have had variable success in explaining differences in responses across interviewers (Groves et al., 2004). The inclusion of interviewer characteristics in the model is done in the same way that neighbourhood contextual effects were included within the neighbourhood models, although in this instance they are included in the interviewer part of the model.

By including interviewer characteristics within the interviewer model, assessments of their level of significance are based on the sample of interviewers, rather than on the full sample of individuals.

This is particularly important when considering interviewer effects, with the number of interviewers significantly less than the number of interviews that they conduct, leading to underestimated standard errors if they are treated as individual level effects. Additionally, within the multilevel framework, interviewers who conduct a larger share of the total interviews will make a larger contribution to the final estimates, ensuring the structure of the data is accurately reflected.

As I outlined in section 7.2, there is now a considerable literature that has examined the impact of interviewer differences on survey estimates, with some studies also highlighting the importance of linking these interviewer differences with characteristics of the sample of respondents that they interview (Schaeffer, 1980). To capture these effects of interviewer matching, the interviewer models will be further extended by incorporating cross-level interactions between interviewer differences and individual demographic variables. This enables a more nuanced understanding of how interviewer effects are related to the individual characteristics that are associated with differences in fear, without having to treat interviewer differences as characteristics of the individual respondents. These cross level interactions are included in the same way as those that were used to extend the neighbourhood level model (see chapter 6).

To retain consistency with all previous models, each cross level interaction was assessed separately, before all significant effects were included in the final model. All models were estimated with a burn in of 500, and a monitoring length of 5,000 chains.

7.7.1 Fear of personal crime

Table 7.5 contains the results from the models focusing on the interviewer characteristics that are associated with fear of personal crime. Model 5 extends the neighbourhood level model to include fixed effects at the interviewer level, along with estimates of the remaining unexplained variability partitioned at the individual, neighbourhood, CDRP and interviewer levels. Model 6 then further extends this model by incorporating any significant cross level interactions between interviewer characteristics and individual relationships with fear of crime. To restrict model complexity a random coefficients model was not specified first. Therefore an exploratory approach to cross level interactions has been adopted.

Table 7.5: Interviewer Effects Models (Personal Crime)

		Model 5: Interviewer effects Effect (S.E)	Model 6: Cross level interactions Effect (S.E)
FIXED EFFECTS			
Constant		.10 (.02)**	.09 (.02)**
Gender (*Ref: Male*)	Female	.44 (.01)**	.44 (.01)**
Age	Age	-.004 (.0004)**	-.004 (.0004)**
	*Female	-.005 (.001)**	-.005 (.001)**
	Age^2	-.0002 (.00002)**	-.0002 (.00002)**
Education (*Ref: No qualifications*)	GCSE	-.05 (.01)**	-.05 (.01)**
	A level	-.07 (.02)**	-.07 (.02)**
	Degree	-.17 (.02)**	-.17 (.02)**
	Other (foreign)	-.04 (.02)	-.04 (.02)
Ethnicity (*Ref: White*)	Asian	.29 (.03)**	.30 (.03)**
	Black	.11 (.04)**	.12 (.04)**
	Mixed/other	.16 (.04)**	.16 (.04)**
Direct Victimisation (*Ref: Non-victim*)	Personal Crime	.26 (.02)**	.26 (.02)**
	Household Crime	.13 (.01)**	.13 (.01)**
Newspaper readership (*Ref: No paper*)	Tabloid	.11 (.01)**	.11 (.01)**
	Broadsheet	-.02 (.02)	-.02 (.02)
	Local	.09 (.02)**	.09 (.02)**
NS-SEC (*Ref: Professional/managerial*)	Intermediate Occupation	.03 (.02)	.03 (.02)
	Small Employer	-.06 (.02)**	-.06 (.02)**
	Lower Supervisory Role	.001 (.02)	.001 (.02)
	Routine or Semi Routine	.05 (.01)**	.05 (.01)**
	Never Worked	.02 (.03)	.02 (.03)
	Student	.16 (.03)**	.16 (.03)**
Marital Status (*Ref: Married*)	Separated or Divorced	-.05 (.02)**	-.05 (.01)**
	Single	-.03 (.01)	-.03 (.01)
	Widowed	-.04 (.02)*	-.04 (.02)*
Health (*Ref: Not ill*)	Non-Limiting Illness	.07 (.02)**	.07 (.02)**
	Limiting Illness	.15 (.01)**	.15 (.01)**
Residence	Length of residence	.01 (.003)*	.01 (.003)*
CONTEXTUAL EFFECTS (Neighbourhood)			
Social disorganisation	Socio-economic disadvantage	.03 (.01)**	.03 (.01)**
	Urbanisation	.07 (.01)**	.07 (.01)**
	Population mobility	-.0004 (.01)	.0002 (.01)
	Age profile	.01 (.01)	.01 (.01)
	Housing profile	-.01 (.01)	-.01 (.01)
	Ethnic heterogeneity	.27 (.07)**	.27 (.07)**
Crime	Local Recorded Crime	.05 (.01)**	.05 (.01)**
Low level disorder	Objective disorder	.02 (.01)**	.02 (.01)**
INTERVIEWER EFFECTS AND CROSS LEVEL INTERACTIONS			
Gender (Ref: Male)	Female	-.02 (.03)	-.03(.03)
Age	Age	-.05 (.02)**	-.05(.02)**
Ethnicity (Ref: white)	Asian	.08 (.12)	.11(.12)
	*Asian		-.35 (.14)**
	*Black		.10 (.15)
	*Mixed		.02 (.15)
	Black	.06 (.11)	.09 (.11)
	*Asian		.09 (.17)
	*Black		-.22 (.11)*
	*Mixed		-.02 (.14)
Experience	Level of experience	-.06 (.02)**	-.06(.02)**
	*Age		-.001 (.0002)**
RANDOM EFFECTS			
CDRP level		.001 (.001)**	.001 (.001)**
Neighbourhood level		.012 (.002)**	.012 (.002)**
Individual level		.759 (.006)**	.758 (.006)**
Interviewer level		.092 (.008)**	.092 (.008)**
Deviance (DIC)		95653.6	95639.5
Number of cases		*37,017*	*37,017*

*** P<(.01)*
**P<(.05)*

Looking first at model 5, which incorporates the fixed effect estimates at the interviewer level, the inclusion of four interviewer characteristics reduces the remaining interviewer variance by 7%. However, not all interviewer characteristics significantly predict differences in fear, reflected by the small improvement in the DIC of 5.1 with 5 degrees of freedom [$p>0.05$]. Additionally, there is still a considerable amount of unexplained variance that is attributable to interviewer differences.

Both the age and experience level of the interviewer are identified as significant predictors of the levels of fear reported by individuals, net of other interviewer effects and the differing characteristics of the people that they are interviewing. This reveals that people who are interviewed by older interviewers will generally report lower average levels of fear than those interviewed by younger interviewers. Similarly, as the experience level of the interviewer increases, there is a corresponding reduction in the average levels of fear reported by the people that they interview, represented by the negative relationship of -.06. In contrast, neither the ethnicity of the interviewer, nor their gender has a significant influence on the levels of fear of the individuals that they are interviewing.

Turning to the extended model (model 6), which also allows for interaction effects between individual relationships with fear and interviewer characteristics, a more complex picture of the influence of interviewer characteristics is evident. This is demonstrated by the inclusion of two interaction effects, one between the ethnicity of the respondent and the ethnicity of the interviewer, and one between the age of the respondent and the interviewers experience level.

The interaction between interviewer ethnicity and respondent ethnicity provides additional detail about the influence of interviewers that was not evident when treating interviewer effects as constant across all individuals. This demonstrates that when the ethnicity of the interviewer is considered in conjunction with the respondent's ethnicity, there is an important effect on levels of fear. The reported levels of fear of White people and those of mixed origin is unaffected by the ethnicity of the person conducting the interview, replicating the findings from model 5. In contrast, when the reported levels of fear of Asian and Black people are examined, there is a significant interaction effect with the ethnicity of the interviewer. This shows that Asians will be more likely to report significantly lower levels of fear when interviewed by another Asian, compared to their reported levels of fear when interviewed by a White or Black interviewer. Similarly, Black respondents will be more likely to report significantly lower levels of fear when they are interviewed by someone who is also Black, when compared against their reported levels of fear when interviewed by a White or Asian interviewer (although this effect only reaches significance at the 5% level). This suggests the existence of an interviewer matching effect, leading BME respondents to respond differentially depending on the ethnicity of the interviewer.

The second significant interaction is a negative interaction between interviewer experience and the estimated relationship between respondent age and fear. This provides additional detail about the relationship between age and peoples' reported levels of fear. Considering first people of average age, when the level of experience of the interviewer is higher than average, reported levels of fear will be significantly lower than average, demonstrated by the negative effect of -.06. The interaction term then indicates that in addition to the lower reported levels of fear from an average aged respondent when the level of interviewer experience is higher, the interviewer's level of experience has a direct impact on the strength of the individual level relationship. This shows that the more experienced the interviewer is, the stronger the expected negative relationship between age and fear. This is a complex interaction because of the included individual level quadratic age term, but can be demonstrated clearly graphically, as shown in figure 7.3.

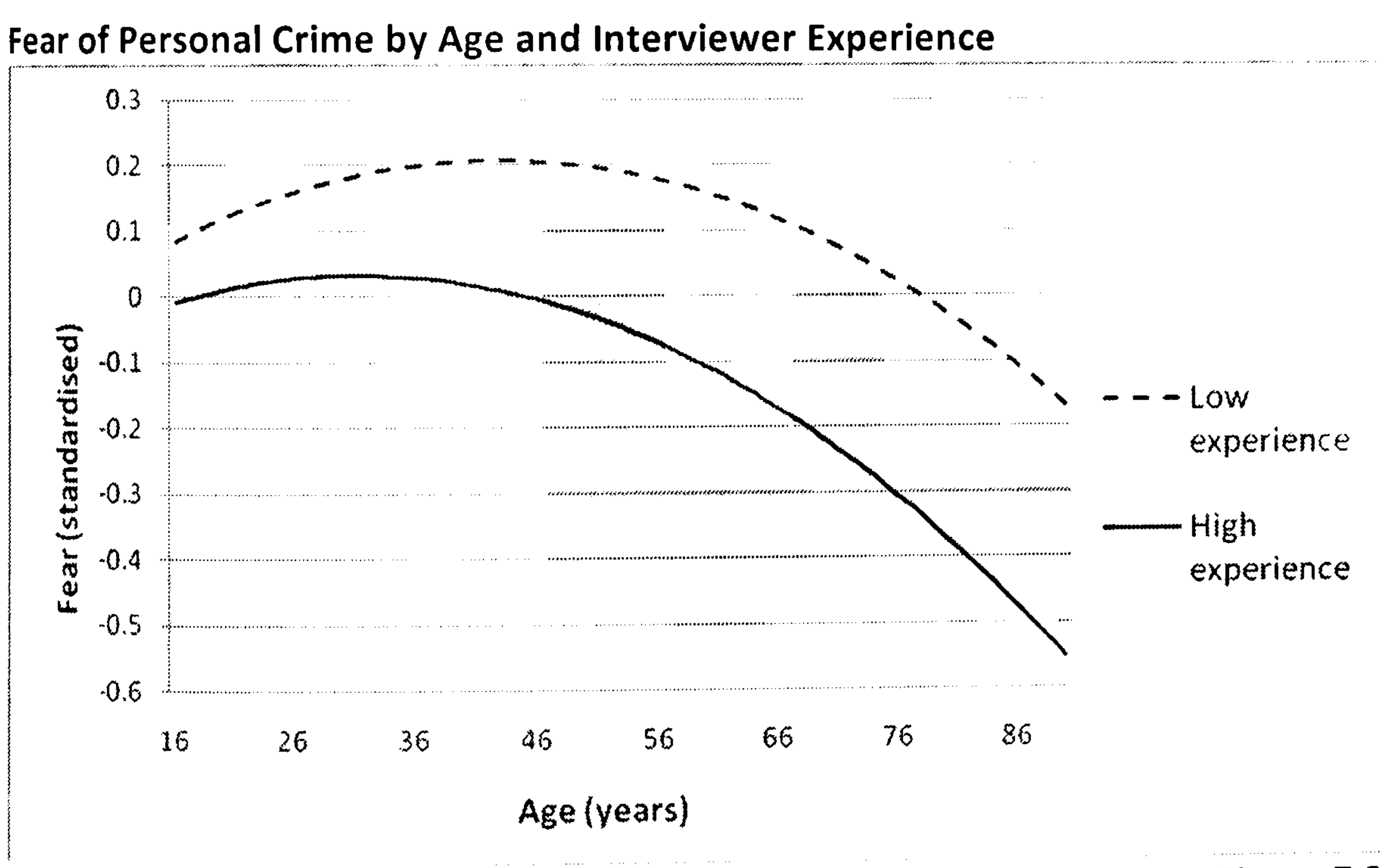

Figure 7.3

The graph shows the changing levels of fear as age changes for an average respondent, contrasting the predicted relationship when they are interviewed by someone with a high level of experience (10 years or more) against the predicted relationship when they are interviewed by someone with a low level of experience (less than 1 year). This shows that there is a stronger drop in fear at higher age ranges amongst those interviewed by someone with more experience. Therefore, the interaction demonstrates that amongst more experienced interviewers there is a larger difference in the levels of fear of young and old respondents, with older respondents significantly less fearful.

7.7.2 Fear of household crime

Looking at how interviewer differences affect people's reported levels of fear of household crime, table 7.6 includes estimates from the equivalent two models. This table has the same structure as the personal crime models, with model 5 including estimates from the model only including main effects of interviewer characteristics. Model 6 then introduces any significant cross level interactions between interviewer characteristics and the individual level relationships with fear.

