The Effect of Crime in the Community on Becoming Not in Education, Employment or Training (NEET) at 18 – 19 years in England

Submitted by

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Declaration

I, Magdalene Karyda, hereby declare that this thesis and the work presented in it is entirely my own. Where I have consulted the work of others, this is always clearly stated.

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Abstract

The increasing number of young people who are inactive and not engaged in education, employment or training (NEETs) in the UK over the last years bears severe implications both for individual young people and for the society. This study explores the processes underlying the effects of neighborhood context on young people who experience NEET status. It relies on quantitative data from a nationally representative study, the Longitudinal Study of Young People in England (LSYPE), linked with the seven decomposed English Indices of Deprivation.

Drawing on previous sociological theories this study puts forward an original theoretical framework, the Ecological Model of Neighbourhood Effects that proposes four pathways that mediate the direct effect of neighbourhoods on young people: a) individual characteristics and attitudes; b) parental characteristics and relationships; c) school experiences and attitudes to schooling, and; d) social epidemics.

Potential causal pathways between neighbourhood context and individual outcomes are explored on a first strand of analysis by employing a logistic regression model. The results show that there is a higher probability for young people who live in high Crime Score areas to become NEETs in comparison to those who live in areas with low Crime Score after controlling for individual, family, school and peer group characteristics.

On a second strand of analysis, I employ counterfactual models, propensity score matching and sensitivity analysis. The findings suggest that when two groups of children with identical observed characteristics at the age 13/14 experience different neighbourhood contexts, those who grow up in high Crime Score areas are more likely to become NEETs in comparison to those who grow up in low Crime Score areas. Unobserved characteristics though indicate the presence of selection bias that could alter the inferences drawn about neighbourhood effects.

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Chapter 1

Introduction

Research on the links between neighbourhood characteristics and young people's outcomes suggests there are several pathways through which neighbourhoods might influence development (Jencks and Mayer [95], 1990; Leventhal and Brooks-Gunn [110] 2000). Many factors such as parental characteristics and practices, school and peer group characteristics have been associated with "Not in Education, Employment or Training" (NEET) status (MacMillan et al [120], 2012; Crawford et al [42], 2011; the Wolf report [202], 2011). This study aims to investigate the neighbourhood mechanisms and the different pathways through which processes may operate and influence the trajectories of young people who struggle to make the transition from school to work ending up in NEET status. In this study it is hypothesized that living in a neighbourhood characterized by high rates of deprivation increases the risk of a young person becoming NEET at the ages $18-19$.

Sociological scholarship focusing on neighbourhood effects was mainly conducted in the US (Ellen and Turner [56], 1997, Leventhal and Brooks-Gunn [110], 2000). Neighbourhood effects research developed more recently in the UK, during the 1990s and a growing body of research has emerged (for example Garner and Raudenbush [71], 1991; McCulloch and Joshi [126], 2001; Gibbons [72], 2002; Bell [10], 2003; Goux and Maurin

[76], 2007) and the National Evaluation of Sure Start Research Team (Barnes, Belsky, Broomfield, Melhuish and the National Evaluation of Sure Start Research Team [6], 2006). The interest in neighbourhood effects research in the UK has been a response to concerns about area effects and was facilitated by availability of data to study neighbourhoods. The large volume of work on neighbourhood effects reports an association between area deprivation and outcomes such as educational attainment, cognitive test scores and low GCSE scores (McCulloch and Joshi [126], 2001; Gibbons [72] 2002; Bell [10], 2003; Leventhal and Brooks-Gunn [111], 2004; Kauppinen [99], 2007). Some of the previous quantitative studies find at best weak neighbourhood effects on educational attainment (McCulloch and Joshi [126], 2001; Leckie 2009; Rasbash, et al. [146] 2010; Midouhas [127] 2012). Other studies find negative neighbourhood effects however a large proportion of the results are explained when controlling for prior attainment and family background (Garner and Raudenbush [71], 1991; Gibbons [72], 2002).

The present study extends prior research of neighbourhood effects as it investigates the association between area deprivation and NEET status. Even though some neighbourhood literature finds at best weak neighbourhood effects on educational attainment, NEET status is different to educational attainment. In addition, the association between NEETs and neighbourhood deprivation is only suggested in the existing UK literature but not directly assessed for young people. It has been found that living in a deprived neighbourhood is associated with individual employment outcomes as it decreases the probability of getting or keeping a job for its residents (van Ham and Manley [188], 2010). It is mentioned that NEET rates are particularly high in specific areas in the UK such as inner London, Merseyside, West Midlands and Strathclyde (the Wolf report [202], 2011). It is easier for young people who live in less deprived areas to find a job after the age of 16 (Crawford et al [42], 2011). The proportion of young people claiming unemployment benefit across Britain varies by area; in some neighbourhoods the proportion of young people claiming benefits is close to zero whereas in others the proportion is over 1 in 4 (MacMillan et al [120], 2012).

Literature on NEETs points to a number of factors associated with entry to NEET status. The current labor market conditions are key in determining employment opportunities and subsequently life trajectories for young people (OECD [137], 2000; Gregg and Wandsworth [78], 2010). In addition, young people are more sensitive to adverse market conditions as is suggested by the fact that youth unemployment in the UK today is two and a half times greater than adult unemployment rates in the UK and a number of other EU countries (Bell and Blanchflower [9], 2010). Other important factors that increase the number of NEETs in the UK today are demographic characteristics such as parental education and socio-economic status (Macmillan et al [120], 2012), disabilities (Rennison et al. [148], 2006; Coles [38], 2002), and ethnicity (Bell and Blanchflower [9], 2010). Other characteristics such as prior educational attainment and individual aspirations (Crawford et al [42], 2011), parental practices, attitudes to schooling and ambitions (Macmillan et al [120], 2012), and school and peer group characteristics (Spielhofer [180], 2009; Macmillan et al. [120], 2012) have been associated with NEET status.

In addition to extending prior research, this study also has important implications for future policy. Policy makers in the UK have been concerned about the existence of neighbourhood effects which is evident through a number of area based policies such as Excellence in Cities and Sure Start or mixed housing strategies in the UK and across Europe aiming to create a diverse socio-economic population in specific areas (Kearns [101], 2002; Atkinson and Kintrea [5], 2002; Musterd and Andersson [132], 2005). At the same time, the direction of policy makers turns to a gradually growing number of young people in NEET status in the UK over the last years. At the end of 2011, 154,900 (8.1 per cent) of 16 to 18 year olds were NEET. The rates vary considerably with age; 2.8 per cent of 16 year olds, 6.7 per cent of 17 year olds and 14.5 per cent of 18 year olds (DfE, `https://www.education.gov.uk/16to19/participation/neet`). The increasing number of NEETs has been a major concern of policy makers in the UK because young people who experience NEET status at an early age are at risk of facing short and long term poor labour market outcomes, such as further unemployment spells and lower wages (Crawford et al [42], 2011; Britton et al [22], 2011). In addition, youth unemployment at ages $16-19$ in England incurs high temporary and further future costs to the national economy because of lost output and benefits (MacMillan et al [120], 2012). Given the importance that NEET status has for young people and the national economy, I believe that the current study may help to inform policy and can contribute some useful evidence as a basis for further policy development for NEETs in the UK.

Background

Sociologists have been concerned with the characteristics of neighbourhoods and their residents for many years and the beginning of the discipline can be traced in the work of DuBois [49] (1899), Park and Burgess [139] (1925) and the publication of "Juvenile Delinquency and Urban Areas" by Shaw and McKay [171] (1942). Shaw and McKay introduced the social organization theory which holds that social order is maintained by three factors: economic status, ethnic homogeneity, and population stability. Disadvantaged neighbourhoods are characterized by lack of resources, ethnic heterogeneity and population instability which lead to fewer social ties, reduced social control and high crime rates. Crime rates were particularly high and remained relatively stable in different areas despite changes in the populations who lived in these areas. Based on these observations, Shaw and McKay concluded that crime was a function of neighbourhood dynamics and not only a function of the characteristics of the individuals who lived in a neighbourhood. The social disorganization theory was highly influential throughout the 1950s and 1960s.

The social disorganization theory was reignited in the 1980s by scholars such as Bursik [26] (1986; 1988), Sampson and Groves [162] (1989), and Wilson [198] (1987; 1990; 1996). In particular neighbourhood effects and their outcomes on young people became the subject of interest in sociological scholarship by William Wilson's "The Truly

Disadvantaged" [199] (2012). Wilson linked social stratification, mobility, and race. Wilson argued that because of the decline of manufacturing and the movement of middle class blacks out of the ghetto, a concentration of poverty and isolation appeared in inner city minorities. This led to social problems in specific areas such as crime, unemployment and single parent families which affected the development and outcomes of young people living in these inner-city communities. Wilson also developed the social isolation theory that holds that there is a higher possibility for people who live in highly deprived areas to be isolated from mainstream society and institutions. This leads to high unemployment rates because people who live in disadvantaged areas are disconnected from the labour market (Wilson [198], 1997). Wilson's theoretical framework has received considerable criticism with regards to ignoring the importance of racial discrimination among blacks of all classes (Massey [125], 1993; Yinger 1995). However this criticism has been confronted by the fact that a decline in residential segregation by race has been reported (Jargowsky [93], 1997). Additionally, critics of Wilson's theory regarding the decline in manufacturing have pointed that it only applies to Chicago and some other northern industrial cities (Jargowsky [93], 1997; Orfield and Ashkinazie [138], 1993). Despite the criticism it has received, Wilson's theoretical framework along with the social disorganization theory and Massey's [125] (1993) work on concentration of poverty reinvigorated the focus of sociologists on neighbourhood effects, social stratification and research on area deprivation effects on outcomes such as education, labour market, crime and health with a special focus on children and young people.

A more recent approach on examining neighbourhood effects that draws on the early sociological theories presented by Shaw and McKay [171] (1942) and Wilson [199] (2012) was the theoretical framework of Jencks and Mayer [95] (1990) that focused on neighbourhood structural dimensions to identify their effects on young people's development through five models; a) The neighbourhood institutional resource model includes neighbourhood resources, security and community services; b) The collective socialization model focuses on adult role models in a neighbourhood and refers to the monitoring function that adults adopt to control negative behavior; c) The contagion or epidemic model points to the behaviour of peers and neighbours that spread on residents in a community; d) The competition model focuses on neighbours' competition for scarce resources; and e) The relative deprivation model concentrates on how individuals judge their own position in relation to their neighbours. A main limitation of theories focusing on neighbourhood effects is that they do not account for individual characteristics. Therefore, the development of young people will be explored in relation to two theoretical frameworks, the Life Course theory (Elder [54], 1998; Giele and Elder [73], 1998) and the Ecological systems framework of development (Bronfenbrenner [23], 1979).

The life course perspective was initially developed in the late 1920's and early 1930's through three pioneering Berkeley studies and further extended in the 1960's (Elder [54], 1995). This approach offers an interdisciplinary research framework based on four key principles: a) The interplay between human lives and historical times, b) the timing within lives that refers to different roles, expectations and beliefs based on age, c) the notion of linked or interdependent lives that studies links such as for example between family members and with the wider world, and d) human agency in making choices which refers to the notion of achieving control and determining an individual life path. The research paradigm proposed by Life Course Theory will be employed to study young people's outcomes in a multidimensional context that includes neighbourhoods, social, cultural and historical factors and allows research to target the particular circumstances that young people experience in deprived areas. To further consider the interaction between the quality and context of the environment and the young person, the Compositional systems framework of development (Bronfenbrenner [23], 1979) will be employed. The Ecological Systems theory (Bronfenbrenner [23], 1979) provides a comprehensive contextual framework of individual development and puts forward a context of six systems; a) the Individual including personality characteristics; b) the Microsystem consisting of the activities and interactions in immediate environment of the individual; c) the Mesosystem providing a connection to the structures of the microsystem; d) the Exosystem linking the context where the individual does not have any active role with the context where the individual is actively participating; e) the Macrosystem encompassing laws and cultural values; and f) the Chronosystem involving the dimension of calendar time. The Compositional framework suggests ways in which the neighbourhood and the settings that surround a young person, from the most proximal to the distal ones, influence a young person's development and outcomes.

A new model of neighbourhood effects on young people's outcomes

Drawing on the assumptions formulated by the Neighbourhood Effects theory Jencks and Mayer [95] (1990), the Life Course perspective (Elder [54], 1998) and the Ecological Systems theory (Bronfenbrenner [23], 1979) this study will put forward the Compositional Model of Neighbourhood Effects to investigate the impact of neighbourhood characteristics on individual outcomes. The framework of linked lives of the life course theory and the multiple spheres of influence of the ecological systems theory will be employed to explore young people's development. The neighbourhood effects theory will provide the basis for exploring specific pathways that link neighbourhood effects to the experience of NEETs. The two linked theoretical frameworks will be offered to understand the impact of neighbourhood context on young people's outcomes in education and employment. The aim of the new framework will be to use different theories and reformulate their arguments to create a context to investigate pathways that mediate neighbourhood effects on young people. The theoretical framework underlies the assumption that neighbourhood characteristics act on young people's development by specifying four levels of influence apart from neighbourhoods: a) individual characteristics and attitudes; b) parental characteristics and relationships; c) institutional resources (schools), and; d) d social epidemics (peer group) that act as pathways mediating the direct neighbourhood association with transition outcomes.

Despite the growing literature on neighbourhoods, little scholarship has been developed to date to identify the causal links and pathways between neighbourhood characteristics and individual outcomes that would be necessary to direct public policy (Small and Feldman [175], 2012; Durlauf [53], 2004). The purpose of the four causal mechanisms of neighbourhood effects to young people's outcomes introduced in this study is to offer a comprehensive and updated framework to identify the circumstances under which neighbourhoods determine the trajectories of young people. Neighbourhood characteristics and the behaviour of their residents can be mediated to individual behaviours and attitudes to education which in turn influence educational and employment outcomes. Parental characteristics refer to parental socio-economic and educational background and the resources and care they can offer to their children which affect the parental attitudes and aspirations and the environment in which young people grow up. The institutional resources pathway refers to availability and quality of public services and local goods. The residents' access to resources ultimately influences the opportunities offered to young people. The social epidemics pathway refers to behaviours influenced by contact with neighbours, conformity to local social norms and role models, and attitudes that may change in the presence of social disorder.

The goal of uncovering the mechanisms of neighbourhood effects in this study is to allow the research hypothesis to be tested and to investigate if there is an association between neighbourhood crime deprivation and young people in NEET status and if this association can be explained after controlling for individual, family, school and peer group characteristics. To further explore how neighbourhood effects transpire, a comparison will be drawn between young people living in high and low crime deprivation areas. After specifying the four mechanisms assumed to produce neighbourhood effects and the research hypothesis that will be explored, it is important to test quantitatively if these assumptions make a contribution to young people's trajectories.

To fully understand which processes in the neighbourhood context affect young people's outcomes, it is important to address key methodological issues in neighbourhood research. Two issues are key to further understand neighbourhood effects: conceptualizing neighbourhoods and reducing selection bias. The first issue relates to the difficulty to conceptualize neighbourhoods and define their boundaries in order to capture both structural and social aspects (Lupton [115], 2003). Structural aspects are captured in administrative data sources such as electoral districts (Sloggett and Joshi [174], 1998) and education authorities (Garner and Raudenbush [71], 1991). Electoral districts provide a useful administrative data source, however political boundaries do not necessarily coincide with the boundaries of local communities. Education authorities capture the community of teachers and students, however a school unit may not correspond to a geographic unit or to the neighbourhood the family lives in. The majority of neighbourhood research relies on administrative spatial units sources as they offer data for entire countries available for researchers to use (Galster 2001 [68]; Manley et al. [121] 2006). Social characteristics of neighbourhoods are included in datasets like community surveys which involve interviews of residents and systematic social observations such as personal, video or audio observations (Rice and Ezzy [149], 1999). Contextual data drawn from non-administrative sources are rare because they substantially increase study costs and are difficult to implement.

A further characteristic of neighbourhoods that needs to be considered is the distinction between compositional factors and contextual factors (Duncan et al [51], 1993, Wiggins et al [194], 2002, Small and Feldman [175], 2012). Compositional factors refer to the attributes of a population that lives in an area. They are characteristics that are usually observed in cross-sectional data from census, surveys or administrative datasets.This data is aggregated to describe the composition of the residents of a neighbourhood. Examples of this data involve residents with a university degree, percentage of families living in social housing or are home owners and demographic characteristics of an area's population. Studies using compositional attributes of a population use aggregated data and therefore cannot predict accurately outcomes for individuals. On the other hand, contextual factors extend over and above aggregated characteristics of residents and are expected to play a role as a function of young people's exposure to certain neighbourhood circumstances. For example, lack of infrastructure and social disorganization are contextual factors that might increase exposure to violence and crime and interaction with antisocial peers which in turn might affect educational and employment outcomes. A further example would be measuring area unemployment. Measuring youth unemployment based on the percentage of young people who are unemployed in a given neighbourhood could describe the composition of a neighbourhood. Conversely, measuring associations between contextual characteristics and young people's employment outcomes could offer a more reliable analysis and report causal associations. Given the constraints and limitations imposed by different measures of defining neighbourhoods, the neighbourhood geography measure used in the current study is the lower Layer Super Output Areas (LSOA) that was developed to facilitate neighbourhood statistics. England and Wales have been divided into 32,482 small areas and each LSOA is a small area of around 1,500 people. The LSOA allows both structural and social aspects of neighbourhoods to be captured. Structural dimensions are provided by consistent geographic boundaries unlike other measures such as for example educational districts employed in past research. At the same time, LSOAs capture social aspects of neighbourhoods, as they attempt to delineate areas with similar social characteristics. Thus the LSOAs allow social interactions to be investigated in consistent geographical boundaries.

The second methodological issue in area research is to choose an approach that will reduce the selection bias associated with living in a specific neighbourhood (Jencks and Mayer [95] 1990; Tienda [185] 1991; Duncan et al [51]. 1997; Galster [69] 2008; Hedman and van Ham [85], 2012). The fundamental reason behind the selection bias problem is that neighbourhood context is not allocated randomly, but it is guided by parental preferences and socio-economic status. Two approaches have been used to estimate neighbourhood effects on young people's outcomes and reduce the selection bias problem; experimental and observational studies. Experimental designs, such as the Moving to Opportunity programme, involve random assignment of individuals to neighbourhoods and therefore permit the investigation of how a change in neighbourhood context influences young people (Goering and Feins [75], 2003). They provide a good estimate of neighbourhood effects by minimizing selection bias, however, they are difficult to implement because of practical and ethical concerns and incur considerable implementation costs. The next solution is quasi experimental designs which involve comparable groups of similar individuals or families. Quasi experimental designs, such as the Gautreaux project (Rosenbaum, [151], 1995) allow selection biases to be reduced and causal relationships to be established (Rosenbaum [151], 1995). They are more easily implemented than randomized designs, however unmeasured differences may still affect the results. Observational studies of neighbourhoods include longitudinal and cross-sectional studies. Longitudinal studies include a sequence range of socio-economic status and income characteristics for families and neighbourhoods and thus allow research on associations between population characteristics and social outcomes. Longitudinal studies permit the researcher to study temporal changes of their observations in neighbourhood characteristics and allow speculations about causal relationships to be tested (recent examples include van Ham and Manley [189] 2012 ; Musterd et al. [133], 2003). Cross-sectional studies are the least preferred approach. Cross sectional studies involve observations and examine correlations between characteristics of neighbourhoods, families and young people at one specific point in time (Goering et al [75], 2003). They reflect associations at the time the census was taken and therefore they do not permit causal relationships to be investigated.

The current study employs observational data to identify neighbourhood effects. The main data selection criterion were to employ a dataset that would allow the research hypothesis to be tested under the selected methodology. For this reason, a rich longitudinal dataset with information on young people's transitions from secondary and tertiary education to economic roles in early adulthood combined with information on area deprivation was required for this study. The Longitudinal Study of Young People in England (LSYPE) was selected as the best available option as it is a rich source of information on background, behaviours, attitudes and experiences of young people and young people's monthly main activity at ages $16-19$. In addition, the LSYPE can be linked to a geographical indicator of deprivation, the general Index of Multiple Deprivation. Finally, the longitudinal nature of the study allows the investigation of neighbourhood characteristics through long-term development processes that start in childhood and continue until adolescence. The LSYPE has been linked to several datasets. First, the National Pupil Database (NPD) which provides pupil information about examination results and pupil and school characteristics about all pupils in state or partially state-funded schools in England. Second, school level data which indicate information about the school each sample member attended and information about primary school attended by the young person at Key Stage 2. Third, for the purposes of this study, the LSYPE has been linked non-disclosively with a geographical indicator, the Indices of Multiple Deprivation (2010) after gaining secure access to the UK Data Service. Fourth, special permission has been gained by the Key to Success, Department for Education, to access combined data of the LSYPE and the Youth Cohort Study (YCS). LSYPE and YCS have collected information on all the activities reported by young people in the four years following compulsory education completing a form on monthly activity history for each respondent.

Analysis based on observational data such as the LSYPE is the most common approach, however careful statistical modelling needs to be employed to address the selection bias issue. The most commonly used statistical approaches are regression models and instrumental variables which include sibling fixed-effects models (Galster [69], 2008). A relatively new approach in the social science literature is propensity score matching (Rosenbaum and Rubin [154], 1983). Regression models need to include a wide range of individual and family variables in the analysis to avoid omitting unmeasured family characteristics that affect both neighbourhood choice and young people's outcomes and could lead to omitted variables or selection bias problems which will subsequently lead to over or under estimates of neighbourhood effects. In the instrumental variables approach (IV), an instrument is used to produce a consistent estimator of a parameter when the explanatory variables are correlated with the error terms. The instrumental variables technique is subject to large standard errors and IV estimators only capture the effect of the treatment on the subset of the sample that is on the margin. Siblings fixed-effects models allow the researcher to difference out the unobserved heterogeneity in the family fixed effects, such as parental ability however, the sibling fixed-effects models often have large standard errors and do not control for unobserved family characteristics that vary over time and are different between siblings (Aaronson [2], 1998). Empirical work in sociology has also used propensity score matching. Propensity score matching approximates a randomized trial by comparing outcomes among units that received a treatment versus those that did not and aims at reducing the selection bias problem. While several econometric techniques are employed to overcome the selection bias problem in observational studies, it is difficult to say that neighbourhood selection which is driven by demographic and socio-economic characteristics of a household (Hedman and Ham [85], 2011) could ever be removed.

Given that an observational dataset is employed in this study, two approaches are incorporated to potentially overcome the problem of selection bias: controlling for individual and family characteristics and comparing young people in deprived and non-deprived areas. The first approach involves logistic regression models with statistical controls for covariates. To control extensively for family and individual attributes to address selection bias, a logistic regression model will be used. Initially, the relationship between the dependent and independent variables will be explored. A series of models will be produced to control the association of NEET status with other factors and to investigate the probability of a young person being NEET or not based on area deprivation characteristics and on individual and family characteristics, as well as school and peer group influences. Controlling for observed characteristics of families and individuals is the most common way of attempting to reduce selection bias in a model as it affects both the selection of neighbourhoods and the individual level outcomes. Unfortunately, it is not possible to measure all the characteristics that are significant and therefore further analysis is required to address the selection bias issue. For this reason, the second approach employs a counterfactual framework, a model that uses the logic of experiments to investigate the potential outcome if one individual lived in both a high and low Crime Score area using observational data. Propensity score matching estimators are used to test the effect of neighbourhood deprivation by comparing outcomes for individuals who grow up in deprived and non-deprived neighbourhoods based on a vector of conditioning covariates. A complimentary analysis will be estimated, Sensitivity Analysis (Rosenbaum [153], 2002) to evaluate the results of the counterfactual model. Sensitivity analysis will test if the estimated propensity score analysis results are overestimated or underestimated because of unobserved biases and subsequently if the statistical associations observed imply causality.

Overview of Chapters

Chapter 2 is composed of two parts that investigated young people in NEET status and neighbourhood context effects. The first part describes NEETs as a group of young people who are inactive and not engaged in any education or training and therefore face the risk of social exclusion. It also depicts a number of barriers associated with entry of young people in the labour market after compulsory education such as the labour market conditions, individual and family characteristics, school and peer group influence. The second part of this chapter explores the key characteristics in defining neighbourhoods to capture both the geographical boundaries and the cultural and social relations developed in neighbourhoods. It also describes neighbourhood differentials at different developmental epochs and explores its effects on educational, social and economic behaviour. **Chapter** 3 aims to investigate theoretically the role of social context on shaping individuals' lives. It explores a compositional framework of young people's lives and outlines the main sociological theories that explain the processes through which the characteristics of poor neighbourhoods influence educational and employment outcomes. Drawing upon theories of individual development and neighbourhood context, this chapter puts forward the Compositional Framework of Neighbourhood Effects that proposes the pathways that mediate neighbourhood effects to young people and will be explored in the current thesis.

Chapters 4 and 5 introduce the methodological approaches undertaken in neighbourhood studies and the dataset selected for this research. **Chapter** 4 points to the key advantages and limitations of methodological approaches employed by previous scholarship in neighbourhood context effects. It addresses how different approaches in defining and conceptualising neighbourhood boundaries as well as the research design and the statistical approach selected can reduce selection bias which suffuses neighbourhood studies that use non-randomized data and does not allow causal inferences to be drawn. **Chapter** 5 presents the dataset, the neighbourhood classification and the measure of area deprivation that will be employed in the study. It also explains the statistical modeling approach that will be used to test the Compositional Model of Neighbourhood Effects.

Chapters 6 and 7 comprise the empirical Chapters. **Chapter** 6 presents the data in the analysis and tests the probability of a young person will become NEET at the ages $18-19$ based on the values of the set of independent covariates proposed by the Compositional model of Neighbourhood effects. The analysis includes descriptive statistics and binary and multivariate logistic regression analysis and controls statistically for a range of characteristics that affect simultaneously neighbourhood choice and young people's outcomes aiming to reduce selection bias. **Chapter** 7 challenges experimental designs as the "golden standard" for drawing causal inferences in neighbourhood effects studies. This chapter employs Propensity Score Matching, a counterfactual framework model that uses the logic of experiments to compare the potential educational and employment outcomes if one individual lived in both a high and low Crime Score area and thus to establish causality. Further analysis is carried out to control for unobserved characteristics that could cause hidden biases and alter the inferences of the results drawn by the propensity score analysis results, Sensitivity Analysis. This type of analysis states the magnitude of hidden bias that would need to be present to explain the observed associations.

Chapter 8 concludes by summarising the major research findings, its strengths and its limitations and by discussing their implications for future research and policy in neighbourhood effects.

Chapter 2

Literature Review

2.1 Introduction

Chapter 1 described the aims, the research hypothesis and the methodology that will be employed in the current thesis. To investigate the relationship between neighbourhood context and young people who are not employed and not engaged in any education or training this chapter evaluates and summarizes previous scholarship and its critical points about two topics: young people in NEET status and neighbourhood deprivation effects. The objective of this chapter will be to address the bodies of previous research on young peoples trajectories and neighbourhood effects to identify the questions that existing neighbourhood research does not answer and to explain why further research on neighbourhood context is required to find its association with young people in NEET status. This literature review is organized in two parts. The first part investigates young people in NEET status while the second examines neighbourhood context effects. In the first part, Section 2.2 aims to identify who are young people in NEET status. As the literature on young trajectories proposes, only a minority of young people end up in persistent inactivity immediately after their school to work transition. Young people today often explore available opportunities churning between different activities, jobs and sectors. Therefore, previous literature is investigated that classifies transition pathways of young people to find the most appropriate definition of NEET status. Section 2.3 analyses the labour market conditions to understand how they affect the smoothness of the transition of young people from school to work. The main issues explored involve whether the labour market conditions in the UK after the 2008 recession (LSYPE Wave 5, young people at the age of 17) affected labour demand and especially whether the effect was severe for young people with low educational qualifications and no previous work experience. Further to the effect of the labour market conditions, four pathways are analyzed to suggest the characteristics that affect the probability that young people follow the NEET pathway. The four pathways included in the analysis are individual and family characteristics, parental practices and interaction and influence of the peer group (Sections 2.3.2 to 2.3.6).

The second part of the literature review concerns neighbourhood context. Section 2.4.1 draws on previous sociological research to examine how neighbourhoods are defined in past literature. The aim is to explain how different neighbourhood dimensions transmit their effects to young people's outcomes notably in the area of educational attainment which is one of the key determinants of youth trajectories.The discussion focuses on the extent to which the definitions provided capture physical and social aspects of neighbourhoods to accurately measure their effect on young people. To better understand neighbourhood effects, Section 2.4.2 draws upon sociological approaches to define how young people's development experience is linked to neighbourhood effects especially at different stages of their lives. Section 2.5 reviews some of the rich literature that provides evidence of adverse neighbourhood effects on educational attainment of young people. The aim of this section is to explore how the development experience of young people in deprived areas is affected by characteristics such as poverty, crime, lack of resources and positive role models, interaction with peer group and lack of social capital. It aims to address the mechanisms that explain neighbourhood influence on young people becoming discouraged and disconnected from mainstream society. Finally, Section 2.6 investigates in depth UK evidence that links neighbourhood context effects on young people's outcomes and especially the effect on educational attainment. This section focuses on the approaches adopted in each study especially in relation to the datasets selected, the measure of area deprivation and the statistical approach. This investigation aims to explore how key difficulties encountered in analyzing neighbourhoods (see Chapter 4) are addressed in previous literature in order to inform the methodology that will be employed in the current thesis.