Table 7.6: Interviewer Effects Models (Household Crime)

		Model 5: Interviewer Effects Effect (S.E)	Model 6: Cross level interactions Effect (S.E)
FIXED EFFECTS			
Constant		.10 (.02)**	.10 (.02)**
Gender (*Ref: Male*)	Female	.16 (.01)**	.16 (.01)**
Age	Age	-.004 (.0004)**	-.004 (.0004)**
	*Female	-.001 (.0005)*	-.001 (.0005)*
	Age^2	-.0002 (.00002)**	-.0002 (.00002)**
Education (*Ref: No qualifications*)	GCSE	-.03 (.01)*	-.03 (.01)*
	A level	-.06 (.02)**	-.06 (.02)**
	Degree	-.14 (.02)**	-.14 (.02)**
	Other (foreign)	-.001(.03)	-.002(.03)
Ethnicity (*Ref: White*)	Asian	.22 (.03)**	.22 (.03)**
	Black	.11 (.04)**	.11 (.04)**
	Mixed/other	.15 (.04)**	.15 (.04)**
Direct Victimisation *(Ref: Non-victim)*	Personal Crime	.16 (.02)**	.16 (.02)**
	Household Crime	.24 (.01)**	.24 (.01)**
Newspaper readership (*Ref: No paper)*	Tabloid	.09 (.01)**	.09 (.01)**
	Broadsheet	.02 (.02)	.02 (.02)
	Local	.08 (.02)**	.08 (.02)**
NS-SEC (*Ref: Professional/managerial)*	Intermediate Occupation	.01 (.02)	.01 (.02)
	Small Employer	-.003 (.02)	-.002 (.02)
	Lower Supervisory Role	.001 (.02)	.001 (.02)
	Routine or Semi Routine	.02 (.01)	.02 (.01)
	Never Worked	.08 (.03)**	.08 (.03)**
	Student	-.06 (.03)	-.06 (.03)
Marital Status (*Ref: Married)*	Separated or Divorced	-.14 (.02)**	-.14 (.02)**
	Single	-.09 (.02)**	-.09 (.02)**
	Widowed	-.09 (.02)**	-.09 (.02)**
Health (*Ref: Not ill*)	Non-Limiting Illness	.05 (.02)**	.05 (.02)**
	Limiting Illness	.09 (.01)**	.09 (.01)**
Residence	Length of residence	.02 (.003)**	.02 (.003)**
CONTEXTUAL EFFECTS (Neighbourhood)			
Social disorganisation	Socio-economic disadvantage	.02 (.01)	.02 (.01)
	Urbanisation	.02 (.01)*	.02 (.01)*
	Population mobility	-.03 (.01)**	-.03 (.01)**
	Age profile	.01 (.01)*	.01 (.01)*
	Housing profile	.02 (.01)**	.02 (.01)**
	Ethnic heterogeneity	.15 (.07)*	.15 (.07)*
Crime	Local Recorded Crime	.06 (.01)**	.06 (.01)**
Low level disorder	Objective disorder	.02 (.01)**	.02 (.01)**
INTERVIEWER EFFECTS AND CROSS LEVEL INTERACTIONS			
Gender (Ref: Male)	Female	-.01 (.03)	-.02 (.03)
Age	Age	-.03 (.01)*	-.03 (.01)*
Ethnicity (Ref: white)	Asian	.11 (.11)	.11 (.11)
	Black	.09 (.09)	.10 (.09)
Experience	Level of experience	-.04 (.01)**	-.04 (.01)**
	*Age		-.001 (.0003)**
RANDOM EFFECTS			
CDRP level		.003 (.001)**	.003 (.001)**
Neighbourhood level		.010 (.002)**	.009 (.002)**
Individual level		.858 (.007)**	.858 (.007)**
Interviewer level		.055 (.005)**	.055 (.005)**
Deviance (DIC)		100586.3	100580.9
Number of cases		*37,187*	*37,187*

*** P<(.01)*

**P<(.05)*

Model 5 is similar to the equivalent personal crime model, with small, but significant negative effects of interviewer age and experience levels on people's reported fear of crime. People interviewed by older interviewers will generally report lower levels of fear than people interviewed by younger interviewers, net of individual and neighbourhood characteristics. Similarly, those interviewed by more experienced interviewers will generally report lower levels of fear. Additionally, like fear of personal crime, the effects of interviewer gender and ethnicity fail to reach significance. The inclusion of these four interviewer effects leads to a small reduction in the remaining unexplained variance partitioned at the interviewer level, dropping by 5%. Since interviewer gender and ethnicity were not judged to be significant, this reduction in unexplained variance is attributable to the effect of interviewer age and experience. This also indicates that the extended model offers very little improvement to model fit, with a drop in the deviance statistic of 9.1 with 5 degrees of freedom [p>0.05]. Again, this reflects the non-significant effects of interviewer gender and ethnicity.

Allowing for specific influences of interviewer characteristics on particular types of people (model 6), one significant interaction is identified. In contrast to fear of personal crime, interviewer ethnicity does not have a specific influence on the levels of fear of BME respondents, meaning no interviewer matching effect is evident. In contrast, the level of interviewer experience is again directly related to the predicted relationship between age and fear of crime. This presents us with a similar differential relationship between age and fear, which is dependent on interviewer experience level. Again, there is a stronger reduction in levels of fear amongst older respondents who were interviewed by someone with relatively more experience, and a weaker relationship between age and fear when the interviewer is less experienced. This is represented graphically in figure 7.4, contrasting the relationship between age and fear for an average resident interviewed by an experienced and inexperienced interviewer.

Figure 7.4

7.8 Discussion IV: The effect of introducing interviewer variability

These models clearly demonstrate that the magnitude of the contribution of unexplained neighbourhood differences to variations in fear of crime have been overestimated, even when controlling for the uneven sample composition within each area. Instead, interviewer differences make a larger contribution to higher level variations in fear. Importantly though, this influence of interviewers is largely restricted to the random part of the model, with the fixed effect estimates at the individual and neighbourhood levels remaining of a similar magnitude and significance in all of the models. Therefore, despite a reduction in the contribution of neighbourhood differences to the overall variance in fear of crime, the contextual effects that have previously been identified are largely unaffected by the reduced influence of neighbourhoods. This means that the direct influence of the structural characteristics of social disorganisation, disorder, and recorded crime on the levels of fear of individuals remain important and substantively interesting.

The larger relative contribution of interviewer differences is a particularly important finding when approached from a survey methodological perspective, with clear implications for sample design. For survey methodologists, considerable energy is spent quantifying the impact of geographic clustering on survey estimates (Kish, 1967). This enables them to design samples that achieve the largest possible effective sample size by balancing the negative effects of response dependency that results from sampling individuals in geographic clusters, against the benefits of an increased sample size that results from the same clustered design. This research suggests that a significantly stronger influence on survey estimates is the dependency that results from people being interviewed by the same interviewers, and that in comparison geographic dependency has a relatively small impact.

To test whether the observed re-partitioning of the contextual variance was simply a reflection of the choice of MSOA as the neighbourhood geography rather than survey clusters, the unconditional cross classified models (table 7.2) were re-specified replacing areas with PSU. These modes were very similar to the models presented in this analysis, with interviewers again accounting for the majority of the clustering effect[3]. This gives us confidence that the observed effects are not simply a function of the decision to use the MSOA geography. The implication of this is that a more efficient sample design might place greater emphasis on limiting interviewer dependency by using a larger number of interviewers who are each given smaller assignments, rather than focusing on the optimal number of geographic clusters and the sample size within clusters.

---

3 ssible to include contextual effects in these models, reflecting the lack of available data supplied

In line with the work of much survey methodology, the extended models incorporating interviewer data demonstrate that basic interviewer characteristics have a relatively small impact on the reported levels of fear of individuals (Groves et al., 2004). This is clearly shown by the small contribution that the four interviewer measures make to explaining the interviewer influences on reported levels of fear, with R^2 equivalents of 7% and 5% for fear of personal and household crime respectively. Therefore, despite interviewer differences making an important contribution to the variability in fear of crime, this variation is not well explained by the basic interviewer characteristics available in this analysis. Whilst it is possible that other factors (such as level of interviewer effort, diverging from the interview script, personality traits, and socio economic status) may have a larger impact on the responses of individuals than the basic demographic measures included here, it is equally plausible that the bulk of the interviewer influence is less systematic, reflecting more complex variations between interviewers (Groves et al., 2004). The VIF (equation [7.1]) informs us that the impact of interviewer clustering on survey estimates is a function of the average interviewer assignment size, therefore this suggests that a more suitable approach to reduce the impact of clustering might be to reduce the assignment loads of each interviewer. This would limit the impact of dependency within interviewers and lead to more accurate estimates at the national level. This is particularly influential in the case of the BCS, where interviewers are assigned an average of 86 interviews per year, meaning the impact of interviewer clustering can be a considerable reduction in the precision of estimates.

In both models, the gender of the interviewer was not significantly related to individual levels of fear. However, it is important to note that this analysis was based on a restricted set of fear items, with the item most likely to have a significant gender matching effect (fear of being raped) omitted as a result of missing data. There is therefore scope to conduct an extended analysis which examines the interviewer level factors most likely to predict non-response to this item (see for example Pickery & Loosveldt, (2001)) and also to assess the potential influence of interviewer differences on responses to this item. In contrast, significant negative effects of interviewer experience and age were identified in both fear models. These indicate that people interviewed by older or more experienced interviewers are likely to report lower average levels of fear than those interviewed by younger interviewers. Additionally, when considering fear of both crime types, there is a significant interaction between the interviewer's level of experience, and the predicted relationship between age and fear of crime. These effects mean that along with generally lower reported levels of fear from respondents interviewed by more experienced interviewers, the reduction in fear as respondents get older is also significantly more pronounced when the interviewer has more experience. There is little evidence about what causes this type of interviewer experience effect, with one possible explanation that more experienced interviewers rush through questionnaires, giving respondents less time to provide an accurate answer (Groves et al., 2004). What is clear, though, is that the presence of these effects of interviewer age and experience represent a new direction for research, particularly studies examining the differences in fear of crime that are evident amongst people of different ages, highlighting the importance of interviewers to the process.

The effect of interviewer ethnicity is less consistent across crime types. In both cases, no effect of interviewer ethnicity is evident when examined as a main effect on all types of people irrespective of their ethnicity. In contrast, when the model is extended to more accurately reflect the potential impact of interviewer matching, an important effect of interviewer ethnicity on BME respondents' levels of fear of personal crime is evident. Whilst the reported levels of fear of White people are not influenced by the ethnicity of the interviewer, Black and Asian respondents who are interviewed by someone of the same ethnicity reported significantly lower average levels of fear. The interaction suggests the existence of an interviewer matching effect, whereby BME respondents adjust their responses based on the ethnicity of the interviewer. This might mean that they overestimate their levels of fear when interviewed by someone of a different ethnicity This has important implications for existing research that has examined the levels of fear of BME groups, demonstrating a need to incorporate this potential methodological influence on results.

Whilst this appears to demonstrate a clear interviewer matching effect, an alternative explanation for the interaction between interviewer and respondent ethnicity is that this reflects a selection bias resulting from the interviewer allocation process. It is plausible that BME interviewers are more likely to be assigned to neighbourhoods where there are higher proportions of BME respondents, a result both of a tendency for these interviewers to live in these types of areas and of a tendency for them to be allocated assignments in these types of area to maximise response rates (Groves et al., 2004). Previous models showed that BME respondents from more diverse neighbourhoods are more likely to report lower levels of fear, reflecting stronger community bonds and increased social integration. Consequently, the apparent interviewer matching effect could simply reflect the fact that BME interviewers are more likely to interview BME respondents from more diverse neighbourhoods. The models in this analysis go some way to mitigating this potential selection effect, controlling for a number of contextual measures including the level of ethnic diversity.

Despite this, it is possible that the observed interaction is picking up an additional effect of BME clustering, with further research required to successfully separate these two potential effects.

Overall, this chapter has provided an alternative explanation for the unexplained variability in fear of crime that was previously attributed to differences at the neighbourhood level, introducing the impact of the clustering of respondents within interviewers as an additional source of dependency. Adopting a complex design capitalising on the naturally occurring cross classified structure of the BCS sample, it has been possible to incorporate interviewer variability within a detailed assessment of the neighbourhood influences on fear. This has resulted in a significant re-partitioning of the unexplained variance, with a large proportion of the variance previously identified as the result of neighbourhood differences re-classified as the result of interviewer differences. This represents a significant shift in focus away from the impact of neighbourhood effects.

However, despite resulting in a significant re-partitioning of the unexplained variance, the fixed effect estimates at the neighbourhood level appear robust, with the effects of ethnic heterogeneity, recorded crime, disorder and socio-economic disadvantage remaining significant in these extended models. Interviewer characteristics were then included to try and explain the interviewer variation, however, a large proportion of the interviewer variance remains unexplained. This suggests the presence of other interviewer differences that are less readily observable, like the level of interviewer effort, the extent that the interviewer diverges from the questionnaire, and the levels of interviewer guidance that is provided to respondents (Groves, 1989).

The models in this chapter did not incorporate random coefficients, reflecting the high level of complexity involved in specifying these models. This means it was not possible to assess the impact that a failure to incorporate interviewer variability might have on the magnitude of the random coefficients identified in chapter 6, or random coefficients models more generally. It is therefore possible that whilst fixed effects appear largely robust when interviewer variability is omitted, the random part of the model may be more seriously affected. This suggests the need for further research to examine the potential influence of interviewer variability on random coefficient estimates.

It is important to note that the current models are restricted in their scope to the influence of interviewer differences on levels of fear of crime. Therefore, despite being largely consistent with the findings of O'Muircheartaigh and Campanelli (1998), and Schnell and Kreuter (2006), the results presented here make no claims of generalisability to other question types. Instead they are intended to act as an illustrative case study, stimulating more detailed research on the potential impact that interviewer variability might have in relation to estimates of the importance of neighbourhood variability within neighbourhood effects research.

CHAPTER 8: DISCUSSION, IMPLICATIONS AND LIMITATIONS

8.1 Introduction

In this thesis I have used multilevel modelling to incorporate area effects within an individual level analysis of fear of crime. By attaching geo-coded data taken directly from the UK census to the BCS, this study has examined people's fear of crime within the local social context in which it is experienced. This was the first multilevel assessment of neighbourhood effects on fear of crime within the UK context, and the first to examine these effects at a national scale, rather than being restricted to a single city. It also uses a more detailed set of neighbourhood measures than pervious assessments, with a factorial ecology methodology adopted to enable a wide range of data to be incorporated within a set of indices of neighbourhood difference.

8.2 Recapping the aims of the thesis

The initial motivation for the current thesis was to integrate individual and contextual theories of fear of crime within a single model, enabling an examination of their relative contribution to understanding variations in fear. Previous assessments of fear of crime have primarily focused on individual *or* contextual theories, with relatively little empirical evidence that accurately combines both within an integrated framework. Instead, ecological data is often incorporated erroneously as additional individual level data, or contextual examinations incorporate aggregated individual data. As a result, formal tests of the relative importance of social disorganisation, low level disorder, and recorded crime in the local neighbourhood on fear of crime have been scarce. In response to this clear limitation with existing research, this thesis capitalised on the recent availability of geographic identifiers on the BCS to conduct a fully integrated assessment of contextual and individual theories of fear of crime. This enabled a test of the extent that social disorganisation, low level disorder, and recorded crime levels in the neighbourhood are relevant predictors of fear over and above individual differences in fear.

A second, closely related aim of this thesis was to plug the gap in existing knowledge between individual and contextual theories of fear of crime that was outlined in Chapter 3. Theoretical links between individual differences in fear of crime and the local context in which they are experienced are evident throughout the literature, describing how particular individuals might be differentially affected by contextual influences (for a review, see Hale (1996)). However, the empirical support for these linkages has been less prominent, with methodological and data limitations preventing researchers from examining in detail how individuals and context interact to generate variations in fear (notable exceptions include Covington & Taylor (1991); Robinson, et al., (2003); Snell (2001); and Wilcox-Rountree & Land (1996a)). By constructing detailed individual and contextual models of fear, and allowing individual relationships with fear to vary as a function of neighbourhood differences, this thesis has gone some way to bridging the gap between individual and contextual theories.

The final goal of this thesis was to examine the contribution of interviewers to variations in fear of crime. This represents a different perspective on the contextual influences that impact on fear of crime, arguing for the importance of methodological factors that have been falsely attributed to social context in past assessments. The influence of interviewer variations has been notoriously difficult to separate from the contribution of social context, with the two sources of variance regularly confounded in survey research (Groves, 1989). This has meant that there has been very little evidence identifying the relative contributions of interviewers and areas, with researchers typically focusing on one source of variance at the expense of the other. The expanded scope of recent waves of the BCS and the use of SOA geography, coupled with the recent expansion of multilevel methodology to cope with non-nested data sources, represented a novel opportunity to tease apart these two competing sources of clustering in this thesis. As a result, this thesis has presented important evidence about the contribution of interviewers, and how this methodological artefact impacts on the contextual theories of fear of crime. Additionally, the availability of information about the interviewers conducting the survey prompted an assessment of how interviewers' bias estimates of fear, above and beyond individual and area variations. Consequently, this thesis has significantly advanced out understanding of the effect of interviewers in the context of fear of crime, acting as a starting point for more detailed analyses.

8.3 Summary of key findings

The following section draws together the key findings from this thesis, considering how successfully the models have answered the initial aims summarised above. This begins by considering how the models have extended our understanding of the contribution of area differences to variations in fear of crime, and how well the concepts of social disorganisation and disorder explain the observed effects. This is followed by an assessment of the extent that the inclusion of interviewer differences further enhances the contextual models of fear of crime.

8.3.1 Neighbourhood context matters (but so do interviewers)

In chapter 4 I demonstrated an important area contribution to variations in fear of crime, accounting for a significant proportion of the total unexplained variability in fear. This provided initial support for using contextual explanations to account for differences in fear of crime. This was not a new finding, with a number of studies demonstrating that area variations are an influential component of fear (see inter alia Robinson et al., (2003); Snell (2001); and Wilcox-Rountree & Land (1996a)). However, it has advanced our understanding of the contextual influences on fear in a number of key ways. First, the models adopted an operationalisation of neighbourhoods that was smaller and more internally stable than many existing studies, demonstrating that the social processes influencing fear operate at a very local level. This provides a more nuanced assessment of the social processes that contribute to people's fear of crime, signalling the existence of small scale differences between local neighbourhoods. In particular, when examined at a small spatial scale a direct relationship between recorded crime in the neighbourhood and fear of crime was observed, suggesting that fear of crime is, at least in part, a direct response to the risk of crime.

Second, social context was found to affect both fear of personal crime, and fear of property crime. This contradicts the work of Robinson et al., (2003) who found that context was only influential when considering global measures, with no contextual influences found when using worry measures. This means that despite important differences in the factors that influence fear of different crime types, social context has an important part to play in both instances. Third, in addition to the important contribution of local neighbourhood differences, the wider context in which fear is experienced also has an important function. Using CDRP to represent broader area differences, Chapter 4 demonstrated a similar sized contribution from this broader geography. Importantly, chapter 5 then showed considerable clustering of neighbourhoods with similar characteristics in the same broader CDRP, with the included contextual effects primarily accounting for CDRP variations. This highlighted the high degree of clustering of neighbourhoods with similar attributes within close proximity to one another, and thus better reflected the complex geographic structure at the local neighbourhood level. This also ensured that contextual effect estimates were corrected for this source of geographic dependency.

Chapter 6 then presented us with a more complex picture of the magnitude of the area contribution to unexplained variations in fear of crime, identifying important differences in the size of the area contribution for different types of people. This presented us with a different picture of the neighbourhood contribution to fear of crime, with the levels of fear of BME groups considerably more influenced by neighbourhood variability than the fear of White residents, and women more influenced by neighbourhood differences than men. By allowing for a complex variance structure at the neighbourhood level, these models came closer to representing the true impact of neighbourhood differences on particular types of resident.

Chapter 7 further extended our understanding of the magnitude of the contextual influences on fear by demonstrating that a significant proportion of the variance initially partitioned at the neighbourhood and CDRP levels was actually better described as interviewer variance. This is a considerable advance over existing studies which have failed to incorporate the influence of interviewers, suggesting that early estimates of the contribution of neighbourhood differences may be unrealistic. Instead, a more conservative picture of the importance of social context was presented when the influence of interviewers was included. This also linked the estimation of contextual effects back to the concerns of survey methodology, separating area differences from the oftentimes confounding effect of interviewer variability (Groves, 1989). Importantly, chapter 7 went on to show that the estimated contextual effects were largely robust to this misspecification error, with the incorporation of interviewer clustering having little effect on the interpretation of the contextual measures that characterised social disorganisation and low level disorder. This means that whilst the size of the area contribution was shown to be significantly over-estimated in models that failed to incorporate interviewer variance, there was still some support for the contextual theories that have been introduced to explain differences in fear.

8.3.2 Clarifying the role of social disorganisation

Looking first at social disorganisation theory, the models in chapter 5 demonstrated some initial support for the effect of factors associated with disorganised communities on levels of fear of crime. More socio-economically disadvantaged and ethnically diverse neighbourhoods were thus shown to have higher average levels of fear, with the incorporation of these contextual measures explaining between 18% and 29% of the neighbourhood level variance in fear. Additionally, areas defined as more urban in nature were associated with higher average levels of fear, as were neighbourhoods that had a generally younger age structure.

However, the relationship between population mobility and levels of fear was not as expected based on social disorganisation theory. Looking at fear of personal crime, no relationship with fear of crime was evident, contradicting the theoretical assertions of Shaw and McKay (1942) that higher levels of mobility reduce the informal controls open to local communities, and hence lead to higher levels of fear amongst residents. In their original work, it was specifically high levels of mobility within lower socio-economic status neighbourhoods that led to increased crime, however even when this more detailed specification was tested there was no relationship with fear of personal crime. In contrast, when considering fear of property crime, a significant relationship with the level of population mobility was evident, although this was in the opposite direction to that predicted by social disorganisation theory. This suggested that in neighbourhoods with a higher population turnover the level of fear from residents tended to be lower than average.

The failure to find a positive relationship with population mobility might be taken as evidence against the importance of social disorganisation on variations in fear of crime, but it is also possible that this is really a reflection of the population mobility index used in this analysis. At face value, this measure appears to successfully measure population mobility, with high factor loadings on the proportion moving into and out of the neighbourhood in the last year. However, there are also fairly high loadings on the proportion of single person non-pensioner households and commercial properties, suggesting that we are also capturing commuter towns with this index. Additionally, the measures of migration used in this study might be considered to be less than optimal, failing to capture the longer term population shifts that may better characterise more disorganised communities. Consequently, the failure to identify a relationship with this measure of population mobility should not be taken as conclusive evidence that social disorganisation does not successfully explain variations in fear of crime at the neighbourhood level, conditional on individual differences.

The extended models in chapter 5 also pointed to a more complex role for disorganisation, showing that when the level of recorded crime and the prevalence of signs of disorder in the neighbourhood were incorporated in the model, the magnitude of the estimated effects of socio-economic disadvantage, neighbourhood age structure and the effect of urbanisation were substantially reduced. This suggests that part of the impact of social disorganisation on fear of crime occurs through its' impact on the levels of disorder and crime within the neighbourhood. This is taken as partial support for the work of Sampson and Groves (1989), who used direct measures of social disorganisation to demonstrate how the structural dimensions of the local neighbourhood influenced crime through social disorganisation. Low level disorder has strong links with the direct measures of disorganisation which they included as mediators of the effect of structural characteristics on levels of crime. Therefore, we might attribute the reduction in the contribution of the structural measures in the current thesis to a similar mediating effect of disorder. Importantly, this also suggests that studies which have failed to incorporate these additional sources of neighbourhood difference may have overestimated the relationship between fear and the structural determinants of social disorganisation (see for example Hale et al., (1994)).

An interesting extension to earlier research looking at the impact of social disorganisation on levels of fear was highlighted in chapter 6, where some clear differences across population groups were identified. This demonstrated that the higher levels of fear in more ethnically diverse neighbourhoods were conditional on the ethnicity of individual residents, with Black residents reporting lower levels of fear in neighbourhoods that were characterised by higher levels of diversity. This means that the effect of diversity on fear predicted by social disorganisation does not hold for all individuals. Instead, the suggestion of Putnam (2007) that in more diverse neighbourhoods Black residents will feel less like outsiders, perhaps fostering increasing feelings of tolerance towards others and thus reducing the gap in fear between them and White people, seems to fit the data better.

In addition to the differential effect of ethnic diversity on fear, the extended models also demonstrated that other individual differences in fear of crime were directly tied to the structural dimensions of social disorganisation. In general, the extended models showed that the more fearful groups in society were more influenced by the structural characteristics of the local neighbourhood, with significant differences in fear depending on the neighbourhood structure. In particular, it was shown that women's fear of crime varied significantly as a function of the levels of socio-economic disadvantage, the age structure and the neighbourhood housing profile. Additionally, the levels of fear of victims of household crime were more affected by the level of neighbourhood disadvantage than non-victims, possibly reflecting the reduced availability of protective measures like security alarms in more disadvantaged neighbourhoods.

8.3.3 *The importance of disorder and recorded crime*

The models estimated in chapter 5 also demonstrated support for the importance of the prevalence of signs of low level disorder in the neighbourhood on levels of fear, as well as the link between the crime rate in the neighbourhood and fear. The link between perceptions of disorder and fear of l known, and regularly documented in criminological research, albeit often referred to under the guise of different labels including incivilities, anti-social behaviour, and signal crimes (see inter alia Hunter, (1978); Innes, (2004); Lewis & Salem, (1986); and Skogan, (1990)). However, the link with perceptions of disorder has been suggested by some to be a problematic relationship, characterising a parallel process rather than a causal process between perceptions of disorder and fear (Tseloni, 2007). As a result, despite often demonstrating a significant relationship with fear, it has not been clearly shown what this relationship means; is it that people who perceive more disorder are consequently more fearful?; or do more fearful people tend to perceive more problems within their local area?

In contrast to this often identified relationship, a link between objective levels of disorder and fear of crime has been much more difficult to establish, with researchers struggling to identify suitable survey measures, and those that do often failing to find support for a relationship (Taylor, 2001). Since a link between the presence of physical signs of disorder and levels of fear represents a stronger test of the impact of disorder than the use of perception measures, the relationship identified in this research between interviewer ratings of disorder and fear of crime is of considerable importance. In addition, this relationship is evident even having controlled for individual differences in fear, along with controls for the structural dimensions of the neighbourhood and the level of crime. As such, this thesis provides support for the influence of disorder on levels of fear, with a robust relationship evident when considering both fear of household and personal crime. In chapter 6, the link between disorder and fear was further elaborated, with a stronger effect of disorder evident amongst women and people with a limiting illness, both groups routinely identified as more vulnerable (Killias, 1990). Like the differential relationships with the structural determinants of social disorganisation, this presents us with a more nuanced picture of the role of signs of disorder in the neighbourhood. This suggests that more vulnerable groups are more susceptible to environmental cues that signal a potential risk of crime.

The effect of the crime profile of the local neighbourhood on levels of fear was also shown to be important in chapter 5, contrasting the large number of studies that have failed to demonstrate a relationship with fear when other factors have been controlled for (for a recent review see Vanderveen, (2006)). This is attributed to the small spatial scale used in the current analysis, and the detailed measure of the neighbourhood crime profile that has been adopted. Typically, studies have had to rely on proxy measures for the crime profile of the local neighbourhood, including measures of the crime rate at a broader spatial scale, or measures that focus on specific crimes. As a result, they have failed to accurately characterise the range of potential crime influences on individual levels of fear.

In contrast, the measure of crime used in this thesis was based on data measured at a very local scale, referring to the crime profile of the area immediately surrounding each respondents home. This makes it a considerably more relevant measure of the level of crime in the neighbourhood for local residents, capturing the extent of crime in the area that they live their daily lives. As such, it provides a more fine-grained assessment of how local differences in crime play out in variations in the levels of fear between local areas, more closely reflecting the findings from local surveys (Young, 1988). Additionally, the measure of crime used within this thesis is considerably more detailed than the measures that have typically been adopted in survey research, covering a range of different crime types; from very serious offences like murder, arson, and burglary; to less serious crimes like criminal damage, harassment and common assault which occur more frequently.

When the multilevel models were extended in chapter 6 to link these contextual measures back to the individual differences in fear, the impact of the level of crime in the neighbourhood was given further clarity by tying it to the crime experiences of local residents. This showed that the higher levels of fear amongst previous victims of crime were directly linked to the neighbourhood crime profile, with a larger gap in fear between victims and non-victims in neighbourhoods where the levels of crime were higher overall. This is an important extension to existing knowledge about the impact of victimisation experience on fear of crime, showing that this relationship is itself moderated by the wider crime profile of the neighbourhood.

8.3.4 Interviewers matter

The final key finding that has come out of this study is the importance of interviewers to variations in fear of crime. Capitalising on the scale and design of the BCS, chapter 7 went some way to separating the effects of geographic clustering on fear from the effects of interviewer clustering. This addresses a longstanding gap in survey literature about the relative contribution of these two sources of measurement error that are typically confounded as a result of sample design. This chapter approached this question from a contextual effects perspective, examining the influence of this additional source of clustering on estimates of contextual effects, and how this altered our understanding of the contextual theories of fear of crime. Having examined the impact of incorporating interviewer variance on the contextual models outlined in chapter 5, interviewer variables were then incorporated to assess how differences between interviewers impacted on reported levels of fear of crime.

The most immediately striking outcome of this research was the comparatively large contribution to the overall variance in fear from interviewers. This meant that estimates of the relative contribution of neighbourhoods and CDRP were substantially reduced, leading to more conservative claims about the importance of area effects for variations in fear of crime. The larger contribution from interviewers is in line with the work of O'Muircheartaigh and Campanelli, (1998), and Schnell and Kreuter, (2006), who demonstrate a similar repartitioning of variance across items when interviewer and area clustering are both incorporated. This points to a need for caution when examining area effects on social outcomes, with other methodological factors playing a crucial role in determining the overall magnitude of unexplained variability. Despite this, the inclusion of this additional source of clustering did not have a substantive impact on the contextual effects included in the model, suggesting that social disorganisation, disorder, and recorded crime in the local neighbourhood still have an important role to play in the levels of fear of local residents.

Chapter 7 then went on to examine whether measurable characteristics of interviewers could be used to predict differences in fear of crime, in the same way that measurable characteristics of the local neighbourhood had been linked to fear. The available measures of interviewer differences were restricted to details of gender, ethnicity, age, and experience, therefore no information was available about their interviewing techniques. Consequently, this was a necessarily limited assessment of interviewer effects, intended to act as a useful starting point for subsequent research. The results of this analysis were mixed, with no direct effects of interviewer ethnicity, or gender, but clear reductions in fear amongst those interviewed by older and more experienced interviewers. This is largely in line with existing research on interviewer effects, where basic demographic measures are rarely found to have a large impact, except when looking at questions that are in some way linked to those characteristics (Groves et al., 2004). Importantly, when assessed in relation to respondent ethnicity, an interesting effect of interviewer ethnicity did emerge. This demonstrated that BME respondents interviewed by someone of the same ethnic origin reported significantly lower levels of fear than those interviewed by someone of a different origin. The level of interviewer experience and age were also shown to be linked with levels of fear, a finding common to research on interviewer effects (Groves et al., 2004). This showed lower reported levels of fear when people were interviewed by an older interviewer or someone with a higher level of experience.