2.2 Who are NEETs?

In a labour market with a strong economy that provides jobs to young people, school to work transitions involve young people leaving education, searching for work and finding a job that allows them to enter the labour market. However, in the current weak economy, prospects for young people are limited in the labour market causing the trajectories of young people to be interrupted by short or long periods of inactivity. In the past inactive young people, neither in education nor in employment, were described by career service records using the term “status zer0”. “Status zer0” was a technical term, where status 1 referred to young people in education after 16, 2 to those in training, and 3 to those in employment. “Status zer0” became a term to describe young people not in employment, training or education that appeared to count for nothing (Williamson, [195] 1997). Other terms that were used are “Getting Nowhere”, and “Off Register” (Bynner, Ferri and Shepherd [27], 1997; Bentley and Gurumurthy [13], 1999). NEET was devised as a more neutral term in academic research. The government's definitions generally focus on youth unemployment rates, much academic research though focuses on all those who are not in full time education, whether they are searching for work, and hence unemployed, or not. Another point of disagreement among policy makers, and even academics, in defining NEETs is that whether those in part time education or training should be treated as NEETs.

It has been argued that economically inactive / unemployed young people are not a homogenous group (Speilhofer [180], 2009; Yates [203], 2011). NEETs can be engaged in different activities such as for example parenthood, illness, criminal activity, or searching for education and training. However, the majority of research on NEETs indicates a number of common characteristics or factors associated with disengagement from education and employment. Most of these studies depict a group of young people characterized by disadvantage and lack of opportunity (MacMillan et al [120], 2012; Crawford [42], 2011; Speilhofer et al. [180], 2009). Time in NEET experience can be short or prolonged or repeated (Spielhofer et al [180], 2009; Raffe [145], 2003). Numerous analyses have been conducted to determine time in NEET status and the majority of literature defines NEETs as "6 months or more during the ages 1618 outside education, employment, or training" (Payne [140], 2000; Bynner and Parsons [29], 2002; Yates et al [203], 2011).

Britton, Gregg, Macmillan and Mitchell [22] (2011) suggest a set of shared characteristics in trying to identify a target population that could potentially be characterized in NEET status at present in the UK. The authors find that 8% of 16 years olds, 10% of 17 year olds and 15% of 18 years olds in the UK are NEET at a point in time and about half of these will stay NEET one year on. They describe people from NEET group as young people from poorer socio-economic backgrounds with lower GCSE attainment than all other groups. Poor educational attainment is a prevalent characteristic of NEETs even in affluent families. Future outcomes for young people in NEET status remain consistently poor since the majority of them remain out of education and employment while a relatively few go back to education at the ages of 17 and 18. Those who manage to move out of the NEET group are young people with higher educational attainment suggesting that educational attainment is a higher predictor of leaving NEEThood than socio-economic background. Additionally, there is a group of young people in NEET status with high educational attainment and from affluent family backgrounds consisting of a group of young people who take a gap year and subsequently returning back to education. Finally, marginal groups which include young people in part-time education or training or in employment without training have more positive future outcomes compared to those in the NEET category. Based on those characteristics of young people's activities, the authors argue that despite the fact that the definition of NEETs is straightforward, it is hard to derive a strict classification of individuals. Therefore they propose six different groups according to young people's main activity: a) Economically inactive with no participation in education or training; b) Unemployed with no participation in education or training; c) Training/Part-Time education with no employment; d) Employed with no training; e) Employed with training/Part-Time education; and f) Full Time education. The authors suggest the most appropriate definition of NEETs should include only the unemployed and economically inactive who are not in any form of education or training (groups 1 and 2) since the way to treat marginal groups such as those in part-time education or training without employment is not clear.

Being in NEET status can be a short-term state or it could have negative long-term implications in determining individual trajectories of young people. Williamson [195] (1997) uses the terms soft and hard category to refer to the time that young people stay out of employment and education. The soft category refers to a group of people who move in or drop out, a condition with permeable boundaries whereas the 'hard' category refers to a fixed group of people with their own solid culture and detached both from education and the labour market. For some people NEET status is only temporary as they try to find a course that would be suitable for them or they explore career opportunities and seek for employment. This is described as churning between different activities which is quite common among young people. The Wolf report [202] (2011) states that nowadays there is significant job, occupation and sector churn in young people. In the first few years after leaving school, 40% of young people in employment changed their occupation and two thirds changed sector. Many young people find themselves in a churn, in and out of education and employment, which reflects a lack of satisfactory options rather than a decision to stay out of education and the labour force. Along with short-term NEETs churning between different activities, there are also young people who remain disengaged from education and employment activities for a prolonged or repeated period of time (Spielhofer et al [180], 2009). Prolonged periods in NEET status for young people potentially incurs negative labour market consequences for extended periods of time or even for much of their future working lives (Gregg [77], 2001; Macmillan et al [120], 2012). The negative consequences of NEET status can be limited for those taking a job (particularly a full-time one) with or without training as suggested by evidence provided by Crawford et al [42] (2011). Additionally, the authors point that there is a lower probability of becoming NEET for young people who combine work with full-time education. Policy aimed at engaging young people with the labour market and securing them jobs, which offer valuable transferable skills, is potentially essential in minimizing the risk of becoming NEET.

To sum up, several definitions of NEETs have been proposed in the literature since young people who are inactive or disengaged from the labour market and educational activities are not a homogenous group. Some of them can be engaged in different activities while other "churn" in between employment, training and education seeking for the suitable educational or employment pathway. Based on past literature an appropriate definition of NEETs should include young people who are a) Economically inactive with no participation in education or training; and b) Unemployed with no participation in education or training (Britton et al [22], 2011) for a period of six months or more (Payne [140], 2000; Bynner and Parsons [28], 2002; Yates et al [203], 2011). Having defined NEETs, the next sections focus on the determinants of NEET status by exploring the labour market conditions to understand the prospects for labour market participation offered to young people.

2.3 Factors affecting post compulsory education trajectories through employment, education and training

2.3.1 Labour market demand

Evidence suggests that economic conditions and the labour market demand help explain young people's trajectories. Gregg [77] (2001) using the National Child Development Study (NCDS), looks at accumulated experience of unemployment, highlighting how unemployment experience is concentrated on a minority of the workforce over extended periods. The author concludes that, men who experience unemployment in youth disproportionally go on to experience further unemployment when they are prime age adults. The study concludes that men who experience an extra 3 months unemployed before age 23 go on to experience another extra 2 months out of work (inactive or unemployed) between ages 28 and 33. In contrast to men, the study finds that the effect for women is about half this, even when inactivity as well as unemployment is considered. Moreover, the author suggests that there are a number of observable characteristics, which raise a person's underlying risk of experiencing unemployment. These are poor educational attainment, a depressed local labour market, coming from a disadvantaged family background and a range of individual ability and behavioural test scores normally unobserved in labour market data.

It is widely accepted that the 2008 recession in the UK resulted in weak labour demand, which had a negative effect on young people and the youth labour market. Prior to the recent financial crisis, good transition outcomes from education to work for young people were easier to achieve when the national economy was advanced and growing and when the labour market was youth friendly (OECD [137], 2000). A well-functioning economy provides opportunities for growth and a framework of low unemployment. Low adult unemployment results in low youth unemployment. Also, a youth friendly labour market provides training and employment opportunities to young people.

The recent recession period 2008-9 in the UK economy has resulted in relatively low loss of employment overall, however it will take a long time for employment to return to levels seen before the recession (Gregg and Wadsworth [78], 2010). The authors note however that the last recession bears severe implications for youth unemployment. Usually youth unemployment rate is double the adult unemployment rate, young people have shorter spells of unemployment than adults and the number of long term unemployed young people is lower than that of adults. However, in the last recession the situation is changing. Young people face higher than adults unemployment rates and long-term unemployment among young people in 2009 was much closer to the share of older workers than in the past.

As a result, key features of the youth labour market need to be considered when studying NEETs. It has been recognised that young people face many difficulties when they attempt to enter the labour market, especially after 2008-9. Young people are disproportionately affected by economic recession as in the fact that youth unemployment in the UK today is two and a half times greater than adult unemployment rates in the UK and a number of other EU countries (Bell and Blanchflower [9], 2010). The authors also suggest that the increase in unemployment had a large impact on young people especially because the recession occurred at a time period that the youth cohort is large.

Despite the fact that participation in education has increased, many young people decide not to follow an employment trajectory after completing compulsory education. Many young people are successful in their transition from school to work, however, a significant minority struggles to make the transition. At the end of 2011, 154,900 (8.1%) of 16 to 18 year olds were NEET. The rates vary considerably with age; 2.8% of 16 year olds, 6.7% of 17 year olds and 14.5% of 18 year olds (Department for Education, `https:///www.Education.gov.uk/16to19/participation/neet`).

It becomes evident in the literature that young people who aim to enter the labour market nowadays are confronted with barriers to entry and have to deal with much higher unemployment rates compared to the past (OECD, 2009; Bell and Blanchflower [9], 2010). A consequence of high unemployment rates and adverse employment market conditions is that young people, who are usually more dynamic than adults, stay out of employment. The barriers to entry to the labour market are higher when young people lack the educational qualifications that would increase their employment opportunities. Conversely, the probability of 'labour market success' is significantly associated with better qualifications (Borooah and Mangan, [18] 2008). Using data from the 2001 UK Census, the authors find that higher levels of qualifications in the UK increase the likelihood of: a) persons in employment to be in 'good jobs', and b) persons in the labour force to be in employment.

In the last years, an increasing number of young people emerges in the UK and worldwide, NEETs, who are out of education, employment or training. The characteristics of this group of people are illustrated and discussed in this literature review that follows in the next section. A systematic review of the factors and characteristics of young people in NEET status will help us identify the predictors of NEET status that will be subsequently employed to define the effect of neighbourhood context on young people becoming NEETs in this study. Scholarship on neighbourhood effects has only considered the effect of neighbourhood deprivation on young people's educational attainment but has not been extended to employment outcomes leaving a gap in the literature. This gap could be explained by the fact that neighbourhood effects have emerged as an important sociological problem since the early 19th century and therefore stimulated the interest of sociologists. Unlike neighbourhood context, young people who face social exclusion because they are inactive and disengaged from education or training have only recently appeared in the sociological discourse and become a key issue in the political agendas of governments across the world.

The gap in the literature connecting NEET status and neighbourhood context effects imposes a division of the current literature review in two parts along particular lines. One part will investigate and discuss the characteristics of young people in NEET status while the second will focus on neighbourhood deprivation effects on young people. The main characteristics addressed in studies and reports on young people in NEET status are going to be explored under four different levels at which young people's trajectories can be investigated (family, individual, school and peer group characteristics). This grouping of characteristics has been employed in neighbourhood effects research (Leventhal and Brooks-Gunn [110], 2000) and will provide a theoretical basis to allow two different literature traditions to be explored and to create a research framework for the current study.

2.3.2 Individual characteristics that increase the risk of becoming NEET

Over the last decades a number of UK education reforms have attempted to widen access to a historically elitist system and to increase participation in education after compulsory education [80]. Despite those efforts, many young people disengage from education as a result of poor educational achievement (Bynner and Parsons, 2002). Low educational attainment not only increases the likelihood of disengaging from education but also constitutes a barrier to enter the labour market (Bell and Blanchflower, 2010) whereas educational qualifications more than double the chance that inactive young people will return to education even if after a short inactivity period (OECD, 2009). Unstable trajectories in relation to poor educational achievement are also reported by Fergusson [60], in a survey of over 800 16 to 18 year olds. The author finds that young people with the lowest levels of educational achievement have the tendency to follow multiple post-16 destinations. They move from employment to education and through periods of NEET status. This tendency is greater for low achievers than for those with high educational attainment.

Rennison et al [148], 2006 study young people in NEET status using quantitative data collected as part of the evaluation of the Education Maintenance Allowance (EMA), covering two cohorts of young people who completed compulsory education (Year 11) in summers 1999 and 2000. The authors find that failure to achieve any GCSEs at the end of Year 11 is strongly associated with becoming NEET for young people who intended to continue in work or training (40.9 per cent had obtained no Year 11 qualifications) and, in particular, among young people who had no clear plans about what they were going to do after completing compulsory schooling (59.9 per cent with no qualifications). These young people enter the NEET group due to feelings of inadequacy as well as because of inability to find courses that would meet their needs.

In a study on worklessness Macmillan et al [120] (2012) use data from British Cohort Study (BCS) and find that young people with no qualifications are more likely to enter into long term worklessness compared to young people who make successful transitions from school to work. This is reinforced by the fact that employers value qualifications which they consider useful skills such as numeracy and literacy skills.

Similar results are reported by Britton et al [22] (2011) who use data from the Labour Force Survey (LFS) and find that young people who are unemployed or inactive without participating in education or training have worse GCSE attainment than all other groups. They also find that GCSE attainment appears to be a stronger indicator of young people's trajectories than socio economic background. Also, the authors find that there are a group of young people in NEET group especially at the age of 18 with good qualifications and good family backgrounds. This reflects a portion of young people taking a gap in between different courses or in between school and higher education.

Crawford et al [42] (2011) use three datasets to study young people's education and labour market choices at ages $16-17$ and $18-19$; the Longitudinal Study of Young People in England (LSYPE, `https://www.education.gov.uk/ilsype/workspaces/public/wiki/Welcome/LSYPE`), the Labour Force Survey (LFS, `http://discover.`

`ukdataservice.ac.uk/series/?sn=2000026`) and the British Household Panel Survey (BHPS, `http://discover.ukdataservice.ac.uk/series/?sn=200005`). The authors find that prior educational achievement levels are similar for young people who pursue jobs with training, jobs without training or who are in NEET status at ages $16-18$. Young people in NEET status at ages $18-19$ have the lowest KS2 and GCSE scores. In contrast, young people who continue in full time education at ages $18-19$ have higher levels of educational achievement and those who go on to university have the highest KS2 exam scores.

Further to academic attainment, another important characteristic that is related to young people's trajectories is ethnicity. Ethnic minorities face the risk of social exclusion. It is well documented that general unemployment rates are high for young people from ethnic minority groups (Bell and Blanchflower [9], 2010). The proportion of ethnic minorities in NEET status is small compared to the general proportion of unemployed people from ethnic minorities and the proportion of white British ethnic group participation in NEET status has increased lately. Additionally, no association was found between ethnic minorities local authorities' deprivation and NEET status (Macmillan et al [120], 2012). Overall, in order to study the effect of ethnicity it is important to consider significant interactions with other factors such as gender and the SEC of the home (Strand [184], 2008).

Special educational needs and health problems also need to be considered when studying NEEThood. Poor health and disabilities are referred in the literature as potential factors that increase the likelihood of young people being NEET (Rennison et al [148], 2006; Coles [38], 2002). It is reported that 24 per cent of young people in the NEET group had Special Educational Needs, whereas 17.5 per cent of young people in work without training and 18.3 per cent in work with training also had special education needs. Young people with learning difficulties and/or a disability are twice as highly represented amongst young people who have experienced 6 months or more NEET

(Macmillan et al [120], 2012).