8.4 Implications of the study

Having drawn together the principle findings from this thesis, the following section considers the implications of these results, both for the design of policy initiatives intended to reduce levels of fear and for subsequent fear of crime research. This emphasises the advantages of the current modelling strategy over existing research approaches, and how the added information gained about the structural influences on fear can be effectively utilised to reduce levels of fear. Additionally, it highlights the need for good quality contextual data, along with clear details about the data structure, to facilitate the estimation of complex models that realistically reflect the structured nature of the various levels of influence on survey outcomes.

8.4.1 Policy implications

The fear of crime has featured heavily within government crime reduction policy since the 1990s, with reductions in fear of crime regularly appearing alongside reductions in crime rates, anti-social behaviour, and repeat offending as the principle objectives of new crime and disorder initiatives. These include the Crime and Disorder Act (1998), the Police Reform Act (2002), and the Safer Communities Initiative (2002). Additionally, reported levels of worry about crime have been used as a BVPI for monitoring the police, and also feature in the recently revised National Indictor Set used to monitor community based crime reduction strategies. As indicators of police performance, they have also been used to monitor the success of the Safer Communities Initiative, latterly known as the Building Safer Communities Initiative, whereby differences between CDRP are assessed to help direct spending at CDRP level. As such, the findings from the current thesis about the neighbourhood and CDRP influences on fear of crime, alongside the variability in individual differences in fear across neighbourhoods have important implications for the continuing focus of policy initiatives. Additionally, the results point to a need to consider how worry measures are used as performance indicators.

The links between fear and more urban and disadvantaged neighbourhood are well documented, and confirmed in the current models. Whilst these models measured crime, socio-economic disadvantage, urbanisation and ethnic diversity at a smaller spatial scale than previous studies, the effect of including these measures was to reduce the size of the differences in fear both at the neighbourhood and the CDRP level. This suggests that there is considerable clustering of similar neighbourhoods within each CDRP. Consequently, initiatives tailored to reducing disadvantage at the CDRP level are expected to be effective at lowering the levels of fear of residents across all neighbourhoods within them.

Despite accounting for a greater proportion of unexplained variability at the CDRP level, the results have also highlighted important variations in fear of crime between local neighbourhoods within CDRP that can be explained by levels of crime, disadvantage, ethnic diversity, and the degree of urbanisation. This suggests the need to also consider fear reduction strategies that operate at this very local spatial scale, rather than concentrating just on differences between CDRP. The extended models from chapter 6 further suggest that initiatives tailored to the local neighbourhood have particular value for reducing the fears of the most vulnerable groups, helping to reduce the disparities in fear of crime at the individual level. Additionally, the models estimated in this thesis show that a considerable proportion of the remaining variability in fear of crime is the result of differences between local neighbourhoods, demonstrating the important role of neighbourhoods in any efforts to lower levels of fear. This additional neighbourhood level variability was not successfully explained with the included contextual measures, suggesting the need for further research to identify other potential neighbourhood influences on fear of crime.

Government initiatives regularly link levels of fear to the extent of antisocial and disorderly behaviour, citing the association that is often reported between perceptions of disorder and fear of crime as evidence in support of this relationship (see for example Allen, (2006); and Nicholas et al., (2007)). This is a problematic finding, with the reliance on perception measures meaning that there is no clear evidence that it is disorder that is resulting in higher levels of fear, as opposed to fear influencing perceptions or another environmental characteristic that is influencing both levels of fear and the amount of disorder that people perceive. In this thesis, a direct link between the interviewer observed levels of disorder in the local neighbourhood and levels of fear is identified, lending support to the contention that reducing the prevalence of disorder will lower levels of fear. As such, this research confirms the existence of a relationship between disorder and fear, supporting the potential efficacy of initiatives that have been introduced to curb antisocial behaviour.

Considering the use of worry measures as performance indicators, some important lessons can be learned from this analysis that highlight the need for a more detailed measurement strategy to generate estimates of the relative differences between CDRP. Typically, point estimates of the average levels of worry within each CDRP are used in tandem with other indicators to assess the relative success of each CDRP. However, in chapter 4, it was shown that approximately 27% of the variation across CDRP was actually the result of the differential sample composition within each CDRP. This suggests that simply looking at the average level of fear within each CDRP, a considerable portion of the differences identified between partnerships will actually be a reflection of the differential sample compositions in each, rather than reflecting real differences. To more accurately estimate the extent of differences between CDRP, estimates should thus be adjusted for differential composition. This can be achieved within a multilevel specification by estimating the individual level model, and then plotting the CDRP level residuals (in a manner similar to the construction of school league tables). This would also allow the incorporation of accurate 95% confidence intervals around each CDRP estimate, better reflecting which CDRP significantly differ in their levels of fear.

In chapter 7 it was further demonstrated that a considerable proportion of the CDRP level variation in fear actually reflected interviewer differences. As a result, estimates of the level of fear in each CDRP should also be adjusted to account for the effect of interviewers, further reducing the identifiable differences in fear between CDRP. This underlines the importance of a careful assessment of the factors that influence levels of fear. In chapter 7 it was shown that the reported levels of fear of an individual is affected by the interviewer collecting the data, with interviewer age, experience, and ethnicity all closely linked to the reported fear of respondents. As a result, in some instances it is likely that observed differences in fear are actually a reflection of differences in the people that are collecting the data, rather than demographic risk factors. Consequently care must be taken when using this data as a performance indicator.

A further implication of the use of fear of crime measures as a performance indicator stems from preliminary analysis of the fear items collected by the BCS in chapter 4. This revealed that two of these measures had high levels of responses classified as not-applicable; *How worried are you about being raped?;* and *How worried are you about being subject to physical attack because of your skin colour, ethnic origin, or religion?* For both of these measures, the non-response mechanism is directly related to the subject of the question, with worry about rape disproportionately missing responses from men, and worry about racial harassment disproportionately missing responses from White people. The inability to identify whether these were missing because the respondent selected not-applicable, or whether the interviewer chose to label these as not-applicable, makes these two measures problematic as performance indicators. As a result, until the source of the missingness can be accurately described and corrected, these items should be omitted from analyses.

8.4.2 Survey design

The results from this thesis also have important implications for survey design, with the large contribution to unexplained variability that is attributed to interviewers pointing to a need to critically assess the sample design of the BCS. Typically, considerable effort is spent trying to minimise the impact of clustering on survey estimates, with survey methodology paying close attention to the optimal number of area clusters and individuals within each cluster to enable precise survey estimates for a given cost. Less time is spent assessing the impact of interviewer clustering on the precision of estimates, or what might be the optimal number of interviews to assign to each interviewer. This is particularly important for the BCS, where the rolling design of the survey means that interviewers are often assigned a large number of interviews within each survey year. In chapter 7, it was clearly shown that a larger proportion of clustering variability was attributed to interviewers, suggesting the need to more carefully consider how interviewer clustering is affecting estimates. This may mean that the optimal survey design for a fixed cost involves the use of more survey interviewers that all conduct fewer interviewers, rather than solely focusing on the optimal number of geographic clusters.

At the very least, the results from chapter 7 demonstrate the importance of having this additional source of information to base inferences on, and the utility of a design that enables researchers to begin to get a handle on the size of the interviewer contribution. Social context was still shown to influence levels of fear, with important links between structural characteristics of the neighbourhood and variations in fear. However fear was also clearly influenced by the person collecting the data. As a result, it is important for researchers to be able to incorporate this additional source of information within their analyses to better understand the complex nature of people's fear of crime. Importantly, the current analysis of the impact of interviewers was restricted to fear of crime. In order to fully assess the effect that interviewer clustering is having on survey estimates, a more extensive assessment of the range of BCS questions is advocated.

The current thesis also identified important interviewer matching effects that suggest current estimates of levels of fear may be unreliable. This showed that BME groups reported significantly lower levels of fear when interviewed by someone who shared their ethnicity. Similarly, people interviewed by someone with a higher level of experience tended to report lower levels of fear, with this effect being more pronounced amongst older respondents. Consequently, research which fails to incorporate this additional source of detail about the correlates of fear is likely to be presenting an incomplete picture.

8.4.3 Data requirements

This thesis has demonstrated the benefit of accurately incorporating the data structure within assessments of fear of crime, and how administrative data can be attached to survey data to better model the various sources of influence on fear. This was made possible with the inclusion of geo-coded data measured at MSOA level alongside individual level BCS data. However, within published figures from the BCS it is currently not common practice to develop these types of complex multilevel models. This reflects a general lack of available information about how survey data are hierarchically clustered, as well as a failure of the BCS to incorporate detailed contextual data within analyses. What little administrative data is typically included alongside individual level BCS records is measured at too broad a spatial scale to enable the accurate identification of neighbourhood level processes, with information usually supplied at the ward level or above. To enable more detailed treatments of the contextual influences on fear of crime and other relevant social outcomes like victimisation experience and trust in the police, there needs to be a shift towards the supply of low level contextual data alongside individual BCS data. This will make it possible for more researchers to successfully incorporate context within individual level analyses.

There is also a need for the construction of more comprehensive contextual datasets, covering other important features of the local environment. These could then be straightforwardly attached to existing survey data to assist in the examination of the impact of context on a range of social outcomes. The failure to explain all of the context level variation in fear demonstrates the need to move beyond simple structural characteristics of the local neighbourhood based on census data to the development of neighbourhood level characteristics that effectively capture its social structure. This might be guided by concepts like collective efficacy and neighbourhood cohesion, allowing researchers to construct more detailed theoretical models to explain higher level clustering effects. What is clear from the current thesis is that this type of variation can be straightforwardly identified, and effectively modelled when relevant data is made available.

The measurement of fear of crime could also be improved, reducing the impact of measurement error on estimates. In this thesis, fear of crime was measured with 4 items, with a further 4 items removed as a result of uncertainties over missing data (see chapter 4). Three of the selected items were identified as measures of fear of personal crime, and one was labelled as fear of household crime. This meant it was not possible to apply corrections for measurement error when considering fear of household crime, making it difficult to quantify the contribution of neighbourhood differences to the overall variations in fear of household crime. Including more indicators of fear of household crime would enable measurement error associated with this type of fear to be corrected for, improving estimates of the individual and contextual effects.

8.4.4 Unexplained variability

The current thesis also has important implications for existing knowledge about the individual risk factors that are associated with higher levels of fear. Considerable variability across neighbourhoods was identified in the effects of ethnicity, victimisation experience, and the effect of having a limiting illness on fear of crime. This variability across neighbourhoods means that there are large differences in the estimated effects of these risk factors in different local neighbourhoods; with higher levels of fear amongst these groups in some neighbourhoods and lower levels of fear in other neighbourhoods. This echoes the findings of the realist assessments conducted throughout the 1980s (Young, 1996), with the broad picture of geographic variations in fear provided by national assessments using ACORN classifications and the distinction between rural and urban areas missing important local level detail about individual experiences of fear. Consequently these broad discussions of risk have very little relevance to the experiences of residents of particular neighbourhoods. Conversely, this also means that local assessments of fear are likely to show considerably different results depending on the local areas from which data are collected.

The high degree of variability in the size of the differences in fear between BME groups and White people is particularly noteworthy, pointing to the potential influence of other processes that lead to large differences in the estimated effect of being from a BME group across neighbourhoods. It is possible that the high degree of observed variability reflects the need to adopt a more complex set of BME classifications within existing studies, picking up differences in fear within the broad classifications of Asian, Black and mixed or other origin. The high level of variability suggests that it may be more informative to examine the differences in fear between types of Black and Asian residents; such as the differences between Black African and Black Caribbean residents; or between Asian Pakistani and Asian Indian residents. Similarly a single category that encompasses all those identified as of mixed or other ethnic origin (including Chinese, Polish etc) is too simplistic and needs to be reassessed. Whilst the current thesis uses a more complex categorisation than the distinction between White and non-White groups, the results suggest that this is still not a fully accurate representation of the differences within BME groups.

8.5 Limitations of the current study

Although this analysis represents a clear advance over many existing treatments of fear of crime, a number of limitations can be identified that need to be addressed. These limitations point to the need for further research to better understand variations in fear of crime. These extensions to the research outlined in the current thesis are discussed in detail below in section 8.6.

8.5.1 Defining neighbourhoods

One important limitation to the current thesis is that the findings about the extent of the influence of context on individuals are dependent on the definition of neighbourhood that has been adopted. Consequently, if neighbourhood boundaries were defined differently, there is no guarantee that the same indices of neighbourhood differences would be identified, or that the same contextual influences on individual's fear of crime would be estimated. Similarly, the variation in the size of individual differences in fear across neighbourhoods is also dependent on the definition of neighbourhoods that has been adopted. This problem, typically referred to as the Modifiable Areal Unit Problem (MAUP), means that it is possible that the findings from this analysis reflect the choice of neighbourhood boundaries and not real contextual processes (Openshaw, 1984).

The current neighbourhood geography was selected for three principle reasons. First, they represent a reasonably concise geographic boundary that does not cross major natural boundaries like main roads or waterways. Additionally, the consultation phase with members of the community to ensure the boundaries represent meaningful local areas gives us additional confidence that they reflect neighbourhood structures. Second, they are geographically and statistically stable, with similar numbers of residents within each that all share similar characteristics, ensuring there is a reasonable degree of internal homogeneity. Third, the decision was also partly based on data availability, with smaller spatial scales not available as a result of confidentiality issues. Additionally, smaller spatial scales did not result in a sufficient number of sampled residents within each local area, limiting the scope of the models that could be estimated. There was also considerably more administrative data available at the chosen spatial scale, enabling more complex neighbourhood scales to be constructed. However, based on the MAUP, there is no way of assessing the generalisability of the current results to other spatial scales. This suggests the need for subsequent analyses that undertake a sensitivity analysis of the current findings, following a methodology similar to the work of Johnston et al., (2005a).

In addition to the potential for different contextual influences to be identified at different spatial scales, the current thesis also fails to deal effectively with spatial dependence, also often referred to as spatial autocorrelation (Elffers, 2003). Spatial dependence refers to the potential for residents to be influenced by the characteristics of neighbouring local neighbourhoods, rather than restricting contextual effects to the local areas that people are actually resident in. This might reflect the impact of spillover effects, whereby the actual sphere of influence for residents encompasses neighbouring areas. Additionally, this helps to capture the fact that residents living on the outskirts of a neighbourhood may actually be more affected by the character of an adjacent neighbourhood.

Some attempt was made to control for the fact that neighbourhoods in close proximity to one another are more likely to share similar characteristics by incorporating the clustering of neighbourhoods within broader CDRP. This captures the increased dependency between neighbourhoods that are spatially close to one another. However, using a geographic modelling procedure, it would be possible to accurately link each neighbourhood with its' closest neighbours, and allow fear to vary both as a function of the actual neighbourhood characteristics, and the characteristics of neighbouring neighbourhoods. This was successfully done in a recent study by Wyant (2008), who found evidence of spatial dependency in an unconditional model, showing that neighbourhoods in closer proximity to one another had more similar levels of fear (an effect also demonstrated in this analysis, where significant clustering within CDRP was evident). When this model was extended to try and model this dependency, Wyant failed to identify a significant effect of surrounding neighbourhoods within a full contextual model, suggesting that the ecological model was robust to this additional clustering. This analysis was based on a small sample of 331 respondents from 45 neighbourhoods in a single city, so it is possible that more evidence of spatial dependency would be observed if examined using a larger dataset.

8.5.2 Measuring contextual differences

A second limitation of this analysis stems from the decision to restrict the ecological model to administrative data collected on all residents of the local neighbourhood (with the exception of disorder, which was based on interviewer assessments of the local neighbourhood). Whilst this ensures that the contextual effects are reliably estimated based on the full resident population, it also restricts the analysis to the effect of broad structural characteristics. Using administrative data from the census has enabled an examination of the effect of the structural precursors to social disorganisation, along with the impact of locally recorded crime, however direct measurement of social disorganisation has not been possible. Other social characteristics of local neighbourhoods are also beyond the scope of this research, with concepts like collective efficacy and social cohesion potentially providing a more detailed picture of how residents fear of crime is affected by the neighbourhood in which they live. It is also likely that other interactions between individuals and their social contexts would be identified if a more detailed set of neighbourhood measures were incorporated.

Coupled with the inability to examine more complex social processes operating at the neighbourhood level when relying on complete census data, the lack of available CDRP level data has restricted the focus of the contextual models to neighbourhood effects. The initial models from chapter 4 demonstrated that CDRP also made a significant contribution to the unexplained variability in fear of crime, indicating that more information about the utility of CDRP level crime reduction initiatives could have been gained if a full CDRP model was constructed. Without suitable and complete CDRP data, the current analysis fails to successfully capitalise on this additional level of clustering, which currently acts only as a control for the dependency between neighbourhoods in close proximity to one another. The interviewer models estimated in chapter 7 would also benefit from a more extended list of interviewer level variables, with the current models restricted to some basic demographic information. Including a range of attitudinal measures alongside these basic demographics might help to identify other important interviewer effects.

8.5.3 Selection bias

A final limitation of this thesis is that it may not fully account for the problem of selection bias (discussed in detail in chapter 4). Essentially, selection bias refers to the inability to be sure that observed neighbourhood effects are the result of neighbourhoods, rather than the result of particular types of individuals selecting themselves into particular types of neighbourhood (Oakes, 2004). A number of alternative methods of dealing with this problem were identified, including the use of randomised experiments, and the incorporation of instrumental variables. However, as a result of data limitations, these more thorough methods were not available for the current analysis. Instead, the potential influence of selection bias was dealt with by incorporating a range of individual level control variables, including marital status, socio-economic status, and education level, all of which have been linked to increased social mobility (Buck, 2001). This has gone some way to ensuring that the results from the ecological model are a real reflection of contextual effects, rather than the differential selection of individuals into different neighbourhoods, yet there is still the possibility that the results are being influenced by unmeasured selection processes.

8.6 Future work

The current thesis represents an important starting point for the integration of individual and contextual models of fear of crime. Additionally, this has identified the important role of interviewer variations to differences in fear of crime, outlining a methodology that enables us to get closer to separating the influence of interviewers from the influence of survey clustering. These models demonstrated the additional insight that can be gained about the social processes influencing fear of crime. However, there are a number of clear areas where this research could profitably be extended.

8.6.1 A closer look at neighbourhood definitions

As I noted above, one of the limitations with the current research design is that the findings are dependent on the neighbourhood definition that has been utilised, with different spatial scales potentially resulting in a different set of neighbourhood indices being identified, and different relationships observed with fear of crime. To better understand the potential effect of the MAUP, the current thesis could be extended by assessing a range of different spatial scales. Looking at a smaller neighbourhood definition like LSOA would be informative, whilst wards, postcode sectors and Local Authorities could also be examined. This would require census data to be made available at a lower spatial scale than was possible for the current analysis, along with geographic identifiers at each of these spatial scales within the BCS sample.

The effect of neighbouring local areas could also be fruitfully examined, representing a more detailed geographic model of contextual effects. New advances in Geographic Information Systems software have made this type of design tenable, allowing researchers to develop an 'adjacency matrix' that details all of the neighbourhoods that surround each local area (Rasbash et al., 2004). It would then be possible to incorporate this adjacency matrix within the multilevel modelling approach to capture the influence of spatial dependency.

8.6.2 The multilevel structural equation model

In chapter 4 I noted the possibility of examining contextual effects within a multilevel SEM framework. This recent extension to SEM methodology makes it possible to correct for measurement error within the same estimation step as the estimation of contextual effects, improving the efficiency of estimates. It would therefore be informative to examine what impact this has on the interpretation of the individual and contextual fear of crime models. An added benefit of adopting a multilevel SEM approach is that it is possible to include contextual effects that are constructed from individual level data in a more efficient manner than simply aggregating individual level responses (Ludtke et al., 2007). Consequently, subsequent research could examine more detailed models that incorporate the impact of the social structure of the local neighbourhood, alongside the basic structural dimensions derived from the census. The multilevel SEM is a very recent modelling procedure that is limited to data measured at two levels. As a result, this analysis would have to omit the added influences of CDRP and interviewer clustering.

8.6.3 Extending the interviewer model

One of the principle outcomes of this thesis was the large contribution of interviewer differences to the unexplained variation in fear of crime. This variation was modelled as a function of some basic interviewer characteristics including their gender, ethnicity and age. Subsequent research could advance the existing analysis by extending the range of interviewer characteristics that are incorporated within the analysis, including information about interviewer technique, workload, and attitudinal responses. This would enable a more detailed assessment of how interviewers affect levels of fear of crime. Additionally, it would be beneficial to extend the scope of the current analysis to examine the relative contribution of interviewer differences to a range of other survey outcomes, mirroring the assessments of O'Muircheartaigh and Campanelli (1998), and Schnell and Kreuter (2006) on a considerably larger dataset. This would help identify whether the neighbourhood contribution has been routinely overestimated, or whether the fear of crime is particularly susceptible to the influence of interviewers.

8.6.4 Developing a better understanding of the relationship between ethnicity, diversity and fear

The random coefficients models estimated in chapter 6 demonstrated that the size of the difference in fear between BME groups and White people varied considerably across neighbourhoods. This was partially accounted for by incorporating the differential effect of ethnic diversity, however considerable variance remained at the neighbourhood level for BME residents. This unexplained variability could be examined in more detail to provide a clearer picture of the contextual influences on the fear of crime of BME residents. Using the BCS ethnic boost sample, it would be possible to examine more carefully how context affects BME residents, with the larger sample within each neighbourhood presenting additional opportunities to explore why such large variation across neighbourhoods exists. This would also allow an examination of the variability in the size of the difference in fear between different BME groups within each larger ethnic category, providing a more detailed treatment of ethnicity than the simple distinction between White, Black, Asian and mixed or other ethnic groups.

8.6.5 A missing level?

Finally, multilevel modelling might also be successfully used to examine the effect of differences at the household level on fear of crime, serving as an additional source of useful information about the contextual influences on fear. The use of multilevel models to examine the importance of household factors on social outcomes is beginning to occur in other disciplines, including politics (Johnston et al., 2005b) and medical research (Butterworth et al., 2006; Rice et al., 1998), where they are consistently identified as influential, but this has yet to be applied to fear of crime. This is despite household characteristics like socio-economic status and marital status featuring regularly within individual level treatments of fear of crime. This failure to accurately incorporate household level effects reflects the lack of suitable household data, with the current BCS sample design preventing analyses of fear of crime from being conducted at the household level, with a single household member selected for interview within each sampled address. Consequently, it may be beneficial for the BCS to incorporate a household design in future waves, whereby each household member is interviewed about their experiences of, and attitudes towards, crime and the criminal justice system. In particular, the household level may be influential for fear of household crime, where anticipated victimisation experiences will be shared by all household members.

REFERENCE LIST

Ackah, Y. (2000). Fear of Crime among an Immigrant Population in the Washington DC Metropolitan Area. *Journal of Black Studies, 30,* 553-573.

Adams, R. E. & Serpe, R. T. (2000). Social Integration, Fear of Crime, and Life Satisfaction. *Sociological Perspectives, 43,* 605-629.

Agnew, R. S. (1985). Neutralising the Impact of Crime. *Criminal Justice and Behaviour, 12,* 221-239.

Agresti, A. & Finlay, B. (1997). *Statistical Methods for the Social Sciences.* (3 ed.) New Jersey: Prentice Hall International, Inc.

Alker, H. R. (1969). A Typology of Ecological Fallacies. In M.Dogan & S. Rokkan (Eds.), *Quantitative Ecological Analysis in the Social Sciences* (pp. 69-86). Cambridge, Massachusetts: M.I.T. Press.

Allen, J. (2006). *Worry about Crime in England and Wales: Findings from the 2003/04 and 2004/05 British Crime Survey* (Rep. No. 15/06). Home Office.

Alvarez, A. & Bachman, R. (1997). Predicting the Fear of Assault at School and While Going To and From School in an Adolescent Population. *Violence and Victims, 12,* 69-85.

Angrist, J. D. & Krueger, A. B. (2001). Instrumental Variables and the Search for Identification: From Supply and Demand to Natural Experiments. *Journal of Economic Perspectives, 15,* 69-85.

Arnold, H. (1991). Fear of Crime and Its Relationship to Directly and Indirectly Experienced Victimisation: A Binational Comparison of Models. In K.Sessar & H. J. Kerner (Eds.), *Developments in Crime and Crime Control Research: German Studies on Victims, Offenders, and the Public* (pp. 87-125). New York: Springer-Verlag.

Babb, P., Butcher, H., Church, J., & Zealey, L. (2007). *Social Trends* (Rep. No. 36). Palgrave, Macmillan.

Bailar, B., Bailey, L., & Stevens, J. (1977). Measures of Interviewer Bias and Variance. *Journal of Marketing Research, 14,* 337-343.

Bailey, L., Moore, T. F., & Bailar, B. (1978). An Interviewer Variance Study for the Eight Impact Cities of the National Crime Survey Cities Sample. *Journal of American Statistical Association, 73,* 16-23.

Baker, M. H., Nienstedt, B. C., Everett, R. S., & McCleary, R. (1983). The Impact of a Crime Wave: Perceptions, Fear, and Confidence in the Police. *Law and Society Review, 17,* 319-336.

Bankston, W. B., Jenkins, Q. A. L., Thayer-Doyle, C. L., & Thompson, C. Y. (1987). Fear of Criminal Victimization and Residential Location: The Influence of Perceived Risk. *Rural Sociology, 32,* 98-107.

Beirne, P. (1993). *Inventing Criminology: Essays on the Rise of 'Homo Criminalis'.* Albany, New York: State University of New York Press.

Beylea, M. J. & Zingraff, M. T. (1988). Fear of Crime and Residential Location. *Rural Sociology, 33,* 479-486.

Biderman, A. D., Johnson, L. A., McIntyre, J., & Weir, A. W. (1967). *Report on a Pilot Study in the District of Columbia on Victimisation and Attitudes toward Law Enforcement.* (Rep. No. Field Surveys I). Washington D.C: U.S. Government Printing Office.

Bitler, M. P. & Wolken, J. D. (2007). *Effects of the Level of Interviewer Effort on the Characteristics of Completed Responses: An Experiment Using the 1998 Survey of Small Business Finances* (Rep. No. 34). Federal Committee on Statistical Methodology.

Blair, T. (1997). Labour Party Brighton Conference. http://www.prnewswire.co.uk/cgi/news/release?id=47983 [On-line].

Bolling, K., Grant, C., & Donovan, J.-L. (2008). *2007-08 British Crime Survey (England and Wales): Technical Report Volume 1* London: Home Office.

Box, S., Hale, C., & Andrews, G. (1988). Explaining Fear of Crime. *British Journal of Criminology, 28,* 340-356.

Box, S., Hale, C., & Pack, P. (1987). *Victimisation and Fear of Crime* University of Kent Applied Statistics Research Unit Report to the Home Office.

Brown, G. (2008). July Press Conference. http://www.number10.gov.uk/Page16320 [On-line].

Browne, W. J. (2005). *MCMC Estimation in Mlwin: Version 2.0.* (2 ed.) Bristol: Centre of Multilevel Modelling: University of Bristol.

Buck, N. (2001). Identifying Neighbourhood Effects on Social Exclusion. *Urban Studies, 38,* 2251-2275.

Bursik, R. J. (1988). Social Disorganisation and Theories of Crime and Delinquency: Problems and Prospects. *Criminology, 26,* 519-551.

Bursik, R. J. & Grasmick, H. G. (1993). *Neighbourhoods and Crime: The Dimensions of Effective Community Control.* New York: Lexington Books.

Butterworth, P., Rodgers, B., & Jorm, A. F. (2006). Examining Geographical and Household Variation in Mental Health in Australia. *Australian and New Zealand Journal of Psychiatry, 40,* 491-497.

Campanelli, P., Sturgis, P., & Purdon, S. (1997). *Can You Hear Me Knocking: An Investigation into the Impact of Interviewers on Survey Response Rates* The Survey Methods Centre at SCPR.

Cannell, C. F., Miller, P. V., & Oksenberg, L. (1981). Research on Interviewing Techniques. In S.Leinhardt (Ed.), *Sociological Methodology* (pp. 389-437). San Francisco: Jossy-Bass.

Carr, P. (2005). *Clean Streets: Controlling Crime, Maintaining Order and Building Community Activism*. New York: New York University Press.

Chaddee, D. & Ditton, J. (2003). Are Older People Most Afraid of Crime? Revisiting Ferraro and LaGrange in Trinidad. *British Journal of Criminology, 43,* 417-433.

Chandola, T. (2001). The Fear of Crime and Area Differences in Health. *Health and Place, 7,* 105-116.

Chaskin, R. (1998). Defining Neighbourhoods. In *American Planning Association Casey Symposium on Indicators*.

Chiricos, T., Eschholz, S., & Gertz, M. (1997). Crime, News and Fear of Crime: Toward an Identification of Audience Effects. *Social Problems, 44,* 342-357.

Chiricos, T., McEntire, R., & Gertz, M. (2001). Perceived Racial and Ethnic Composition of Neighborhood and Perceived Risk of Crime. *Social Problems, 48,* 322-340.

Clarke, A. & Lewis, M. J. (1982). Fear of Crime among the Elderly: An Exploratory Study. *British Journal of Criminology, 22,* 49-62.

Clemente, F. & Kleiman, M. B. (1977). Fear of Crime in the United States: A Multivariate Analysis. *Social Forces, 56,* 519-531.