Apart from health and disability, gender has also been studied in relation to NEET status. It is considered that young women's trajectories are more likely to be interrupted at ages $16-21$ as they are have the risk of becoming mothers. Therefore there is a higher possibility for young women with caring responsibilities to become disengaged from the labour market (Wolf [202], 2011; OECD, 2009; Macmillan et al [120], 2012, Coles [38], 2002; Bynner and Parsons [29], 2002). These findings are reversed in recent studies that focus on the association between NEET status and gender. Crawford et al [42] (2011) find that girls are more likely than boys to stay in full time education, to be in university or to combine full time education and work. However girls who enter the labour market at $17-18$ or $18-19$ are more likely to end up in jobs without training. Additionally, Duckworth and Schoon (2012) find that the number of young women in NEET status is significantly reduced in the last years. This finding suggests that the expansion of education has helped improve the life chances of young women and decreased the risk of social exclusion.

2.3.3 Family characteristics associated with NEET status

Family characteristics are important factors of NEET status in the same way that individual characteristics such as educational attainment is revealing about the probability of disconnecting from the labour market and education. The family characteristics that define the pathways of young people involve parental socio-economic background and parental practices. An individual's socio-economic background can be defined by characteristics such as their parents' socio-economic class, their parents' highest educational qualification and whether or not they live in a single parent family.

Parental occupation is one of the family characteristics associated with educational and employment outcomes for young people (Coles [38], 2002; Crawford et al [42], 2011; Payne [140], 2000; Pearce and Hillman [142], 1998; Rennison et al [148], 2006;

Duckworth and Schoon [50], 2012). More specifically, young people from unskilled manual backgrounds are five times more likely to become NEETs than young people from managerial or professional backgrounds. Britton et al [22] (2011) find that family characteristics such as parents in routine occupations or parents who are unemployed are predictors of NEET status for young people.

Young people whose parents belong to the lowest socio-economic groups and /or are benefits claimants and have poor educational background are more likely to leave education and school and to become NEETs (Yates et al [203], 2011; Office for National Statistics, 2008). Furlong et al [66] (1996) also focus on the possible protective role of socio-economic advantages and positive educational values and experiences, drawing on data from two comparable longitudinal surveys; the England and Wales Youth Cohort Survey (YCS), and the Youth Cohort Study of Japan (YCSJ) to compare the destinations of 19/20 year olds in England and Wales and Japan. The authors explore young people engaged in full time, or part time work (referred to as freeters in Japan), and NEETs. The authors find that social class and parental education are associated with continued educational participation at age 19/20 in both England and Wales and Japan, however the overall impact on early destinations is relatively weak. Britton et al [22] (2011) also find that NEETs come from poor socio-economic backgrounds and that young people who move out of the NEET group are from better socioeconomic backgrounds. The social grading of work and study options that young people follow in their lives is also suggested by Crawford et al [42] (2011). The authors find that young people whose parents belong to low socio-economic status or are less educated are more likely to be in NEET status or in full time education but less likely to continue to higher education. On the contrary, young people whose parents have higher education and occupation status are more likely to continue to full time education, rather than follow any other transitions. Wolf (2011) uses data from the Longitudinal Study of Young People in England and the British Household Panel Study (BHPS) and finds that 80% of young people from higher socio-economic background continued in higher education.

Educational qualifications of the individual's parents are associated with young people's trajectories (Crawford et al [42], 2011; Feinstein and Sabates [58], 2006). Young people whose parents have low educational qualifications are more likely to have problematic trajectories whereas young people from families with medium or high qualifications are more likely to continue in education. More specifically, 9% of the young people aged 16 to 21 whose trajectories are a potential cause for concern are more likely to have parents with lower educational qualifications and to live in social housing. On the contrary, 91% of the people aged $16-21$ who continue in education come from families with medium or high qualifications (Macmillan et al [120], 2012).

The socio-economic status of parents has a very significant effect on young people's educational attainment and employment trajectories through intergenerational transmission of parental characteristics (Dearden, Machin, and Reed [45], 1997). It has been found that the intergenerational transmission of parental unemployment plays an important role and shapes young people's employment outcomes (Macmillan [120], 2012). Sons with unemployed fathers when they are age 10 and 16 spend on average 12.4% more time out of work between the ages of 16 and 29 than sons with employed fathers at the same age. Macmillan also suggests that they are also 25% more likely to experience a year or more in concurrent spells out of work across the same time period than sons with employed fathers. In addition, Blanden, Hansen and Machin [14] use longitudinal evidence from the BCS and find that there is a higher probability for young people who grow up in poverty being unemployed at age 34.

Finally, transitions are strongly associated with parental aspirations. Crawford et al [42] (2011) find an intergenerational transmission of attitudes to orientation about what course to take after completing compulsory education. Young people at 17/18 and 18/19 whose parents consider it is important for their children to get a job with a "trade" or to continue on apprenticeship or vocational training are more likely to follow these trajectories than to continue in full time education. Low parental aspirations and a lack of appreciation of the significance of education on young people's lives are associated with unsuccessful trajectories after compulsory education (Rennison et al [148], 2005).

2.3.4 Parental practices and young peoples outcomes

Parental interest and involvement in a young person's activities and decisions are found to be crucial in the trajectories young people follow after 16. Rennison et al [148] (2006) find that parents of young people in the NEET group were most likely to say they had not been involved in the young person's activities and decision making. Parents of NEETs were not as supportive and involved in education oriented activities as were parents of those who continued in education or employment. Characteristics of parents such as low attendance of open days, negative attitudes towards education, unwillingness to cooperate with teachers, and scarce or no attendance of parents' events are strongly associated with young people's decisions not to continue in post-compulsory education. Parental advice plays a role in education and employment outcomes. Young people from disadvantaged backgrounds cannot rely on their parents for information and advice about careers (Macmillan and Britton [120], 2012). Parents from disadvantaged backgrounds feel that they do not have the knowledge and ability to give their children advice and guidance about what to do when they leave school. On the contrary, the transitions after compulsory education are well managed and clear for young people from more socio-economically privileged families.

2.3.5 Attitudes to schooling and young people's destinations

This section concentrates on links between attitudes to school and NEET status. Some of the links are mediated through characteristics such as truancy and attitudes to education and disaffection with education. In a study based on in-depth interviews of fifty 16-19 year olds, young people who had experienced extended periods outside work or learning, Stone et al [183] (2000) found that NEET status was associated with individual characteristics, such as personality, behavioural difficulties and confidence issues. Participants in the interviews described they were difficult children towards their parents and teachers. Truancy was also reported by the majority of young people which sometimes resulted in leaving school before taking Year 11 public exams. Truancy is a common characteristic of the NEET group reported in the literature. NEET young people truant more compared to other young people (Raffe [145], 2003) and persistent truancy increases the likelihood of being NEET at age 18 (Coles [38], 2002).

Research also indicates that young people who have negative attitudes about school and low aspirations are not likely to continue to post-compulsory education (Crawford et al [42], 2011). Macmillan et al [120] (2012) find that attitudes of young people to schooling is a characteristic that influences outcomes. Young people who enjoyed school were more likely to continue to full time education rather than follow other trajectories after compulsory education. The authors report that positive attitudes to schooling may also be related to unobserved characteristics of young people that make it easier for them to progress to better employment opportunities and to succeed in getting higher wages in the future.

Rennison et al. [148] (2006) also refer to disaffection with schools as another potential reason for not continuing in education. Disaffection was related to negative attitudes towards school but did not necessarily result in NEET status. A stronger predictor of NEET status was advice received about post 16 destinations. Young people in the NEET group were least likely to have discussed post 16 options with a career teacher or tutor. 43.5% of NEETs are reported to have contacted the careers services after year 11. Levels of contact were lower for young persons in work or training and lowest for young people who continued in full time education.

2.3.6 Peer group influence and young persons' destinations

The behaviours of young people's peer group affect entry to NEET status. Drawing on data from the Youth Cohort Study, Spielhofer [180] (2009) points out that young people not engaged in employment, training or education often faced issues such as bullying, exclusion and behavioural difficulties. Young people in the NEET group did not have any clear thoughts about what to do after leaving school and did not speak to anyone else except for their parents about their choices for the future. Absent or unclear direction was also accompanied by low future career aspirations, since for many young people the main motivation was to earn money. Informal networks such as peer groups appear to have provided less advice and guidance about options after compulsory education to young people from underprivileged family backgrounds (Macmillan et al [120], 2012).

Friends appeared to be a strong influence on the decisions of young people who were in NEET status since peer group was one of the influences reported to affect young people entering in NEET status (Spielhofer [180], 2009). The decisions of young people not to participate in education or training had a strong influence on their friends' decision making. NEETs reported that they preferred going out with their friends rather than focusing on their education.

Stone et al [183] (2000) report that the peer group influence was reported by young people to be a strong barrier for NEETs to move on or to go back into mainstream society. Due to low self confidence levels NEETs accepted a role model into their group of friends which often was the route to criminal activities and drug and alcohol use. They also reported low confidence issues which resulted in feelings of isolation and acceptance of bullying behaviour.

In summary there are a number of barriers that delay the entry of young people in the labour market after compulsory education. The current economic conditions and the labour market demand are key factors associated with the number of young people in

NEET status. Other important factors such as demographic characteristics, individual skills and abilities, and also parental, school and peer group characteristics increase the number of NEETs in the UK today.

The first part of the literature review identified young people at risk of being NEET and discussed the characteristics that influence the probability of disconnecting from the labour market and education rather than choosing a stable pathway. The second part of this review will focus on defining neighbourhoods, describing their influence on young people and investigating the effect of living in a high poverty neighbourhood on young people's outcomes.

2.4 Neighbourhood effects on young people's outcomes

2.4.1 Neighbourhood definition

Conceptualising neighbourhoods is a complex task since neighbourhoods are not only geographical but also sociological structures. Economic, cultural and social relationships which develop in a neighbourhood help develop a sense of locality among its residents. In this section we are going to define what is meant by the term neighbourhood and how it is used in the literature. A definition of neighbourhood should look into the meanings of "Neighbourhood" and "Community" to understand how they are used and why they are important indicators in determining young people's outcomes. There has been extensive investigation among researchers and sociologists on the definition of these terms, with some using the terms community and neighbourhood interchangeably in several contexts (i.e. to define geographical or virtual boundaries), while others make a concrete distinction between those two based on a clearly defined set of characteristics.

The ancient Greek historian Herodotus (484BC-425BC) gave one of the first definitions of the characteristics that people share when they live in the same geographical region and share a common sense of belonging. Extending the notion of community, he pointed three characteristics that describe common identity: People speaking the same language language (homoglosson), sharing common kinship (homaimon) and having the same religion (homothriskon) (Ahrweiler [4], 2000). Lupton [114](2003) raised three issues; First, the concept that neighbourhoods are both physical and social spaces. Second, that the size and boundaries of neighbourhoods can change over time, and subsequently residents experience different neighbourhood characteristics. And third, that neighbourhoods cannot be seen in isolation, since other places and internal processes in neighbourhoods influence their characteristics. The sociologist Hillery [87] (1955) investigated the common definitional components of community and noted ninety four different definitions of community influenced by the main two schools of thought. The first one, consists the very many definitions coming from the advocates of a territorially-based conception of community. In that case, the two notions are used interchangeably based on the question the researcher aims to address. The second one, consists of the definitions coming from the advocates of a notion of community based on social network relationships. The technological advancements of the last decade, and especially the internet, has motivated sociologists to define "virtual" communities based on a set of social characteristics, common beliefs and interests, sparking a great debate among scientists.

Following Hillery, Willmott [197] (1989) extended the classification of the two notions by proposing a sub-classification applied in both categories. Based on the assumption that the notion of neighbourhood includes that of community in some cases, he argues that an additional distinction between local and non-local communities applies. In the first case, in which a local community identifies a specific cluster of people within a certain geographical region, one may additionally argue that the notions of community and neighbourhood coincide. Willmott even suggested a third dimension in trying to define the notion of community, that of "community of attachment". He argues that necessary elements in identifying a sense of community among people are social interaction and a sense of common identity.

Chaskin [32] (1997) made a distinction between the terms community and neighbourhood. Community on the one side is not only a division of land, but also it consists of common concerns, shared beliefs, relationships, and a shared culture. Neighbourhood on the other side refers to a spatial construction and a geographical unit. Despite the initial distinction that he made, he further noted that in the urban context a neighbourhood is a unit of social cohesion. A neighbourhood is a combination of a geographical unit and of community characteristics of social cohesion. He noted that a neighbourhood is not only a place on the map but it is an open system linked to other systems and that different populations live and participate in neighbourhoods in a different way.

Boyle and Lipman [20] (1998) also point a difference between the term "neighbourhood" and the term "place". Despite the fact that they have common characteristics, place is a geographical structure whereas neighbourhood can be defined as a sociological structure. There are three common features that define neighbourhood and distinguish it from place: shared identity, shared social relations and locality. The geographical boundaries alone do not include all of the economic, cultural and social relationships that develop in a neighbourhood.

Neighbourhoods are defined as a set of three different levels, each with a distinct function, the home area, locality and urban district or region (Kearns and Parkinson [102] 2001). The first level, which is the home area, is the area of $5-10$ minutes walk from an individual's home. There are psycho-social benefits associated with the home area, such as the sense of identity and belonging, self-recreation, network possibilities, reflection of one's own values. Locality, which is the second level, is related to residential activities, social status and position. Some people spend a lot of time in their neighbourhood and thus take part in local activities, while others spend more time in places outside their neighbourhood. The third level is the urban district or region, which is defined as a landscape of social and economic opportunities. It is related to employment, leisure activities, family connections and social networks and explains why some people benefit more from a neighbourhood than others.

Despite the debate on defining the notions of neighbourhood and community, it is clear that even though almost all people live in neighbourhoods, they do not necessarily take an active role in their area of residence in the sense of interactions with other people. In the United Kingdom, the Home Office-sponsored active citizenship website provides the following information: "There is no one definite definition of community. A community is a specific group of people who all hold something in common. Community has tended to be associated with two key aspects: firstly people who share locality or geographical place; secondly people who are communities of interest". Communities of interest are groups of people who share an identity - for example Afro-Caribbean people; or who share an experience for example people with a particular disability (`http://www.active-citizen.org.uk`. February, 2005).

In conclusion, it is generally accepted that in order to define the notion of neighbourhood, a fundamental element is that of geographical region. Additionally, in the case in which a set of social characteristics are shared among people living in a specific geographical region, the two notions might coincide. Finding a measure to define neighbourhood boundaries that captures both geographical boundaries and social spaces has been a key issue in neighbourhood effects research (Macintyre, Maciver, and Sooman [119], 1993). The difficulties and constraints a researcher faces in capturing both structural and social neighbourhood boundaries are going to be analytically discussed in Section 4.2 below.