Collins, M. & Butcher, B. (1982). Interviewer and Clustering Effects in an Attitude Survey. *Journal of the Market Research Society, 25,* 39-58.

Covington, J. & Taylor, R. B. (1991). Fear of Crime in Urban Residential Neighbourhoods: Implications of Between- and Within- Neighbourhood Sources for Current Models. *The Sociological Quarterly, 32,* 231-249.

Crawford, A. (2003). The Pattern of Policing in the UK: Policing Beyond the Police. In T.Newburn (Ed.), *The Handbook of Policing* (pp. 136-168). Collumpton: Willan.

Crowne, D. P. & Marlowe, D. (1960). A New Scale of Social Desirability Independent of Psychopathology. *The Journal Of Consulting Psychology, 24,* 349-354.

Ditton, J., Chaddee, D., Farrall, S., Gilchrist, E., & Bannister, J. (2004). From Imitation to Intimidation: A Note on the Curious and Changing Relationship between the Media, Crime and Fear of Crime. *British Journal of Criminology, 44,* 595-610.

Ditton, J. & Farrall, S. (2007). The British Crime Survey and the Fear of Crime. *Crime Prevention Studies, 22,* 223-242.

Dohrenwend, B. S., Colombotos, J., & Dohrenwend, B. P. (1968). Social Distance and Interviewer Effects. *Public Opinion Quarterly, 32,* 410-422.

Donnelly, P. G. (1988). Individual and Neighbourhood Influences on Fear of Crime. *Sociological Focus, 22,* 69-85.

Dubow, F., McCabe, E., & Kaplan, G. (1979). *Reactions to Crime: A Critical Review of the Literature* Washington, D.C: U.S. Government Printing Office.

Elffers, H. (2003). Analysing Neighbourhood Influence in Criminology. *Statistica Neerlandica, 57,* 347-367.

Ellaway, A. & McIntyre, S. (1998). Does Housing Tenure Predict Health in the UK because it Exposes People to Different Levels of Housing Related Hazards in the Home or its Surroundings? *Health and Place, 4,* 141-150.

Emsley, C. (1987). *Crime and Society in England 1750-1900.* New York: Longman.

Ennis, P. H. (1967). *Criminal Victimisation in the United States: A Report of a National Survey* (Rep. No. Field Surveys II). Washington D.C: U.S. Government Printing Office.

Ericson, R. (1991). Mass Media, Crime, Law, and Justice. *British Journal of Criminology, 31,* 219-249.

Eschholz, S., Chiricos, T., & Gertz, M. (2003). Television and Fear of Crime: Program Types, Audience Traits, and the Mediating Effect of Perceived Neighborhood Racial Composition. *Social Problems, 50,* 395-415.

Farrall, S. (2004). Revisiting Crime Surveys: Emotional Reponses without Emotion? OR Look Back at Anger. *International Journal of Social Research Methodology, 7,* 157-171.

Farrall, S., Bannister, J., Ditton, J., & Gilchrist, E. (1997). Questioning the Measurement of the Fear of Crime: Findings from a Methodological Study. *British Journal of Criminology, 37,* 657-678.

Farrall, S. & Ditton, J. (1999). Improving the Measurement of Attitudinal Responses: An Example from a Crime Survey. *Social Research Methodology, 2,* 55-68.

Farrall, S. & Gadd, D. (2004a). Evaluating Crime Fears: A Research Note on a Pilot Study to Improve the Measurement of the 'Fear of Crime' as a Performance Indicator. *Evaluation, 10,* 493-502.

Farrall, S. & Gadd, D. (2004b). Research Note: The Frequency of the Fear of Crime. *British Journal of Criminology, 44,* 127-132.

Farrall, S., Gray, E., & Jackson, J. (2006). Combining the New and Old Measures of the Fear of Crime: Exploring the 'Worried Well'. *ESRC Research Methods Programme Working Paper, 4.*

Fattah, E. A. (1993). Research on Fear of Crime: Some Common Conceptual and Measurement Problems. In W.Bilsky, C. Pfeiffer, & P. Wetzels (Eds.), *Fear of Crime and Criminal Victimisation* (Stuttgart: Ferdinand Enke Verlag.

Fattah, E. A. & Sacco, V. F. (1989). *Crime and Victimisation of the Elderly*. New York: Springer-Verlag.

Fellegi, I. P. (1964). Response Variance and its Estimation. *Journal of American Statistical Association, 59,* 1016-1041.

Ferraro, K. F. (1995). *Fear of Crime: Interpreting Victimization Risk*. Albany, New York: State University of New York Press.

Ferraro, K. F. (1996). Women's Fear of Victimisation: Shadow of Sexual Assault? *Social Forces, 75,* 667-690.

Ferraro, K. F. & LaGrange, R. (1987). The Measurement of Fear of Crime. *Sociological Inquiry, 57,* 70-101.

Ferraro, K. F. & LaGrange, R. (1992). Are Older People More Afraid of Crime? Reconsidering Age Differences in Fear of Victimisation. *Journal of Gerontology, 47,* -233.

Figgie, H. E. (1980). *The Figgie Report on Fear of Crime: America Afraid* (Rep. No. Part 1: The General Public). Willloughby, Ohio: A-T-O Inc.

Finkel, S. E., Guterbock, T. M., & Borg, M. J. (1991). Race-of-Interviewer Effects in a Pre-election Poll. *Public Opinion Quarterly, 55,* 313-330.

Fisher, B. & Nasar, J. L. (1995). Fear Spots in Relation to Microlevel Physical Cues: Exploring the Overlooked. *Journal of Research in Crime and Delinquency, 32,* 214-239.

Fitzgerald, M. & Hale, C. (1996). *Ethnic Minorities: Victimisation and Racial Harassment: Findings from the 1988 and 1992 British Crime Survey* (Rep. No. 134). Home Office Research and Statistics Directorate.

Fowler, F. J. J. & Mangione, T. W. (1985). *The Value of Interviewer Training and Supervision*.

Ganninger, M., Hader, S., & Gabler, S. (2007). *Design Effects and Interviewer Effects in the European Social Survey: Where are we now and where do we want to go tomorrow?* Mannheim, Germany: Centre for Survey Research and Methodology (ZUMA).

Garofalo, J. (1981). The Fear of Crime: Causes and Consequences. *Journal of Criminal Law and Criminology, 72,* 839-857.

Garofalo, J. & Laub, J. (1978). The Fear of Crime: Broadening our Perspective. *Victimology, 3,* 242-253.

Gerbner, G. & Gross, L. P. (1976). Living with Television: the Violence Profile. *Journal of Communication, 26,* 172-199.

Gerbner, G., Gross, L. P., Morgan, M., & Signorelli, N. (1980). The 'Mainstreaming' of American: Violence Profile no.11. *Journal of Communication, 30,* 10-27.

Gibbons, S., Green, A., Gregg, P., & Machin, S. (2005). Is Britain Pulling Apart? Area Disparities in Employment, Education and Crime. *CMPO Working Paper Series, 5.*

Gill, M. & Spriggs, A. (2005). *Assessing the Impact of CCTV* (Rep. No. 292). London: Home Office Research, Development and Statistics Directorate.

Goldstein, H. (2003). *Multilevel Statistical Models.* (3 ed.) London: Arnold.

Gomme, I. M. (1986). Fear of Crime amongst Canadians: A Multivariate Analysis. *Journal of Criminal Justice, 14,* 249-258.

Goodey, J. (1997). Boys Don't Cry: Masculinities, Fear of Crime and Fearlessness. *British Journal of Criminology, 37,* 401-418.

Graber, D. (1980). *Crime News and the Public.* New York: Praeger.

Grant, C., Harvey, A., Bolling, K., & Clemens, S. (2006). *2004-5 British Crime Survey (England and Wales): Technical Report Volume 1* Home Office.

Griffith, D. A., Wong, D. W. S., & Whitfield, T. (2003). Exploring Relationships Between the Global and Regional Measures of Spatial Autocorrelation. *Journal of Regional Science, 43,* 683-710.

Groves, R. M. (1989). *Survey Errors and Survey Costs.* New York: John Wiley & Sons.

Groves, R. M. & Couper, M. P. (1998). *Non-response in Household Interview Surveys.* New York: John Wiley and Sons.

Groves, R. M., Fowler, F. J. J., Couper, M. P., Lepkowski, J. M., Singer, E., & Tourangeau, R. (2004). *Survey Methodology.* (1 ed.) Hoboken, New Jersey: John Wiley and Sons.

Groves, R. M. & Magilavy, L. J. (1986). Measuring and Explaining Interviewer Effects in Centralised Telephone Surveys. *Public Opinion Quarterly, 50,* 251-266.

Gunter, B. (1987). *Television and the Fear of Crime.* London: John Libbey.

Hale, C. (1996). Fear of Crime: A Review of the Literature. *International Review of Victimology, 4,* 79-150.

Hale, C., Pack, P., & Salkfeld, J. (1994). The Structural Determinants of Fear of Crime: An Analysis Using Census and Crime Survey Data from England and Wales. *International Review of Victimology, 3,* 211-233.

Hanmer, J. & Saunders, S. (1984). *Well Founded Fear*. London: Hutchinson.

Harding, D. J. (2003). Counterfactual Models of Neighbourhood Effects: The Effect of Neighbourhood Poverty on Dropping Out and Teenage Pregnancy. *American Journal of Sociology, 109,* 676-719.

Heath, L. (1984). Impact of Newspaper Crime Reports on Levels of Fear of Crime: Multimethodological Investigation. *Journal of Personality and Social Psychology, 47,* 263-276.

Herbert, S. (2005). *Citizens, Cops and Power*. Chicago: University of Chicago Press.

Hollway, W. & Jefferson, T. (1997). The Risk Society in an Age of Anxiety: Situating Fear of Crime. *The British Journal of Sociology, 48,* 255-266.

Hough, M. (1985). The Impact of Victimisation: Findings from the British Crime Survey. *Victimology: An International Journal, 8,* 488-497.

Hough, M. (1995). *Anxiety about Crime: Findings From the 1994 British Crime Survey* (Rep. No. 147). London: Home Office.

Hough, M. (2004). Worry About Crime: Mental States or Mental Events. *International Journal of Social Research Methodology, 7,* 173-176.

Hough, M., Lewis, H., & Walker, N. (1988). Factors Associated with 'Punitiveness' in England and Wales. In M.Hough & N. Walker (Eds.), *Public Attitudes to Sentencing: Surveys from Five Countries* (1 ed., pp. 203-217). Aldershot: Gower.

Hough, M. & Mayhew, P. (1983). *The British Crime Survey: First Report* (Rep. No. 76). London: Home Office.

Howitt, D. (1998). *Crime, The Media and The Law*. London: Wiley.

Hox, J. J. (1994). Hierarchical Regression Models for Interviewer and Respondent Effects. *Sociological Methods and Research, 22,* 300-318.

Hox, J. J. (2002). *Multilevel Analysis: Techniques and Applications*. MahWah, New Jersey: Lawrence Erlbaum Associates.

Hox, J. J., de Leeuw, E., & Kreft, I. G. G. (1991). The Effect of Interviewer and Respondent Characteristics on the Quality of Survey Data: A Multilevel Model. In P.P.Biemer, R. M. Groves, L. E. Lyberg, N. A. Mathiowetz, & S. Sudman (Eds.), *Measurement Errors in Surveys* (pp. 439-459). New York: John Wiley & Sons.

Hunter, A. (1978). *Symbols of Incivility: Social Disorder and Fear of Crime in Urban Neighbourhoods* NCJRS.

Hutchinson Wallace, L. & May, D. C. (2005). The Impact of Parental Attachment and Feelings of Isolation on Adolescent Fear of Crime at School. *Adolescence, 40,* 457-474.

Illner, M. (1998). The Changing Quality of Life in a Post Communist Country: The case of Czech Republic. *Social Indicators Research, 43,* 141-170.

Innes, M. (2004). Signal Crimes and Signal Disorders: Notes on Deviance as Communicative Action. *British Journal of Sociology, 55,* 335-355.

Jackson, J. (2004). Experience and Expression: Social and Cultural Significance in the Fear of Crime. *British Journal of Criminology, 44,* 946-966.

Jackson, J. (2005). Validating New Measures of the Fear of Crime. *International Journal of Social Research Methodology, 8,* 297-315.

Jackson, J. (2006). Introducing Fear of Crime to Risk Research. *Risk Analysis, 26,* 253-264.

Jackson, J., Farrall, S., & Gray, E. (2006). The provenance of fear. *ESRC Research Methods Programme Working Paper, 2.*

Jackson, J., Kuha, J., & Farrall, S. (2007). Measuring the Fear of Crime. *Working Paper.*

Jensen, G. (2005). Social Disorganisation Theory. In R.A.Wright & J. M. Miller (Eds.), *Encyclopedia of Criminology* (New York: Routledge.

Johnston, L. (2001). Crime, Fear and Civil Policing. *Urban Studies, 38,* 956-976.

Johnston, R., Jones, K., Burgess, S., Propper, C., Sarker, R., & Bolster, A. (2005a). Fractal Factors? Scale, Factor Analyses and Neighbourhood Effects. *ESRC Research Methods Programme Working Paper, 2.*

Johnston, R., Jones, K., Sarker, R., Burgess, S., Propper, C., & Bolster, A. (2005b). A Missing Level in the Analysis of British Voting Behaviour: The Household as Context as Shown by Analyses of a 1992-1997 Longitudinal Survey. *ESRC Research Methods Programme Working Paper, 3.*

Johnston, R., Jones, K., Sarker, R., Burgess, S., Propper, C., & Bolster, A. (2005c). Party Support and the Neighbourhood Effect: Spatial Polarisation of the British Electorate, 1999-2001. *ESRC Research Methods Programme Working Paper, 4.*

Jones, K. & Duncan, C. (1995). Individuals and Their Ecologies: Analysing the Geography of Chronic Illness within a Multilevel Modelling Framework. *Health and Place, 1,* 27-40.

Jones, T., MacLean, B., & Young, J. (1986). *The Islington Crime Survey: Crime, Victimization and Policing in Policing in Inner City London*. Aldershot: Gower.

Kahneman, D. & Krueger, A. B. (2006). Developments in the Measurement of Subjective Wellbeing. *Journal of Economic Perspectives, 20,* 3-24.

Kahneman, D., Slovic, P., & Tversky, A. (1982). *Judgement under Uncertainty: Heuristics and Biases*. Cambridge: Cambridge University Press.

Kanan, J. W. & Pruitt, M. V. (2002). Modeling Fear of Crime and Perceived Victimisation Risk: The (In)significance of Neighbourhood Integration. *Sociological Inquiry, 72,* 527-548.

Kearns, A. & Parkinson, M. (2001). The Significance of Neighbourhood. *Urban Studies, 38,* 2103-2110.

Kershaw, C., Nicholas, S., & Walker, A. (2008). *Crime in England and Wales 2007/08* (Rep. No. 14/08). London: Home Office.

Kershaw, C. & Tseloni, A. (2005). *Predicting Crime Rates, Fear and Disorder Based on Area Information: Evidence from the 2000 British Crime Survey* London: Home Office.