2.4.2 Developmental epochs

The structural and social neighbourhood boundaries provide the place and context where young people live. The effect of neighbourhoods on educational advancement may be different across different periods of development for young people (Aber, Gephart, Brooks-Gunn, Connell, and Spencer [3], 1997). In preschool years the effect of the neighbourhood is hypothesised to be insignificant mainly because children spend their time at home with their parents. However McCulloch and Joshi ([126], 2001) found that the level of deprivation in electoral wards has a significant association with low test scores in pre-school years after controlling for family socio-economic characteristics. Central to development in early childhood is the time that parents or child carers spend with children and the quality of activities used to stimulate children's imagination and mathematical and linguistic reasoning abilities. The use of the facilities offered locally, such as the playground, as well as the time children spend there, occurs under the supervision of the parents. Therefore, the effects of the neighbourhood occur mainly through the effects of neighbourhood on the home environment. During school years children spend less time at home than when infants and more time at school and with peers. The quality of interactions with teachers and students influences development during childhood. During early adolescence, young people change both biologically and psychologically; they become more autonomous, and get a sense of personal identity. During this period, young people come closer to peer groups, get involved with school and leisure activities and with formal and informal organisations in their neighbourhood. As young people become more involved locally, neighbourhood effects are presumed to increase in scale. Late adolescence and early youth signify the preparation to work and independent family life and presuppose higher contact with neighbourhood institutions such as for example networks for employment opportunities.

The majority of research on neighbourhood effects has focused on young people in their late adolescence or early adult life (Leventhal and Brooks-Gunn [110], 2000; Brooks-Gunn et al [24], 1997; Brooks-Gunn, Duncan, Klebanov, and Sealand [25], 1993).In the current study, neighbourhood effects are studied when young people are in their early adolescence at the ages 13/14 and interactions with other people, peer group, formal and informal organisations in their community increase. This age was also selected as it coincides with the age group that is considered important in predicting young people who are most at risk becoming NEETs (Britton et al [22], 2011). At the age of 13/14 neighbourhood characteristics can exert a positive or a negative effect on their residents. A positive effect could be the outcome of interaction with institutions and services available in the community such as for example police stations, schools, sports and recreation centres that can encourage and sustain positive development of young people in a neighbourhood. Conversely, the influence of a neighbourhood can be negative on future trajectories in areas where young people interact with peer groups associated with crime and drug dealing or areas where monitoring from formal institutions is very limited.

2.5 Neighbourhoods effects on young people

Neighbourhood effects are the effects on educational, social and economic behaviour that develop as a result of living in a specific area. Neighbourhoods determine personal characteristics, facilitate or constrain interactions among individuals, and exercise economic pressures (Atkinson and Kintrea [5], 2001; Garner and Raudenbush [71] 1991). In general, neighbourhood effects in poor places will have a negative effect on people's life chances over and above any other negative effects that reinforce inequalities such as education and ethnicity. Neighbourhoods exert an indirect influence on personality development, which causes either positive or negative predisposition towards the educational process and subsequently influences employment outcomes.

The neighbourhood is the defining world for many of its residents as it determines social interaction or social isolation. People are more likely to have more contact with the people who live in their area of residence than with people who live further away. In poor areas, residents associate mostly with people like themselves and they often share the same beliefs, attitudes and expectations. Living in a stigmatised neighbourhood may provoke the isolation of poor people (Atkinson and Kintrea [5] 2001, Musterd et al [133] 2003). A neighbourhood is stigmatised when the people who live there are isolated from mainstream society mainly due to economic reasons and subsequently face discrimination by outsiders. Stigmatisation in a deprived neighbourhood, poor public services and joblessness may provoke adjustment to unconventional social norms, which in turn causes social exclusion.

Young people who live in poor neighbourhoods are more likely to experience negative outcomes in the future compared to those who grow up in more affluent areas (Klebanov, Brooks-Gunn, and Duncan [105] (1994). Certain mechanisms reinforce the isolation of poor people in their neighbourhoods and influence negatively the life chances of young people. Since residents do not make contacts with more affluent people, young persons have few role models of people who are successful in their education and thus are discouraged from having high expectations for their future. In areas where people stick to group norms, there is a lack of mainstream role models and there is no perception that education is meaningful, it is unlikely for young people to become competitive or to be interested in pursuing education (Wilson [199], 2012). In contrast, young people who grow up in affluent areas tend to have lower dropout rates and to stay in education longer compared to young people in poor areas (Brooks-Gunn et al [24], 1993, 1997)

The quality and frequency of social relations can have an effect on educational attainment and employment outcomes. Research has identified links between deviant peer group influence in disadvantaged neighbourhoods and anti-social behaviour (Dubow et al 1997), negative behaviours, crime and disengagement from the labour market (Case and Katz [31] 1991; Sinclair et al [173] 1994; Ginther et al [74] 2000; Oberwittler [136], 2004). The effect of social relations on neighbourhood effects can be explained through the concept of social capital (Coleman [37] 1988; Croll [43], 2004) (see Section 3.3.1). Social capital describes the frequency and quality of social relationships in a neighbourhood and a community. Social capital is transmitted through interaction with people in an individual's residence, as well as through institutions such as schools. For example, living in an area where educational attainment is highly considered could reinforce school achievement and participation to young people who live there. Lack of social capital is a characteristic of individuals who live in socially disorganized communities (Sampson [161], 1997) (see Section 3.3.1). For example strong ties with the peer group in areas characterised by high crime rates could be a strong negative influence on young people. Young people who spend a lot of time in their neighbourhood and relate to a deviant peer group might develop anti-social behaviour or engage in criminal activities which can have a negative effect on their self-esteem and aspirations about education and employment.

Literature on neighbourhood effects also focuses on the link between neighbourhood context and crime. Hirschfield and Bowers [88] (1997) find a strong association between lack of neighbourhood social control cohesion and antisocial behaviour. In addition, Veysey and Messner [190] (1999) revisit an analysis of 238 British neighbourhoods conducted by Sampson and Groves [162] (1989) and find that social disorganization is related to adverse outcomes such as victimization of residents in a deprived area. Markowitz et al [124] (2001) estimate the association between social disorganization, burglary and fear of crime using data from the British Crime Survey. The authors find that low neighbourhood cohesion results in higher crime, disorder and fear among residents of an area.

Moreover, the resources in poor areas are not sufficient to allow young people to receive high quality education in order to become more involved in economic and social life (McCulloch, A., and Joshi, H., [126] 2001). School resources can impact on young people's outcomes. Evidence from the NPD and PLASC suggests that extra resources at school can have a significant impact on the educational attainment of high ability pupils who come from low-income families (Jenkins et al [97] (2005). In addition, higher levels of per pupil expenditure and lower pupil-teacher ratios are associated with higher levels of GCSE attainment (Jenkins et al, [96] 2006). Scarcity of family resources may have important adverse consequences on young people. When families can access greater economic resources, such as for example better paying jobs, they can invest more in educational items. Because of limited resources, poorer families cannot afford to live in attractive neighbourhoods and therefore have to concentrate in areas with cheap housing or public rental housing estates and poor conditions of life which nurture a culture of low expectations and aspirations for the future of the individuals living there. Noble and Smith (1996) find that poverty creates spatial segregation among rich and poor families in UK communities. Lupton and Power [116] (2006) also suggest that specific families are likely to live in deprived areas with noticeable characteristics such as council houses and socio-economic disadvantage. Those established characteristics that involve both physical characteristics and social interaction are difficult to change although they can change over a number of years (Lupton [114] (2003). Young people who live in deprived areas with limited school and family resources have limited education, employment and socio-economic life prospects and therefore are more likely to abandon education and pursue manual employment or become unemployed.

To sum up, there is a plethora of research on the effects of neighbourhood context on educational attainment of young people (Garner and Raudenbush [71], 1991; McCulloch and Joshi [126], 2001; Leventhal and Brooks-Gunn [111], 2004; Kauppinen [99], 2007) however the association between area deprivation and young people at risk of becoming NEETs and area deprivation has only been referred in the UK literature but not directly assessed. Living in a deprived area has been associated with lower probability of getting or keeping a job for its residents (van Ham and Manley [121], 2006). Evidence shows that NEET rates are particularly high in specific areas in the UK such as inner London, Merseyside, West Midlands and Strathclyde (Wolf [202], 2011). Crawford et al [42] (2011) find that it is easier for young people who live in less deprived areas to find a job after the age of 16. This could be attributed to the fact that local labour market conditions are better in less deprived areas, thus making it easier for young people to find employment during and after leaving school. Macmillan et al

[120] (2012) refer to 152 local authority areas across Britain which are characterized as 'hotspots of youth unemployment. Youth unemployment can vary from neighbourhood to neighbourhood within one local authority area. The authors use the proportion of young people claiming benefits as a measure of area youth unemployment and find that striking differences exist; in some neighbourhoods the proportion of young people claiming benefits is close to zero whereas in others the proportion is over 1 in 4. It becomes evident that research of neighbourhood effects on young people's trajectories is limited suggesting a potential area of investigation to inform policy.

2.6 Evidence linking neighbourhood effects to educational attainment

Existing research on area deprivation focuses less on employment outcomes and more on educational attainment. High levels of area deprivation are associated with lower rates of participation in higher education (Crawford et al [42], 2011), low educational attainment and high unemployment rates (Coles [38], 2002). Given that poor educational attainment is one of the key determinants associated with entry to NEET status (Rennison et al [148], 2006; Britton et al [22], 2011; MacMillan and Britton [120], 2012), this section reviews literature of neighbourhood effects on educational attainment of young people. Due to the interest of sociologists across the world in neighbourhood effects, there has been a big number of studies on this subject.

So far in this review the impact of neighbourhood context has been discussed in relation to key studies that investigate effects on educational attainment. The focus now turns to four UK studies that investigate neighbourhood effects on educational attainment and were selected in order to explore how existing literature encounters some of the key problems associated with neighbourhood research. The most important concerns in studying neighbourhood effects relate to: a) the difficulty to draw causal relations since associations do not imply causality, b) causality is difficult to explore as the relationship between neighbourhood economic characteristics and the young person's attainment is not a direct relationship; intervening variables such as neighbourhood social capital may have an effect on young people's outcomes over and above area characteristics, c) the difficulty to separate neighbourhood effects from a large number of other factors that influence educational attainment, d) unmeasured variables may influence children's educational achievement and thus suppress neighbourhood variables, when neighbourhood effects and outcomes are not correlated, and e) Selection bias may arise from the fact that to some degree families can choose the neighbourhood where they live. The majority of research in neighbourhood effects aims to address these key methodological issues which will be discussed in detail in Chapter 4 . In this section, evidence is reviewed in the light of how the datasets employed, the econometric techniques used to study neighbourhood effects and the key variables included in the analysis attempt to solve key methodological issues of neighbourhood research. The studies were selected for review because they employ different datasets in the analysis involving census, longitudinal and experimental data. Additionally, they employ different approaches to handle data such as multilevel modeling, instrumental variables and ordinary least squares regressions. These studies are:

Bell [10] (2003) studies the effects of characteristics of the neighbourhood in which a school is situated. The author uses information about electoral districts obtained from the internet based Neighbourhood Statistics Service of the Office of National Statistics and from the OFSTED reports and the awarding bodies' national centre database. The area investigated covered two diverse local authorities in the East Midlands representing a wide range of values of the Indices of Deprivation. Six separate indices for various domains of deprivation were provided: income, employment, health deprivation and disability, education skills and training, housing and geographical access to services. Two types of LEAs are studied. The first type of LEA is urban industrial and has deprivation indicators which are higher than average, i.e. high unemployment, low car ownership and low socioeconomic status. The second type of LEA is characterized by average indices of prosperity and deprivation in small-scale communities. Family background is measured by Child Poverty Index. Multilevel analysis is used (shool and LEA level) to explore the relationship between neighbourhood deprivation, quality of teaching and student level GCSE results. The author finds that neighbourhood child poverty and teaching quality have a negative 'effect' on GCSE attainment. However, the authors stress that like most research in the area of education, it is difficult to establish causality due to the the endogeneity problem.

McCulloch and Joshi [126] (2001) use local government electoral wards and data from the NCDS to study the association between family poverty, the level of deprivation in electoral wards and children's cognitive test scores. The sample involves only children who lived in England and Wales in 1991 and come from young mothers and for this reason less educated mothers. The dataset consists of 1,532 families and 2,290 children. The authors examine the association between children's cognitive functioning with a range of factors that show socioeconomic position. Socioeconomic position of the family is studied through the employment status of the mother, the presence of the father, living in social housing and having no access to a car. Other predictors of children's cognitive ability which are explored are the number of children, the level of income and mothers level of education. Neighbourhood deprivation is measured using the Townsend indicator of deprivation. The Peabody Picture Vocabulary Test (PPVT) is used as an indicator of children's cognitive functioning. The method employed in the study is ordinary least square regression models. The initial model controlled for child age and gender, and then further analysis was conducted to explore the effect of deprivation in child and adolescent educational outcomes. After that, family level variables were added and additional home environment tests were performed. The authors found that the index of neighbourhood deprivation is significantly associated with lower cognitive test scores in children aged $4-5$. The association between neighbourhood deprivation and young people's outcomes is statistically accounted for by individual characteristics in children aged $6-9$. Neighbourhood poverty effects were statistically insignificant for children aged between 10 and 18 years. A potential cause of concern in this study is that electoral districts as a measure of neighbourhood boundary does not necessarily coincide with the boundaries of local communities even though it provides a useful ready-made framework for the purposes of neighbourhood analysis.

Garner and Raudenbush [71] (1991) define neighbourhood through the boundaries of one education authority (school district) in Scotland combining data from four different sources. The first source contains individual and family background characteristics from a sample survey by the Centre for Educational Sociology at the University of Edinburgh and the Scottish Education Department. The second source of data includes information from one Educational Authority about pupils' attainment before entry to secondary school. The third comes from the Examination Board and contains results of the Scottish Certificate of Examination for the last two years of non-compulsory schooling. Finally, the fourth source of data is the 1981 Census of Population. Data were combined at the level of the enumeration district (census tract in U.S. terms). The level of disadvantage in the neighbourhood is given by measures such as unemployment, youth unemployment, single parent families, low earning socio economic groups, overcrowding, and percentage of permanent sick individuals thus allowing the estimation of social deprivation separately from other neighbourhood characteristics. The educational outcome measure is attainment score at the completion of secondary school (age 16). Schooling measures include the effect that pupil membership of a school has on individual pupils educational attainment. Family characteristics such as father's occupation, parental schooling, family size and single parent families are also included in the model. Prior attainment measures are test results from a verbal reasoning ability test and test of reading ability. A two level hierarchical model was used. The within unit model explores the relationship between individual educational outcomes and prior attainment, sex, family background and schooling variables within each neighbourhood. The between unit model explores parameters of the deprivation score. A large proportion of the results are explained when the authors control for prior attainment and family background. Control for prior attainment shows that children with high prior attainment tend to live in neighbourhoods with high average educational attainment.

Gibbons [72] (2002) uses data from the National Child Development Study (NCDS), a British dataset that identifies the cohort members residential location to a neighbourhood level. Census data was used at enumeration district (ED) and local authority level (LA). The enumeration district (ED) is the smallest unit for which Census Statistics are available and around 10 EDs make up a Census ward. A potential cause of concern is that EDs contain only $150 - 200$ households and therefore may not capture area poverty effects. The sample used in the models consists of men and women from the 1991 NCDS sweep at age 33 who reported their highest educational qualifications. Parental characteristics and information on early abilities and school performance come from the 1974 measurements. The sample consists of 4,538 men and 4,835 women. The author finds that children who grow up in the same neighbourhood end up with similar educational attainments, however it is found that this is due to the fact that children who live in the same neighbourhood have parents with similar educational backgrounds. Overall, the author finds real benefits from living in more educated neighbourhoods. Children who live in neighbourhoods ranked at the bottom of educational hierarchy would need parents educated to degree level in order to have the same opportunities as children who grow up in an average background.

Finally, Leventhal and Brooks-Gunn [111] (2004) use an experimental approach to investigate the effects of neighbourhood context for young people and their families who moved from high to low deprivation areas under the Moving To Opportunity programme (MTO). The authors use low income and minority families who live in public housing and have at least one child less than 18 years old in five urban cities. These families were given the opportunity to leave high poverty areas and to reside in higher income ones. The impact of moving from high to low poverty neighbourhoods on educational attainment was positive. Both male and female young people aged $14-20$ in low poverty neighbourhoods had higher school grades and engagement compared to young people who stayed or moved back to high poverty neighbourhoods. The effect was higher for boys than girls.

The majority of literature on neighbourhood effects employs observational data such as longitudinal studies, census or electoral datasets whereas a limited research uses experimental designs. In the current review, the first three of the investigated studies used observational data while the last one adopts an experimental approach. Observational data such as electoral wards employed by Bell [10] (2003) and McCulloch and Joshi [126] (2001) and educational authority boundaries employed by Garner and Raudenbush [71] (1991) provide a useful ready-made framework for the purposes of neighbourhood analysis but can cause problems in defining neighbourhood boundaries since political or educational boundaries do not necessarily coincide with the boundaries of local communities. Additionally, electoral wards data cannot involve repeated measurements as longitudinal studies do. The experimental design adopted by the MTO allows causal relations to be tested due to the random assignment of treatment experiments but involves practical and ethical implementation difficulties.

The econometric approach employed in the reviewed studies is multilevel analysis by Bell [10] (2003) and Garner and Raudenbush [71] (1991) which allows the incorporation of theory about individual and group processes to be tested using a clustered sampling scheme. For example pupils are nested in schools, schools are nested in neighbourhoods, and neighbourhoods are nested in larger groups such as areas, towns, cities etc. Gibbons employs the instrumental variables approach that employs an instrument to remove spurious correlations between neighbourhood factors and young people's outcomes. McCulloch and Joshi [126] (2001) use ordinary least squares regressions which given that certain assumptions are satisfied offers the minimum variance of all unbiased estimators. The main findings of the studies reviewed can be summarized as follows. Neighbourhoods influence outcomes regardless of other measured or unmeasured variables. However, parental education and family influence are reported in most of the studies as the major influence on children's educational attainment over and above neighbourhood effects. One of the main difficulties addressed in the literature is to disentangle neighbourhood effects from other influences on attainment in order to draw causal associations. Also, it is important to include all the relevant variables in estimating neighbourhood effects in order to avoid omitted variable bias. These methodological issues are only briefly referred in this section but will be further and critically discussed in Chapter 4.

2.7 Summary and Conclusions

This section summarises and emphasizes the major points of this review, including evidence about young people's trajectories and neighbourhood context effects. The first part of this review included transitions of young people. School to work transitions for young people today do not follow the pattern of young people leaving education, finding a job and thus entering the labour market that used to be the norm in the past. In fact, the majority of literature on young people's transitions suggests that school leavers' transitions may be unstable, characterized by churning between different jobs, returning back to education or staying inactive. Young people who spend long periods of time inactive, disengaged from either employment, training or education and subsequently face the risk of social exclusion are commonly referred in the literature using the acronym NEETs.

Many different definitions have been proposed by the literature to describe the NEET group of young people. The predominant definition includes two categories: a) young people who are economically inactive with no participation in education or training and b) young people who are unemployed with no participation in education or training (Britton et al [22], 2011). The length of time in the workless state has also been an issue in the literature and the majority of analyses stipulate a minimum of six months out of employment, training or education is required for a young person to be included in the NEET group (Payne [140], 2000; Bynner and Parsons [29], 2002; Yates et al [203], 2011).

There are a number of barriers that delay the entry of young people in the labour market after compulsory education. The low labour market demand is a key factor associated with the number of young people in NEET status. Other important factors such as demographic characteristics, individual skills and abilities, and also parental, school and peer group characteristics increase the number of NEETs in the UK today. Smooth transition outcomes from education to work for young people are easier to achieve when the national economy is growing and when the labour market is youth friendly (OECD, 2000). Young people face many difficulties when they attempt to enter a hard labour market in a stagnating economy (OECD, 2000). The recent recession period 2008-9 in the UK economy has resulted in relatively low loss of employment overall, however the implications were more severe for youth unemployment (Gregg and Wadsworth [78], 2010); MacMillan et al [120], 2012). In addition, the individual characteristics of young people affect transitions from education to employment such as poor educational attainment and low levels of qualifications which constitute the most important barriers to enter the labour market, along with health and special education needs and ethnicity. Family demographic characteristics such as parental socio-economic status, parental educational attainment, mothers age at birth of the young person and whether young people live in single parent families have been found to influence young people's trajectories. Parental practices also influence NEET status. Parental characteristics such as low interest and involvement to young person's schooling, negative attitudes towards education and low aspirations are associated with young peoples decisions not to continue in higher education. Young people's attitudes to school such as low levels of truancy and not enjoying schooling are found to maximize the likelihood of disengagement from education. Peer group characteristics such as engagement in antisocial and / or criminal activities and exclusion can have a negative influence and create a barrier to smooth transitions for young people.

The second part of the literature review concerns the study of neighbourhood effects. A key point that emerges from the literature is the difficulty to conceptualize neighbourhoods since they are not only geographical but also sociological structures. These two aspects of neighbourhoods have been pointed in various definitions stressing that neighbourhoods are both physical and social spaces for their residents and that it is difficult to capture both of these aspects in defining neighbourhood boundaries. The context provided by the structural and social neighbourhood boundaries can have different effects on young people's development across different ages and periods of their lives. Neighbourhood context effects are mostly insignificant in preschool years with the exception of the study of McCulloch and Joshi, [126] 2001). As children grow up, they spend less time at home and more time at school and with peers and the neighbourhood effects are only mediated by the quality of these interactions and the resources available in their schools.

Numerous studies have examined the characteristics of neighbourhoods that affect young people and their families, the effects they exert on their residents and the key mechanisms and pathways through which these effects operate. A review of this research demonstrates a significant relationship between neighbourhood deprivation characteristics and educational attainment which is mediated by parental socio-economic and educational level, personal characteristics, resources available in the community to deter antisocial and criminal behaviour and the strength and type of social relations developed. There are a number of problems encountered in studying neighbourhood effects such as the difficulty to draw causal conclusions, to separate neighbourhood effects from a large number of other associated influences, to control for unmeasured variables, and to reduce the selection bias associated with the fact that families chose to some extend the places where they live. Based on the key problems associated with studying neighbourhood effects, studies that explore neighbourhood context effects need to carefully select the datasets to be analyzed, the measure of deprivation and the variables employed and the econometric approach selected for the analysis.

In conclusion, this chapter defined the key concepts that will be investigated, young people in NEET status and neighbourhood characteristics, and pointed the key issues that have been emphasized in previous literature in relation to the research goals of the current study. What emerged from the literature review, is that young people in NEET status face the problem of social exclusion and future spells of unemployment. Additionally, research has only referred to the effects of neighbourhoods on young people's educational attainment but not on their employment outcomes. Thus, the current thesis extends prior research by investigating the links between area deprivation and NEET status. Having reviewed the literature, the next chapter attempts to provide an explanation to why young people who live in deprived areas characterized by Crime might have lower educational and employment outcomes and introduces the theoretical model that will be investigated in this study.

Chapter 3

Theoretical Framework

3.1 Introduction

Chapter 2 outlined and reviewed the key literature associated with young people in NEET status and neighbourhood effects on young people's educational and employment outcomes. Chapter 3 focuses on the systems and processes that influence young people's development in an ecological approach that addresses geographical, family, individual, institutional and social settings together. The aim of this chapter is to investigate a fundamental sociological question, the role of social context in individuals' lives. To provide a theoretical explanation to the question: Why might one expect local crime rates to influence young people's educational and employment outcomes? We investigate the features and mechanisms underlying neighbourhood effects on young people: first, the development of young people in an ecological context and the features of disadvantaged communities that cause serious consequences on young people are explored, and second, the processes through which the characteristics of poor neighbourhoods influence educational and employment outcomes.

The development of young people will be explored in relation to two theoretical frameworks: the Life Course theory (Elder [55], 1999; Giele and Elder [73], 1998) and the Ecological Systems framework of development (Bronfenbrenner [23], 1979) in Section 3.2 The Life Course theory (Section 3.2.1) is an interdisciplinary approach that proposes a research framework to study the dynamics between human lives and historical time, timing of lives, linked or interdependent lives, and human agency in making choices. The research paradigm proposed by Life Course Theory will be employed to study individual development in a multidimensional context that incorporates social, cultural and historical factors and allows research to target the particular circumstances that young people experience in deprived areas. To further consider the interaction between the quality and context of the environment and the young person, the Ecological Systems framework of development (Bronfenbrenner [23], 1979) will be employed; see Section 3.2.2. This theoretical framework explores the multidimensional context of an individual's environment, from the immediate family environment to the wider community and the social and historical context, through five interrelated systems: the Microsystem, the Mesosystem, the Exosystem, the Macrosystem and the Chronosystem. The Ecological framework suggests ways in which the neighbourhood and the settings that surround a young person, from the most proximal to the more distal, influence a young person's development and outcomes.

Section 3.3.4 will employ theories of community influence in an attempt to understand the context of neighbourhood crime on young people's development and outcomes. Numerous neighbourhood theories from different research traditions have been developed over the years. The study focuses on social disorganization theory (Shaw and McKay [171], 1942), a fundamental sociological approach that links crime and neighbourhood deprivation with delinquent behaviour (Section 3.3.1). Section 3.3.3 introduces the Underclass theory (Murray [131], 1999; Wilson [196], 1977) to describe socially excluded people cut off from the mainstream society who live in communities where anti-social behaviour and crime prevail. Section 3.3.4 draws attention to a more recent theoretical framework, the neighbourhood effects theory (Jencks and Mayer [95], 1990) that describes the causal relations between structural neighbourhood conditions and young people's outcomes through five models: the neighbourhood institutional resources, the collective socialization, the contagion, the competition and the relative deprivation model. Section 3.3.5 presents the Leventhal and Brooks-Gunn model of neighbourhood effects (2000) which draws on the Jencks and Mayer framework and focuses on availability of resources, relationship among residents in a community and norms and collective efficacy to explain neighbourhood deprivation effects on young people. Finally, Section 3.3.6 presents the epidemic hypothesis (Crane [41], 1991) which draws on the contagion model proposed by Jencks and Mayer which posits that the lower the quality of the neighbourhood, the higher are the chances for its residents to develop antisocial behaviour.

Section 3.4 formulates the Compositional Model of Neighbourhood Effects that is put forward in the current thesis. The model proposes four pathways that mediate the direct effect of neighbourhoods on young people: a) individual characteristics and attitudes; b) parental characteristics and relationships; c)) school experiences and attitudes to schooling, and; d) social epidemics. The Compositional Model of Neighbourhood Effects stands on previous theoretical models to help us understand the experiences of young people who grow up in deprived areas. It draws upon and reformulates theories of individual development and neighbourhood effects to illuminate individual development and the processes that influence young people in deprived areas. Thus, the model allows the research hypothesis and the research questions of this study to be explored (Section 3.5).

3.2 Development and Context

3.2.1 Life Course Theory

Life Course Theory as a Developmental Theory traces its roots in the late 1920s and early 1930s, when three pioneering longitudinal studies in Child Development were launched at the University of California, Berkeley: the Oakland Growth Study, the Berkeley Guidance Study and the Berkeley Growth Study. In the early 1960s the studies were extended well beyond childhood in an effort to tie together a central premise: the notion that changing lives alter development. It is worth mentioning, that early research efforts to develop the theory followed the life pathways of the same groups of children in all three Berkeley studies in the late 1920s and early 1930s; see Elder [54] (1998). Life Course Theory as a Developmental Theory proposes a new research paradigm in how we think about and study human lives. More precisely, it proposes a new framework in an effort to study the dynamics between human lives and historical time, timing within lives, linked or interdependent lives, and human agency in making choices. Hence it can naturally be considered as an interdisciplinary theory that incorporates ideas from economics, psychology, history, sociology, demography and biology. The central notion of the theory is that of the life course, a sequence of socially defined events and roles that the individual enacts over time (Elder and Giele [73], 1998).

There are four key principles that define the research paradigm of the Life Course Theory. First is the interplay between human lives and historical time. Sociologists and social historians in studying individual and family life trajectories noted that persons born in different years face different historical worlds, with different options and constraints. For example, Elder's research [54] (1974, 1998) on children and the Great Depression found that the life course trajectories of the cohort that were very young at the time of the economic downturn were more seriously affected by family hardship than the cohort that were in middle childhood and late adolescence at the time. Second is timing in lives. Broadly speaking, in a social context, the notion of timing refers to the incidence, duration, sequence of roles and to relevant expectations and beliefs based on age. For example, marriage may be relatively early or late within certain age norms according to specific demographic patterns. Third is linked or interdependent lives. A common sub-classification in studying linked or interdependent lives is that of links between family members and links with the wider world. Certainly, parents' and young people's lives are linked. For example, Elder's longitudinal studies research of the Great Depression found that as parents experienced great economic pressures, they faced a greater risk of depressed feelings and marital discord. As a result, their ability to nurture their children was compromised, and young people were more likely to face emotional distress, academic trouble and problematic behaviour (Elder [54], 1974, 1998). Links with the wider world refer to the interdependence between individuals and families with other groups and collectivities. Fourth there is human agency in making choices. It refers to the capacity of the individual to make choices. One may argue that this is the most controversial of all four dimensions that comprise the Life Course Theory. Clearly, human agency has limits. For example, individuals' choices are constrained by the structural and cultural arrangements of a given historical era, but individual choices and intentional actions may influence outcomes over and above other conditions.

The research paradigm proposed by Life Course Theory has many advantages over traditional theories of human development. It provides a multidimensional conceptual framework to study a person, under a unified context incorporating social, cultural and historical factors. It encourages attention to the impact of historical and social change on human behaviour, which seems particularly important in a rapidly changing society such as ours. It also gives emphasis on linked lives, and as a result it allows focus on intergeneration relationships and the interdependence of lives. At the same time, taking into account the human agency, the life course perspective avoids the strict deterministic approaches taken by earlier theories of human development. A weakness of this the Life Course theory is that it does not offer a description of the pathways through which historical, environmental, social and cultural experiences interact with young peoples cognitive and social development (Miller [129], 2010). Additionally, the Life Course theory does not provide the tools to test its assertions from a quantitative point of view. Life Course theory incorporates such differential contexts that raises several technical difficulties in following existing models to develop a quantitative approach to test its assumptions.