Killias, M. (1990). Vulnerability: Towards a Better Understanding of a Key Variable in the Genesis of Fear of Crime. *Violence and Victims, 5,* 97-108.

Killias, M. & Clerici, C. (2000). Different Measures of Vulnerability in their Relation to Different Dimensions of Fear of Crime. *British Journal of Criminology, 40,* 437-450.

Kinsey, R. (1984). *The Merseyside Crime Survey, First Report* Liverpool: Merseyside Metropolitan Council.

Kish, L. (1962). Studies of Interviewer Variance for Attitudinal Variables. *Journal of American Statistical Association, 57,* 92-115.

Kish, L. (1967). *Survey Sampling.* (2 ed.) New York, London, Sydney: John Wiley and Sons, Inc.

Kling, J. B., Liebman, J. B., & Katz, L. F. (2005). *Experimental Analysis of Neighbourhood Effects*.

Kling, J. B., Liebman, J. B., Katz, L. F., & Sanbonmatsu, L. (2004). *Moving to Opportunity and Tranquillity: Neighbourhood Effects on Adult Economic Self-Sufficiency and health from a randomized housing voucher experiment* Princeton, New Jersey: Princeton University.

Krannich, R. S., Berry, E. H., & Greider, T. (1989). Fear of Crime in Rapidly Changing Rural Communities: A Longitudinal Analysis. *Rural Sociology, 54,* 195-212.

Krannich, R. S., Greider, T., & Little, R. L. (1985). Rapid Growth and Fear of Crime: A Four Community Comparison. *Rural Sociology, 30,* 195-209.

LaGrange, R. & Ferraro, K. F. (1987). The Elderly's Fear of Crime: A Critical Examination of the Research. *Research on Aging, 9,* 372-391.

Lane, J. & Meeker, J. W. (2003a). Ethnicity, Information Sources and Fear of Crime. *Deviant Behaviour, 24,* 1-26.

Lane, J. & Meeker, J. W. (2003b). Fear of Gang Crime: A Look at Three Theoretical Models. *Law and Society Review, 37,* 425-436.

Lawton, M. P. & Yaffe, S. (1980). Victimisation and Fear of Crime in Elderly Public Housing Tenants. *Journal of Gerontology, 35,* 768-779.

Lebel, A., Pampalon, R., & Villeneuve, P. Y. (2007). A Multi-Perspective Approach for Defining Neighbourhood Units in the Context of Health Inequalities in the Quebec City Region. *International Journal of Health Geographics, 6,* 1-15.

Lebowitz, B. (1975). Age and Fearfulness: Personal and Situational Factors. *Journal of Gerontology, 30,* 696-700.

Lee, G. R. (1982). Residential Location and Fear of Crime Among the Elderly. *Rural Sociology, 47,* 655-669.

Lee, M. (1999). The Fear of Crime and Self-Governance: Towards a Genealogy. *The Australian and New Zealand Journal of Criminology, 32,* 227-246.

Lee, M. (2001). The Genesis of Fear of Crime. *Theoretical Criminology, 5,* 467-485.

Lee, M. (2007). *Inventing Fear of Crime: Criminology and the Politics of Anxiety*. Portland, Oregon: Willan Publishing.

Lewis, D. A. & Maxfield, M. G. (1980). Fear in the neighbourhoods: An investigation of the impact of crime. *Journal of Research in Crime and Delinquency, 17,* 160-189.

Lewis, D. A. & Salem, G. (1986). *Fear of Crime: Incivility and the Production of a Social Problem*. New Brunswick: Transaction Books.

Liska, A. E. (1990). The Significance of Aggregate Dependent Variables and Contextual Independent Variables for Linking Macro and Micro Theories. *Social Psychology Quarterly, 53,* 292-301.

Liska, A. E. & Baccaglini, W. (1990). Feeling Safe by Comparison: Crime in the Newspapers. *Social Problems, 37,* 360-374.

Liska, A. E., Lawrence, J. J., & Sanchiricom, A. (1982). Fear of crime as a social fact. *Social Forces, 60,* 760-770.

Lowenkamp, C. T., Cullen, F. T., & Pratt, T. C. (2003). Replicating Sampson and Groves's Test of Social Disorganisation Theory: Revisiting a Criminological Classic. *Journal of Research in Crime and Delinquency, 40,* 351-373.

Lowry, D. T., Ching, T., Nio, J., & Leitner, D. W. (2003). Setting the Public Fear Agenda: A Longitudinal Analysis of Network TV Crime Reporting, Public Perceptions of Crime, and FBI Crime Statistics. *Journal of Communication,* 61-73.

Ludtke, O., Marsh, H. W., Robitzsch, A., Trautwein, U., Asparouhov, T., & Muthén, B. (2007). *The Multilevel Latent Covariate Model: A New, more Reliable Approach to Group-Level Effects in Contextual Studies.*

Lupton, D. & Tulloch, J. (1999). Theorizing Fear of Crime: Beyond the Rational/Irrational Opposition. *British Journal of Sociology, 50,* 507-523.

Lupton, R. (2003). *'Neighbourhood Effects': Can We Measure them and does it Matter?* (Rep. No. 73). London: London School of Economics.

Lynn, P. (1998). The British Crime Survey Sample: A Response to Elliot and Ellingworth. *Sociological Research Online, 3.*

Lynn, P. & Elliot, D. (2000). *The British Crime Survey: A Review of Methodology* London: National Centre for Social Research.

Maas, C. J. M. & Hox, J. J. (2005). Sufficient Sample Sizes for Multilevel Modelling. *Methodology, 1,* 86-92.

Macallister, I., Johnston, R., Pattie, C., Tunstall, H., Dorling, D., & Rossiter, D. (2001). Class Dealignment and the Neighbourhood Effect: Miller Revisited. *British Journal of Political Science, 31,* 41-60.

Maccoby, E. (2000). Perspectives on Gender Development. *International Journal of Behavioural Development, 24,* 398-406.

Maguire, M. (2007). Crime Data and Statistics. In M.Maguire, R. Morgan, & R. Reiner (Eds.), *The Oxford Handbook of Criminology* (4 ed., pp. 241-300). Oxford: Oxford University Press.

Mahalanobis, P. C. (1946). Recent Experiments in Statistical Sampling in the Indian Statistical Institute. *Journal of the Royal Statistics Society, 109,* 325-378.

Marquis, K. H. & Cannell, C. F. (1969). *A Study of Interviewer-Respondent Interaction in the Urban Employment Surveys*. Michigan: Ann Arbor, Institute for Research.

Marsh, H. L. (1991). A Comparative Analysis of Crime Coverage in Newspapers in the United States and Other Countries From 1960-1989: A review of the Literature. *Journal of Criminal Justice, 19,* 67-80.

Martin, D. (1998). 2001 Census Output Areas: From Concept to Prototype. *Population Trends, 94,* 19-24.

Martin, D. (2001). Geography for the 2001 Census in England and Wales. *ONS.*

Mawby, R. I. (1988). Age, Vulnerability and the Impact of Crime. In M.Maguire & J. Pointing (Eds.), *Victims of Crime: A New Deal?* (1 ed., pp. 127-137). Milton Keynes: Open University Press.

Maxfield, M. G. (1984). *Fear of Crime in England and Wales* (Rep. No. 78). London: Home Office.

Maxfield, M. G. (1987). *Explaining Fear of Crime: Evidence from the 1984 British Crime Survey* (Rep. No. 43). London: Home Office.

May, D. C. & Dunaway, R. G. (2000). Predictors of Fear of Crime Among Adolescents. *Sociological Spectrum, 20,* 149-168.

May, D. C., Vartanian, L. R., & Virgo, K. (2002). The Impact of Parental Attachment and Supervision on Fear of Crime Among Adolescent Males. *Adolescence, 37,* 267-289.

Mayhew, P. & Hough, M. (1988). The British Crime Survey: Origins and Impact. In M.Maguire & J. Pointing (Eds.), *Victims of Crime: A New deal?* (1 ed., pp. 156-163). Milton Keynes: Open University Press.

McCoy, H. V., Wooldredge, J., Cullen, F. T., Durbeck, P. J., & Browning, S. L. (1996). Lifestyles of the Old and Not So Fearful: Life Situation and Older Persons' Fear of Crime. *Journal of Criminal Justice, 24,* 191-205.

McGarrell, E. F., Giacomazzi, A., & Thurman, Q. C. (1997). Neighbourhood Disorder, Integration, and the Fear of Crime. *Justice Quarterly, 14,* 479-500.

McIntyre, J. (1967). Public attitude toward crime and law enforcement. *Annals of the American Academy of Political and Social Science, 374,* 34-46.

Merry, S. E. (1981a). Defensible Space Undefended: Social Factors in Crime Control Through Environmental Design. *Urban Affairs Review, 16,* 397-422.

Merry, S. E. (1981b). *Urban Danger: Life in a Neighbourhood of Strangers*. Philadelphia: Temple University Press.

Miethe, T. D. & Lee, G. R. (1984). Fear of Crime Among Older People: A Reassessment of the Predictive Power of Crime Related Factors. *The Sociological Quarterly, 25,* 397-415.

Miethe, T. D. & Mcdowall, D. (1993). Contextual Effects in Models of Victimisation. *Social Forces, 71,* 741-759.

Miller, J. J. (1977). Asymptotic Properties of Maximum Likelihood Estimates in the Mixed Model of the Analysis of Variance. *The Annals of Statistics, 5,* 746-762.

Millie, A. & Herrington, V. (2005). Bridging the Gap: Understanding Reassurance Policing. *The Howard Journal, 44,* 41-56.

Moore, S. & Shepherd, J. (2007). The Elements and Prevalence of Fear. *British Journal of Criminology, 47,* 154-162.

Morenoff, J. D. & Sampson, R. J. (1997). Violent Crime and the Spatial Dynamics of Neighbourhood transition: Chicago, 1970-1990. *Social Forces, 76,* 31-64.

Moser, C. O. N. & Kalton, G. (1971). *Survey Methods in Social Investigation.* (2 ed.) Gower.

Muthén, L. & Muthén, B. (2007). *Mplus: Statistical Analysis with Latent Variables User's Guide.* (5 ed.) Los Angeles, CA: Muthén and Muthén.

Myung, I. J. (2003). Tutorial on Maximum Likelihood Estimation. *Journal of Mathematical Psychology, 47,* 90-100.

Nayak, A. (2003). Through Children's Eyes: Childhood, Place and the Fear of Crime. *Geoforum, 34,* 303-315.

Newburn, T. (2007). *Criminology.* (1 ed.) Devon: Willan Publishing.

Newman, O. (1978). *Defensible Space: Crime Prevention Through Urban Design.* New York: McMillan.

Newman, O. & Franck, K. A. (1982). The Effects of Building Size on Personal Crime and Fear of Crime. *Population and Environment, 5,* 203-220.

Nicholas, S., Kershaw, C., & Walker, A. (2007). *Crime in England and Wales 2006/07* London: Home Office.

Nicholas, S., Povey, D., Walker, A., & Kershaw, C. (2005). *Crime in England and Wales 2004/05* (Rep. No. 11/05). London: Home Office.

Noble, M., Wright, G., Dibben, C., Smith, G., McLennan, D., Anttila, C. et al. (2004). *The English Indices of Deprivation 2004* London: ODPM Publications.

O'Muircheartaigh, C. (1976). Response Errors in an Attitudinal Sample Survey. *Quality and Quantity, 26,* 115.

O'Muircheartaigh, C. & Campanelli, P. (1998). The Relative Impact of Interviewer Effects and Sample Design Effects on Survey Precision. *Journal of the Royal Statistics Society A, 161,* 63-77.

O'Muircheartaigh, C. & Campanelli, P. (1999). A Multilevel Exploration of the Role of Interviewers in Survey Non-Response. *Journal of the Royal Statistics Society A, 152,* 437-446.

Oakes, J. M. (2004). The (Mis)estimation of Neighbourhood Effects: Causal Inference for Practicable Social Epidemiology. *Social Science and Medicine, 58,* 1929-1952.

Oakley, A. (1974). *Housewife*. (1 ed.) London: Allen Lane.

Olson, K. & Peytchev, A. (2007). Effect of Interviewer Experience on Interview Pace and Interviewer Attitudes. *Public Opinion Quarterly, 71,* 273-286.

ONS (2006). Super Output Areas. http://www.statistics.gov.uk/geography/soa.asp [On-line].

Openshaw, S. (1984). *The Modifiable Areal Unit Problem*. Norwich: Geo Books.

Ortega, S. & Myles, J. (1987). Race and Gender Effects on Fear of Crime: An Interactive Model with Age. *Criminology, 25,* 133-152.

Osborn, D. R., Trickett, A., & Elder, R. (1992). Area Characteristics and Regional Variates as Determinants of Area Crime Levels. *Journal of Quantitative Criminology, 8,* 265-285.

Pain, R. H. (1995). Elderly Women and Fear of Violent Crime: The Least Likely Victims? A Reconsideration of the Extent and Nature of Risk. *British Journal of Criminology, 35,* 584-598.

Pain, R. H. (1997). 'Old Age' and Ageism in Urban Research: The Case of Fear of Crime. *International Journal of Urban and Regional Research, 21,* 117-128.

Pantazis, C. (2000). 'Fear of Crime': Vulnerability and Poverty - Evidence from the British Crime Survey. *British Journal of Criminology, 40,* 414-436.

Park, R. (1916). Suggestions for the Investigations of Human Behaviour in the Urban Environment. *American Journal of Sociology, 20,* 577-612.

Perkins, D. D. & Taylor, R. B. (1996). Ecological Assessments of Community Disorder: Their Relationship to Fear of Crime and Theoretical Implications. *American Journal of Community Psychology, 24,* 63-107.

Pickery, J. & Loosveldt, G. (2001). An Exploration of Question Characteristics that Mediate Interviewer Effects on Item Non-Response. *Journal of Official Statistics, 17,* 337-350.

Pickery, J., Loosveldt, G., & Carton, A. (2001). The Effects of Interviewer and Respondent Characteristics on Response Behaviour in Panel Surveys: A Multilevel Approach. *Sociological Methods and Research, 29,* 509-523.

Pointing, J. & Maguire, M. (1988). The Rediscovery of the Crime Victim. In J.Pointing & M. Maguire (Eds.), *Victims of Crime: A New Deal?* (1 ed., pp. 11-16). Milton Keynes: Open University Press.

Propper, C., Jones, K., Bolster, A., Burgess, S., Johnston, R., & Sarker, R. (2005). Local Neighbourhood and Mental Health: Evidence from the UK. *ESRC Research Methods Programme Working Paper, 6.*

Putnam, R. D. (2000). *Bowling Alone - The Collapse and Revival of American Community.* New York: Simon and Schuster.

Putnam, R. D. (2007). E Pluribus Unum: Diversity and Community in the Twenty-first Century. The 2006 Johan Skytte Prize Lecture. *Scandinavian Political Studies, 30,* 137-174.