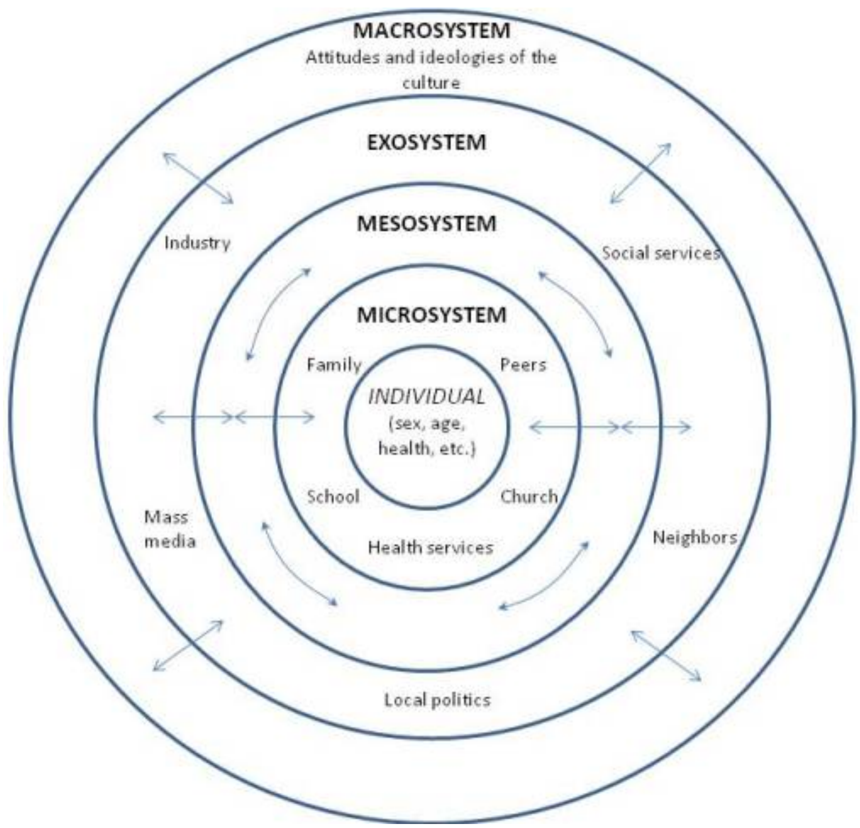
Despite the methodological difficulties encountered, a life course approach can be adopted in explaining neighbourhood deprivation effects on young people's outcomes. This approach requires research to take into consideration the social, cultural and historical context in which a young person lives and its dynamic influence and interaction with the personality, abilities and attitudes of the individual. Young people who live in high Crime areas have different social, cultural and environmental experiences compared to young people who live in low Crime areas. These experiences in turn might influence young people's academic achievement, aspirations, attitudes and educational and employment outcomes. Additionally, according to the life course theory, environmental influences have a different impact at different ages in determining outcomes. Therefore, it would be important to measure neighbourhood effects at an early age to check their influence on early adolescence. The concept of linked lives needs to be considered as well. For example parents who live in high crime areas might face financial hardship which could affect relationships in the home, increase stress levels and parenting practices which affect the development of young people. Finally the theory posits a role of the individual in making choices. For example the structural and cultural setting of deprived areas could affect young people's attitudes and fear of crime and influence negatively their choices about their educational and employment direction. Given the difficulties encountered in testing quantitatively the Life Course theory and the effects of different structural and cultural settings on young people's outcomes, this study employs the counterfactual framework and propensity score matching. Matching, as a method, is becoming a widely used technique to address the process of causal exposure as well as the limitations of observational data. The core of the counterfactual model, which is important for this study, lies on the premise that each individual in the population of young people at $18-19$ can be exposed to two alternate states of a cause, a high and a low crime area. A different set of conditions characterize each of the two states, which could potentially affect a young person being in NEET status or not. Each young person could have a potential outcome under each of the two states, even though they can be observed only in a high or a low crime score area.

3.2.2 Ecological systems theories and young people's development

Although the Life Course theory offers a research paradigm in how we think about and study human lives, it is also important to understand the ecological influences of interlinked systems on young people's development. For this reason, an ecological approach is introduced in this section to address how events and particular circumstances shape development. In the past, psychologists emphasized the role of the parents focusing on things such as their behaviour, health condition, educational qualifications, employment, personality and the extent to which they provided development opportunities to their children. Sociologists focused on community influences in addition to parental characteristics. In the sociological view, young people's development needs to be considered in the context of the environment where they grow up. The Ecological theories of development take into consideration the individual, their family and community factors and how they interact and shape individual development. The origins of the ecological systems theories became popular by Bronfenbrenner [23] (1979), followed by Garbarino [70] (1992) and Steinberg [182] (1990). The key focus of the ecological systems theories is on individual development in context taking into consideration the impact of multiple contexts such as school, peer group and neighbourhood. Human development takes place in a social context and results from the interaction between a changing individual and a changing context (Elder [54], 1998; 1999, Lerner [108], 1984; 1996; Sameroff [160], 1983, Vondraceck, Lerner and Schulenberg [191], 1986).

Although a number of theories have been developed, the work of Bronfenbrenner [23] (1979) has been definitive in understanding the ecological framework and has inspired research on young people's development. Bronfenbrenner suggests that young people's development is the result of the interaction between the quality and context of the environment and the young person (see Figure 3.1: 'Bronfenbrenner's Ecological Model'). The context of an individual's environment is multidimensional extending from the immediate family environment to the wider community and the social and historical context. Developmental processes that interact and link parental characteristics, neighbourhood characteristics, socio-historical conditions and individual ability help explain the directions that young people follow in life. Developmental processes act in the proximal and the distal environment experienced by the individual. The proximal environment is the basic context for development and refers for example to the family environment which offers daily contact and experiences. The influence of the proximal environment varies in relation to the individual and to the environment both immediate and remote. Distal cultural and social values have an indirect effect on the individual and are often mediated by the proximal environment.

Figure 3.1: Bronfenbrenner's Ecological Model



Bronfenbrenner's model involves five interrelated systems which are:

(1) The ***Microsystem*** refers to activities, interactions and interpersonal relations in the individual's immediate setting. This setting contains other individuals with different personality characteristics and systems of beliefs. Examples of such settings include parents, school, friends and neighbourhood. The Microsystem is the system in which the individual encounters the most social relations and the most direct ones. The relationships in the microsystem are bi-directional, for example the young person has an influence on the parents and at the same time the parents have an influence on the young person. The role of the individual is not constrained in observing these relationships; instead the individual has an active role in constructing the experiences in these settings.

(2) The ***Mesosystem*** refers to the interactions between the microsystems. It provides a connection to the structures of the microsystem, such as for example the connection between the child's teachers and parents or social services and the neighbourhood. The Mesosystem is not as proximal as the Microsystem since unlike parents, teachers are concerned with a number of individuals simultaneously. In addition, a child's education does not depend only on their teachers but also on parental assistance on learning.

(3) The ***Exosystem*** is the setting that links the context where the individual does not have any active role and the context where the individual is actively participating. An example of an exosystem would be a husband losing their job and the direct impact of unemployment on the family's financial situation which could affect their daily lives and increase stress in the home.

(4) The ***Macrosystem*** encompasses a variety of influences such as the cultural values, customs, resources or the broader context in which an individual lives. The macrosystem has a cascading influence on all other systems; the exosystem, the

macrosystem and the microsystem. Examples of the Macrosystem include ethnicity, race, poverty and broader contexts such as developing and industrialized countries. The culture or the ideology of the Macrosystem could influence the young person directly but the young person is not in a position to influence his/her surrounding Macrosystem.

(5) The ***Chronosystem*** encompasses the dimension of time in a young person's development. It refers to cumulative experiences of the individual, environmental events and socio-historical circumstances. It includes transitions and shifts in one's lifespan and also the socio-historical context that may influence a person. The Chronosystem includes life changes such as for example starting school, getting married, starting a job, having children, moving house, getting divorced, or retiring. An example of socio-historical circumstances would include a financial crisis and its effects on the daily life of a family.

The central point in the ecological systems theory is the role of the individual in a social context. The theory encourages the investigation of how the environment, from the most distal to the closest, influences the individual and provides a basis to consider how the neighbourhood, family, school and peer group characteristics interact and influence educational and vocational development. Bronfenbrenner stressed that the determinant of individual development is the environment as it is perceived rather than as it may exist in reality. What is original in Bronfenbrenner's theory is the set of nested structures, each inside the next. In some of these settings the young person could make an impact (microsystems; eg the classroom), others describe the interactions of the settings the young person occupies (mesosystems; eg parents and school), others reflect key figures in their lives (exosystems; eg parental workplace), others are influenced by the young person's culture (macrosystems; eg race and ethnicity), and finally others reflect socio-historical circumstances (chronosystems; eg weak labour market, financial crisis). A key strength of the ecological systems theory is that it considers all the settings of a child's life and the dynamic interactions between them. However, a critique of the theory is that it does not describe the pathways and processes through which the different settings of a young persons life have an impact on development and how the individual interacts with the settings in which they live.

The ecological systems theory has been employed in various disciplines and numerous research areas some of which involve youth transitions into adulthood (Mitchell [130], 2000), Families, delinquency and crime (Sampson and Laub [163], 2005), Young adults' transitions in the Netherlands (Liefbroer and De Jong [112], 1995) to name a few. The theory has also been employed in neighbourhood effects research (Leventhal and Brooks-Gunn [110], 2000).

The ecological theory can suggest ways in which living in a deprived neighbourhood influences a young person's development. The neighbourhood where a young person lives can be the microsystem setting which influences directly their activities, social relations and interactions in the immediate setting. The young person experiences the interaction between the settings that surround them in the Mesosystem such as for example parental relations with their school which could influence participation and motivation to school. There is a bidirectional role since the young person does not only experience a set of activities, roles and responsibilities with other individuals in their neighbourhood, but at the same time influences events that occur in their neighbourhood.

This section reviewed theories of human development that will be employed to inform the theoretical framework of the current thesis.These theories consider the interaction between the quality and context of the environment and the individual in a comprehensive way, and also can help explain how the context from the immediate family environment to the community and the historical conditions can influence young people's trajectories. While these frameworks provide a basis to understand individual development, understanding neighbourhood context effects on young people's trajectories requires a thorough investigation of the literature on the effect of neighbourhood context on individuals. The next section presents the key sociological approaches that have been developed to explain the consequences of deprived areas on young people.

3.3 Neighbourhood Effects Theories Relevant to Crime in the area of living and its effects on young people

3.3.1 The social disorganization theory

There has been extensive literature in the past by sociologists concerned with the effect of neighbourhood context on individuals (Du Bois [49], 1899; Park et al. [29], 1925, Bursik, 1986; 1988). In theories focusing on crime, neighbourhood deprivation has been associated with delinquent behaviour among its residents. In the classic study, Juvenile Delinquency and Urban Areas, Shaw and McKay [171] (1942) introduced a fundamental sociological approach, social disorganization theory, and suggested that high crime and delinquency rates are explained by low economic status of the area, ethnic heterogeneity that increases fear and reduces social cohesion, and residential mobility that disrupts community networks and social relations. Criminal acts are reinforced in those communities especially among young people who participate in groups that share the same system of values and take part in antisocial behaviour. The authors found that high delinquency rates in Chicago appeared in neighbourhoods characterized by low-income and ethnic heterogeneity which persisted in the long term even though the structure of the population changed in the inner-city areas. Residents of these communities did not share a set of common values, communication was disrupted, the community was not controlled or policed by outside agencies, criminal behaviour was prevalent and unrestricted freedom of individuals resulted in delinquent behaviour.

The key characteristics of socially disorganized communities were public incivilities, i.e. social behaviour lacking civility in public spaces. Lack of physical organisation appeared in those areas in the form of destroyed buildings, graffitis, litter and lack of greenery. Social disorganization also appeared not only in the form of poverty but also through public drinking and social disorder. When public incivilities occur, lack of collective efficacy is also observed in a community. Lack of collective efficacy refers to indifference of residents about what happens in their communities, lack of social cohesion and unwillingness to improve residential areas (Sampson et al [165], 1997). A further important characteristic of such communities is lack of social control which does not refer to controls imposed by the police but reflects the ability of a group of people to control and regulate the members of a community towards common collective goals. Young people in a community with low collective efficacy and high social disorder participate in a culture that accepts delinquent behaviour and crime. At the same time, adults in such communities may be discouraged to prevent young people from participating in criminal activities due to fear or lack of support and thus there is a higher likelihood for young people to become involved in crime when they live in disadvantaged neighbourhoods. Parental neglect also appears in high delinquency areas. The family structure weakens and the number of female-headed households increases, there is a high drop-out rate from schools and unemployment increases. As a result young people are neglected or abused by their parents which in turn increases the rates of delinquency and suicide rates (Barry and Garbarino [8], 1997).

3.3.2 Social Capital

Closely related to the theory of social disorganization is the concept of social capital. Drawing on the American social scientist James Coleman [37] (1988), Croll [43] (2004) places emphasis on social ties and community values. The main idea behind social capital is that social relationships, norms and personal networks are resources which can be used to generate valuable outcomes for young people's development. Communities, neighbourhoods, schools and families help transfers of social capital because they constitute social structures. Neighbourhood connections can support individual development through interaction and support between parents and young people and exchange of resources for young people's educational development. The lack of social capital is one of the distinguishing features of individuals in socially disorganised communities. Thus, the level of social capital in a community is directly related to the structure of communities and the cognitive development of young people.

3.3.3 The Underclass

The Underclass appeared in the late 1980s and early 1990s to refer to socially excluded people cutoff from the mainstream society (Murray [131], 1999; Wilson [199], 2012; Field [61], 1989). The term Underclass initially emerged in the American academic field and subsequently moved to Europe. The focal point of this theory is that it refers to specific groups of poor people but it is not synonym with poverty or disadvantage. It refers to low income people, societies which are socially disorganized, with anti-social behaviour and crime, low aspirations among young people, poor parenting skills, high truancy rates, drug addiction and weak social networks. Similar to socially disorganized communities, the underclass persists through time and is transmitted from one generation to the other.

The American sociologist Murray [131] (1999) was one of the proponents of the Underclass theory. Murray suggested that what defines people who belong to the Underclass is their behaviour and not structural economic factors. He defined three indicators of the people who belong to the underclass group: criminality, drop-out from the labour force among young males and illegitimacy. Repeated criminal activity characterizes the members of the underclass who make a living out of stealing and crime. Crime has adverse consequences on people in a society who feel that not obeying the law is tolerated and thus a demoralized ethic is created that is transmitted to other individuals in the society. Dropping out from the labour force comes in contrast to the economic and social institutions of the mainstream society. Finally, illegitimacy provides negative role models for young people who grow up in families without fathers. That is because young people and especially men lack the paternal role model and when they grow up they are not ready to undertake roles of responsibility in work and family and often engage in anti-social or criminal activities.