Quann, N. & Hung, K. (2002). Victimization Experience and the Fear of Crime: A Cross National Study. In P.Niuwbeerta (Ed.), *Crime Victimisation in Comparative Perspective: Results from the International Crime Victims Survey, 1989-2000* (1 ed., pp. 301-316). Boom Juridische Uitgevers.

Rasbash, J., Browne, W. J., Goldstein, H., Yang, M., Plewis, I., Healy, M. et al. (2002). *A User's Guide to Mlwin.* (2 ed.) London: Centre for Multlevel Modelling: Institute of Education.

Rasbash, J., Steele, F., Browne, W. J., & Prosser, B. (2004). *A Users Guide to Mlwin: Version 2.0.* (2 ed.) London: Centre for Multilevel Modelling: Institute of Education.

Rees, P. H. (1971). Factorial Ecology: An Extended Definition, Survey and Critique of the Field. *Economic Geography, 47,* 220-233.

Reiner, R. (1996). Media Made Criminality: The Representation of Crime in the Mass Media. In M.Maguire, R. Morgan, & R. Reiner (Eds.), *The Oxford Handbook of Criminology* (2 ed., pp. 189-232). Oxford: Oxford University Press.

Reiner, R. (2007). Media-made Criminality: The Representation of Crime in the Media. In M.Maguire, R. Morgan, & R. Reiner (Eds.), *The Oxford Handbook of Criminology* (4 ed., pp. 302-340). Oxford: Oxford University Press.

Reiner, R., Livingstone, S., & Allen, J. (2000). No More Happy Endings? The Media and Popular Concern About Crime Since the Second World War. In T.Hope & R. Sparks (Eds.), *Crime, Risk and Insecurity* (1 ed., pp. 107-126). London: Routledge.

Reiss Jr, A. S. (1967). *Studies in Crime and Law Enforcement in Major Metropolitan Areas, Volume I* (Rep. No. Field Surveys III). Washington D.C: U.S. Government Printing Office.

Rice, n., Carr-Hill, R., Dixon, P., & Sutton, M. (1998). The Influence of Households on Drinking behaviour: A Multilevel Analysis. *Social Science and Medicine, 46,* 971-979.

Robinson, J. B., Lawton, B. A., Taylor, R. B., & Perkins, D. D. (2003). Multilevel Longitudinal Impacts of Incivilities: Fear of Crime, Expected Safety, and Block Satisfaction. *Journal of Quantitative Criminology, 19,* 237-274.

Rock, P. (2007). Sociological Theories of Crime. In M.Maguire, R. Morgan, & R. Reiner (Eds.), *The Oxford Handbook of Criminology* (4 ed., pp. 3-42). Oxford: Oxford University Press.

Roh, S. & Oliver, W. M. (2005). Effects of Community Policing Upon Fear of Crime: Understanding the Causal Linkage. *Policing: An International Journal of Police strategies and Management, 28,* 670-683.

Rosenbaum, D. P. (1987). The Theory and Research Behind Neighbourhood Watch: Is it a Sound Fear and Crime Reduction Strategy? *Crime and Delinquency, 33,* 103-134.

Sacco, V. F. (1982). The Effects of Mass media on Perceptions of Crime: A Reanalysis of the Issues. *Pacific Sociological Review, 25,* 475-493.

Sacco, V. F. (1990). Gender, Fear and Victimisation: A Preliminary Application of Power-Control Theory. *Sociological Spectrum, 1,* 485-506.

Sampson, R. J. & Groves, W. B. (1989). Community Structure and Crime: Testing Social Disorganisation Theory. *American Journal of Sociology, 94,* 774-802.

Sampson, R. J., Morenoff, J. D., & Earls, F. (1999). Beyond Social Capital: Spatial dynamics of Collective Efficacy for Children. *American Sociological Review, 64,* 633-660.

Sampson, R. J., Morenoff, J. D., & Gannon-Rowley, T. (2002). Assessing "Neighbourhood Effects": Social Processes and New Directions in Research. *Annual Review of Sociology, 28,* 443-478.

Sampson, R. J. & Raudenbush, S. W. (1999). Systematic Social Observation of Public Spaces: A New Look at Disorder in Urban Neighbourhoods. *American Journal of Sociology, 105,* 603-651.

Sampson, R. J., Raudenbush, S. W., & Earls, F. (1997). Neighbourhoods and Violent Crime: A Multilevel Study of Collective Efficacy. *Science, 277,* 918-924.

Schaeffer, N. C. (1980). Evaluating Race-of-Interviewer Effects in a National Survey. *Sociological Methods and Research, 8,* 400-419.

Schnell, R. & Kreuter, F. (2006). Separating Interviewer and Sampling-Point Effects. *Pre-print version.*

Schreck, C. J. & Miller, J. M. (2003). Sources of Fear of Crime at School: What is the Relative Contribution of Disorder, Individual Characteristics, and School Security? *Journal of School Violence, 2,* 57-77.

Schwarz, N. & Sudman, S. (1995). *Answering Questions.* San Francisco: Jossey-Bass.

Schweitzer, J. H., Woo Kim, J., & Mackin, J. R. (1999). The Impact of the Built Environment on Crime and Fear of Crime in Urban Neighbourhoods. *Journal of Urban Technology, 6,* 59-73.

Scott, H. (2003). Stranger Danger: Explaining Women's Fear of Crime. *Western Criminology Review, 4,* 203-214.

Shaw, C. R. & McKay, H. D. (1942). *Juvenile Delinquency and Urban Areas.* Chicago: University of Chicago Press.

Shaw, C. R. & McKay, H. D. (1969). *Juvenile Delinquency and Urban Areas: A Study of Rates of Delinquency in Relation to Differential Characteristics of Local Communities in American Cities.* (2 ed.) Chicago and London: The University of Chicago Press.

Skogan, W. (1978). *Victimisation Surveys and Criminal Justice Planning* Washington D.C: Government Printing Office.

Skogan, W. (1986). Fear of Crime and Neighbourhood Change. In A.S.Reiss Jr & M. Tonry (Eds.), *Communities and Crime* (pp. 203-229). Chicago: University of Chicago Press.

Skogan, W. (1987). The Impact of Victimisation on Fear. *Crime and Delinquency, 33,* 135-154.

Skogan, W. (1990). *Disorder and Decline: Crime and the Spiral of Decay in American Neighbourhoods.* Berkeley: University of California Press.

Skogan, W. & Maxfield, M. G. (1981). *Coping with Crime: Individual and Neighbourhood Reactions.* Beverly Hills, CA: Sage.

Snell, C. (2001). *Neighbourhood structure, crime, and fear of crime: testing Bursik and Grasmick's neighbourhood control theory.* New York: LFB Scholarly Publishing LLC.

Snijders, T. A. B. & Bosker, R. J. (1999). *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modelling.* London: Sage.

Sparks, R., Genn, H., & Dodd, D. (1977). *Surveying Victims.* Chichester.

Stafford, M., Chandola, T., & Marmot, M. (2007). Association between Fear of Crime and Mental Health and Physical Functioning. *American Journal of Public Health, 97,* 2076-2081.

Stanko, E. (1988). Hidden Violence Against Women. In M.Maguire & J. Ponting (Eds.), *Victims of Crime: A New Deal?* (1 ed., pp. 40-46). Milton Keynes: Open University Press.

Stanko, E. (1995). Women, Crime and Fear. *Annals of the American Academy of Political and Social Science, 539,* 46-58.

Stanko, E. (2000). Victims R Us: The Life History of 'Fear of Crime' and the Politicisation of Violence. In T.Hope & R. Sparks (Eds.), *Crime, Risk and Insecurity* (1 ed., pp. 13-30). London and New York: Routledge.

Stern, M. & Hildebrandt-Karraker, K. (1989). Sex Stereotyping of Infants: A Review of Gender Labelling Studies. *Sex Roles, 20,* 501-522.

Sudman, S. (1977). Modest Expectations: The Effect of Interviewers Prior Expectations on Responses. *Sociological Methods and Research, 16,* 171-182.

Sundeen, R. A. & Matthieu, J. T. (1976). The Fear of Crime and its Consequences Among the Elderly in Three Urban Communities. *The Gerontologist, 16,* 211-219.

Surette, R. (1998). *Media, Crime and Criminal Justice: Images and Realities*. Belmont, California: Wadsworth.

Suttles, G. (1968). *The Social Order of the Slum*. Chicago: University of Chicago Press.

Sutton, R. M. & Farrall, S. (2005). Gender, Socially Desirable Responding and the Fear of Crime: Are Women Really More Anxious About Crime? *British Journal of Criminology, 45,* 212-224.

Sykes, G. & Matza, D. (1957). Techniques of Neutralization. *American Sociological Review, 22.*

Taylor, R. B. (2001). *Breaking Away from Broken Windows: Baltimore Neighbourhoods and the Nationwide Fight against Crime, Grime, Fear, and Decline.* Boulder, Colorado: Westview Press.

Taylor, R. B. & Covington, J. (1993). Community Structural Change and Fear of crime. *Social Problems, 40,* 374-397.

Taylor, R. B., Gottfredson, S. D., & Brower, S. (1984). Block Crime and Fear: Defensible Space, Local Social Ties and Territorial Functioning. *Journal of Research in Crime and Delinquency, 21,* 303-331.

Taylor, R. B. & Hale, M. (1986). Testing Alternative Models of Fear of Crime. *The Journal of Criminal Law and Criminology, 77,* 151-189.

Tseloni, A. (2005). *Multilevel Modelling of the Number of Property Crimes: Household and Area Effects* London: Home Office.

Tseloni, A. (2007). Fear of Crime, Perceived Disorders and Property Crime: A Multivariate Analysis at the Area-Level. *Crime Prevention Studies, 21,* 163-185.

Tulloch, M. (2000). The Meaning of Age Differences in the Fear of Crime: Combining Quantitative and Qualitative Approaches. *British Journal of Criminology, 40,* 451-467.

Tyler, T. R. (1980). Impact of Directly and Indirectly Experienced Events: The Origin of Crime Related Judgements and Behaviours. *Journal of Personality and Social Psychology, 39,* 13-28.

Vanderveen, G. (2006). *Interpreting Fear, Crime, Risk and Unsafety*. Boom Juridische Uitgevers.

Veysey, B. M. & Messner, S. F. (1999). Further Testing of Social Disorganization Theory: An Elaboration of Sampson and Groves's "Community Structure and Crime". *Journal of Research in Crime and Delinquency, 36,* 156-174.

Vickers, D. (2006). *The Difficulty of Linking Two Differently Aggregated Spatial Datasets: Using a Look-up Table to Link Postal Sectors and 1991 Census Enumeration Districts.*

Vrij, A. & Winkel, F. W. (1991). Characteristics of the Built Environment and Fear of Crime: A Research note on Interventions in Unsafe Locations. *Deviant Behaviour, 12,* 203-215.

Walker, A., Kershaw, C., & Nicholas, S. (2006). *Crime in England and Wales 2005/06* (Rep. No. 12/06). Home Office.

Warr, M. (1984). Fear of Victimisation: Why are Women and the Elderly More Afraid? *Social Science Quarterly, 65,* 681-702.

Weinrath, M. & Gartrell, J. (1996). Victimization and Fear of Crime. *Violence and Victims, 11,* 187-197.

Weiss, L. (2007). Defining Neighbourhood Boundaries for Urban Health Research. *American Journal of Preventative Medicine, 32,* 154-159.

Wilcox-Rountree, P. (1998). A Re-examination of the Crime-Fear Linkage. *Journal of Research in Crime and Delinquency, 35,* 341-372.

Wilcox-Rountree, P. & Land, K. C. (1996a). Burglary victimization, perceptions of crime risk, and routine activities: A multilevel analysis across Seattle neighbourhoods and census tracts. *Journal of Research in Crime and Delinquency, 33,* 147-180.

Wilcox-Rountree, P. & Land, K. C. (1996b). Perceived Risk versus Fear of Crime: Empirical Evidence of Conceptually Distinct Reactions in Survey Data. *Social Forces, 74,* 1353-1376.

Wilcox-Rountree, P. & Land, K. C. (2000). The Generalizability of Multilevel Models of Burglary Victimization: A Cross-City Comparison. *Social Science Research, 29,* 284-305.

Wilcox-Rountree, P., Quisenberry, N., & Jones, S. (2003). The Built Environment and Community Crime Risk Interpretation. *Journal of Research in Crime and Delinquency, 40,* 322-345.

Wilkinson, K. P. (1984). Rurality and Patterns of Social Disruption. *Rural Sociology, 49,* 23-36.

Will, J. A. & Mcgrath, J. H. (1995). Crime, Neighbourhood Perceptions, and the Underclass: The Relationship Between Fear of Crime and Class Position. *Journal of Criminal Justice, 23,* 163-176.

Williams, F. P., McShane, M. D., & Akers, R. L. (2000). Worry about victimisation: An alternative and reliable measure for fear of crime. *Western Criminology Review, 2.*

Williams, P. & Dickinson, J. (1993). Fear of Crime: Read All About It? The Relationship Between Newspaper Crime Reporting and Fear of Crime. *British Journal of Criminology, 33,* 33-56.

Wilson, J. Q. & Kelling, G. L. (1982). Broken Windows. *Atlantic Monthly,* 29-38.

Winkel, F. W. (1998). Fear of Crime and Criminal Victimisation: Testing a Theory of Psychological Incapacitation of the 'Stressor' Based on Downward Comparison Processes. *British Journal of Criminology, 38,* 473-484.

Winkel, F. W. & Vrij, A. (1990). Fear of Crime and Mass Media Crime Reports: Testing Similarity Hypotheses. *International Review of Victimology, 1,* 251-266.

Wittebrood, K. (2002). Fear of Crime and Victimisation in Western Industrialised Countries: A Multilevel Analysis. In P.Niuwbeerta (Ed.), *Crime Victimisation in Comparative Perspective: Results from the International Crime Victims Survey, 1989-2000* (1 ed., pp. 285-299). Boom Juridische Uitgevers.

Woldoff, R. A. (2006). Emphasizing Fear of Crime in Models of Neighbourhood Social Disorganisation. *Crime Prevention and Community Safety, 8,* 228-247.

Wyant, B. R. (2008). Multilevel Impacts of Perceived Incivilities and Perceptions of Crime Risk on Fear of Crime. *Journal of Research in Crime and Delinquency, 45,* 39-64.

Young, J. (1988). Risk of Crime and Fear of Crime: A Realist Critique of Survey-Based Assumptions. In M.Maguire & J. Pointing (Eds.), *Victims of Crime: A New Deal?* (1 ed., pp. 164-176). Milton Keynes: Oxford University Press.

Young, J. (1996). Left Realist Criminology: Radical in its Analysis, Realist in its Policy. In M.Maguire, R. Morgan, & R. Reiner (Eds.), *The Oxford Handbook of Criminology* (2 ed., pp. 473-498). Oxford: Oxford University Press.

Zedner, L. (1996). Victims. In M.Maguire, R. Morgan, & R. Reiner (Eds.), *The Oxford Handbook of Criminology* (2 ed., pp. 577-612). Oxford: Oxford University Press.