Wilson [199] (2012) studied the Underclass and focused on the influence of neighbourhoods on their residents, unlike Murray whose main point were the individual characteristics of the people who belong to the Underclass group. Wilson studied deprived communities in Chicago inhabited by low-income individuals and ethnic minorities. He suggested that young people living in deprived areas would have adverse outcomes in the future and become part of the Underclass. In a similar way to Murray [131] (1990) and Shaw and McKay [171] (1942), he referred to intergenerational transmission of the culture of the Underclass. Wilson put forward that the “pool of marriageable” black men declined between 1960 and 1980 which helped explain the link between single parenthood and female headed households, unemployment and neighbourhood poverty in black communities.

While there is a common acceptance of the existence of a socially dislocated group of the population which forms the Underclass, several criticisms have emerged of theorists on the Underclass theory. Wilson’s approach received considerable criticism by Jargowsky (1997) and Orfield and Ashkinazie (1991) with regards to residential segregation by race and to the decline in manufacturing. Murray’s focus on illegitimacy as the key reason of moral decline in the underclass society has received substantial criticism. Additionally, Walker [193] (1996) challenged Murray’s ideas especially with regards to the ideological constructs of the Underclass theory rather than the factual. Also Bourgois [19] (2001) suggested that Wilson’s work deterred social scientists from undertaking ethnographic studies of the poor.

Both of theoretical frameworks reviewed in the previous sections, the Social Organization theory (Shaw and McKay [171], 1942) and the Underclass (Murray [131], 1999; Wilson [199], 2012) describe deprived neighbourhoods as contexts that are linked to social stratification, low incomes, lack of opportunity and unemployment. The social processes by which deprived areas cause social problems to emerge and exert causal influences on young people's outcomes are described by the Neighbourhood Effects theory proposed by Jencks and Mayer [95] (1990).

3.3.4 The Neighbourhood Effects theory

While the influence of social disadvantage and the Underclass has received much attention, subsequently the focus has been directed to the ways that neighbourhood deprivation influences families and young people taking into consideration both insufficient resources and the context in which the family lives. The geographic clustering of disadvantage and the negative outcomes on its residents and especially on young people was investigated by Jencks and Mayer [95] (1990) who focused on the causal relations between neighbourhood conditions and young people's outcomes. Jencks and Mayer focused on neighbourhood structural dimensions and characteristics and behaviours of neighbours to identify their effects on young people's development through five theoretical models. The models focus both on the financial capital of the family and the neighbourhood as well as on the behaviour of neighbours. The first three models (resource, collective socialization and epidemic models) help explain how high socioeconomic status neighbours can have a positive or negative effect on young people's outcomes. The last two models (competition and relative deprivation model) focus on the reasons that people consider themselves successful or not by comparing themselves with their neighbours.

(a) The neighbourhood institutional resource model includes neighbourhood resources, libraries security and community services. It focuses on mechanisms of neighbourhood effects that relate to adult supervision, role models, monitoring and supervision and their effect on young people's development. It also refers to the resources available in a community or a school and the fact that schools with more "advantaged" pupils are more likely to have more resources available.

(b) The collective socialization model focuses on adult role models in a neighbourhood and refers to the monitoring function that adults adopt to control negative behaviour, based on social norms. This model suggests that the social capital which is defined by the level of organization and the social norms of the community encourages socialisation and promotes positive role models, supervision and monitoring which in turn affect young peoples development.

(c) The contagion or epidemic model points to the behaviour of peers and neighbours that spreads to residents in a community. This model suggests that behaviours are copied by young people in a community. It emphasizes the role of peer influence suggesting that anti-social neighbours or young people can spread negative behaviours. Conversely, positive behaviour, such as for example doing someone's homework or attending all classes can be spread among young people in a classroom.

(d) The competition model focuses on neigbours competition for scarce resources. This model is linked with poverty and emphasizes how neighbours might challenge each other for resources. Scarce resources such as low medical support could increase competition and influence the emergence of an "underclass" composed by residents with the fewest resources (Wilson [199], 2012).

(e) The relative deprivation model concentrates on how individuals judge their own position in relation to their neighbours and peers. The theory proposes that when poor people live among other poor people, they give moderate value to material things. However, poor people who live among wealthy individuals may be subject to negative labeling by wealthy neighbours. Poor neighbours may also be demoralized if their neighbours are more affluent.

The neighbourhood institutional resource, the collective socialization and the contagion models assume that the presence of affluent or more advantaged neighbours would have a positive impact on young people's development. The institutional model focuses on the influence of adults who work in a community on young people. For example adults who work in schools or the police in a neighbourhood might provide social and educational resources to the community to help promote opportunities for young people and prevent antisocial behaviour. The collective socialisation model focuses on the role models of adults in a community and their influence on young people who are not their children. Positive adult models can influence young people who might want to become similar to them when they grow up. Additionally, adults can keep social control in a neighbourhood by employing the help of social services or calling the police when it is necessary. The contagion model could have beneficial effects on young people as it suggests that the behaviour of young people is influenced by their peer group. For example if a young person lives in an area where the majority of young people continue in education after they complete compulsory education, they might decide to continue in full time education as well. The fourth model of the neighbourhood effects theory is the competition model which emphasizes the negative implications of the presence of affluent neighbours. This model draws on potential negative effects if individuals have to challenge each other for scarce resources such as for example jobs in a weak economy. The relative deprivation model also focuses on the negative effect of having more advantaged peers. This model points that disadvantaged young people who might compare themselves to their advantaged neighbours can become discouraged or disengaged from trying to improve their position. Disadvantaged young people might choose to reject the behaviour of their advantaged peers and dissociate from their group. This model implies that young people compare their success or failure in relation to their neighbours and peers. An example of such a comparison would be academic achievement. Young people from disadvantaged families or communities tend to have lower educational attainment compared to their more advantaged peers. If a young person from a disadvantaged background attends a school in an affluent area, they might have a lower opinion of their academic ability than they would have if they attended a disadvantaged school.

3.3.5 Leventhal and Brooks-Gunn model of neighbourhood effects

Drawing on the theoretical framework of Jencks and Mayer [95] (1990), Leventhal and Brooks-Gunn [110] (2000) proposed three models of influence of neighbourhood deprivation on young peoples development that focus on resources and relationships. The pathways of neighbourhood influence are described through three models: a) the Institutional resources model, b) the Relationships and ties model, and c) the Norms and collective efficacy model. The Institutional resources model incorporates the institutional and competition models of the Jencks and Mayer theory. The institutional and competition models discriminate between the existence of resources in a neighbourhood whereas Leventhal and Brooks-Gunn include both of them in one model. This model refers to the quality and quantity of community resources available to influence young people's development such as for example libraries, community centres, schools, and literacy programmes. The availability of such institutional resources allows young people to take advantage of them and subsequently to improve their school performance and academic achievement. If however, only a few resources are available in a community, families and young people may need to challenge each other. The second model proposed by Leventhal and Brooks-Gunn focus on the role of parental relationships in relation to neighbourhood characteristics and young people's development. It refers to parental physical and mental health, parental practices, social networks and the quality of the home environment. For example, parents who suffer from physical or mental health problems could be negatively affected by neighbourhood deprivation and economic hardship which in turn influences parental practices and behaviour. Finally, the norms and collective efficacy model refers to formal and informal institutions that exist in a neighbourhood to monitor and control the behaviour of residents to prevent antisocial behaviour. This model relates to peer group influences, exposure to violence and presence of physical risk for young people. The collective efficacy refers to positive collective socialisation and willingness to participate in a community for the common good.

3.3.6 The epidemic hypothesis

The epidemic hypothesis (Crane [41], 1991; Case and Katz [31], 1991) is a framework that is closely related to the contagion or epidemic model proposed by Jencks and Mayer. The word epidemic is used to refer to the frequency social problems occur in deprived neighbourhoods. The origins of the epidemic hypothesis come from the idea that US ghettos experience epidemics of social problems. Neighbourhood quality and antisocial behaviour are inversely related. As the quality of the area of residence decreases, the probability that its residents will develop antisocial behaviour increases. Concentrated poverty and deprivation of social networks in disadvantaged neighbourhoods increase the likelihood that young people will be exposed to antisocial behaviour and violence through regular interaction with their peer group. The appearance of social problems in such neighbourhoods spreads like an epidemic when the frequency of negative behaviours increases at seriously dangerous levels. Antisocial behaviours that spread in a community include substance abuse or criminal activity. For example it is more likely for young people living in socially deprived areas to engage to criminal activities if crime is prevalent in their area of residence and they lack social networks that would permit them to get positive influence from mainstream behaviours and attitudes.

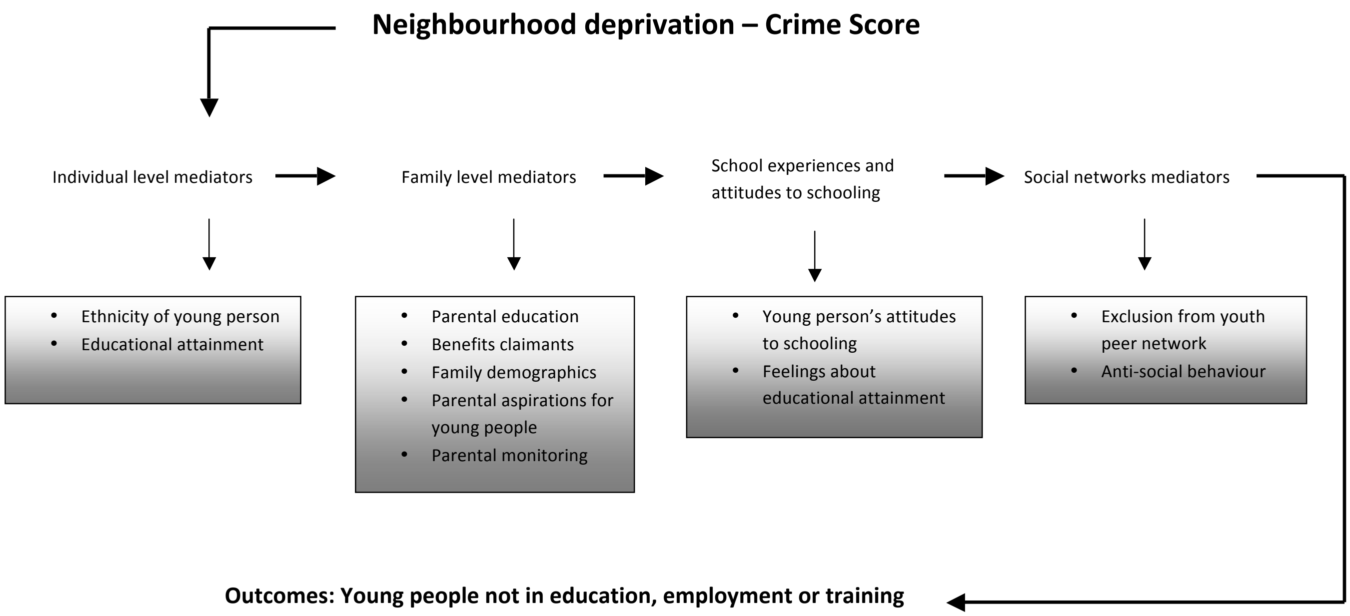
To sum up, several theories have been proposed to explain the effect of neighbourhood deprivation on young people. The key point addressed by theories of neighbourhood effects is that neighbourhood deprivation causes disengagement from mainstream society and social exclusion. Some theories stress the role of individuals on influencing their communities (social disorganization, contagion theory) while others focus on the effect of neighbourhoods on shaping individuals (Wilson [199], 1987). The social disorganization and the underclass theories emphasize the negative effects of neighbourhood poverty whereas the neighbourhood Effects theory focuses both on the family and neighbourhood financial capital and on the behaviour of neighbours. In addition, the neighbourhood Effects theory incorporates elements of previous theories such as the association between illegal behaviour and the community presented by Shaw and McKay and the attitudes and beliefs of people who live in ghettos presented by Wilson. Finally, the neighbourhood effects theory is the only theory that provides an analytical approach of five different models to help explain the processes by which neighbourhood effects are mediated to its residents. For all these reasons, the neighbourhood Effects theory was selected to inform the integrated model of neighbourhood effects that will be put forward and tested in this study. Because of data limitations in this current study it is only possible to test the three first models of the neighbourhood effects theory. The competition and the relative deprivation models refer to characteristics that are not in practice captured by a longitudinal survey.

3.4 The Compositional Framework of neighbourhood Effects

Drawing on the assumptions formulated by the neighbourhood Effects theory (Jencks and Mayer [95], 1990), the Life Course perspective (Elder [54], 1998) and the Ecological Systems theory (Bronfenbrenner [23], 1979) this study puts forward the Compositional Framework of neighbourhood effects. Young people's development is informed by the framework of linked lives of the life course theory and the multiple spheres of influence of the ecological systems theory. Assumptions about specific pathways linking neighbourhood effects to the experience of NEET are informed by the neighbourhood effects theory. The Compositional Framework (Graph 2) introduces four pathways that link neighbourhood deprivation to educational and vocational transitions of young people. The goal of the framework is to use the different theories discussed in the previous sections to reformulate strategies for investigating pathways through which neighbourhood effects are mediated to young people and affect their employment outcomes.

The theoretical models that have been proposed in the literature to explain how neighbourhoods influence young people do not explicitly determine how neighbourhoods affect young people in terms of specific mediators or pathways. The models do not specify how the actual processes operate but they provide a basis for researchers to hypothesize how mechanisms operate. The Compositional Framework of neighbourhood Effects (see Figure 3.2: 'Hypothesized pathways of neighbourhood effects') underlies the assumption that neighbourhood characteristics act on young people's development by specifying four levels of influence on young people's development apart from neighbourhoods: a) individual characteristics and attitudes; b) parental characteristics and relationships; c) school experiences and attitudes to schooling, and; d) d social epidemics (peer group) that act as pathways mediating the direct neighbourhood influence on transition outcomes. The model starts with the premise that neighbourhoods are likely to affect young people directly and indirectly as they operate through four proximal pathways. The variables selected for this schema will be discussed in Section 6.6 and the empirical implementation will take place in Chapters 6 and 7.

Figure 3.2: Hypothesized pathways of neighbourhood effects



The ecological framework, the different theories employed to construct it and the links with NEET status are described below:

Neighbourhood deprivation: Understanding environmental conditions such as social disorder and crime in neighbourhoods is fundamental to understanding neighbourhood effects. Neighbourhood Crime is measured by the Crime Score of the general Index of Multiple Deprivation measured at small area level. The neighbourhood context is understood to refer to the Exosystem in the Ecological Systems Theory (Bronfenbrenner [23], 1979), following the assumption that deprivation in the exosystem can affect experiences in the immediate setting of the individual, and provides a context where in the person lives but does not have any active role. Neighbourhood crime is also linked to the epidemic model which assumes that antisocial behaviour is copied and spread to residents of a community. Neighbourhood crime develops as a result of concentrated disadvantage, structural disorder, high unemployment and financial difficulty and is considered a significant factor in explaining young people's outcomes.

Living in a high Crime area has direct effects on employment opportunities. Limited availability of choices predicts difficulties in finding employment in the area of residence (Bynner et al [27], 1997) while crime fosters a culture where attachment to labour market is weakened (Wilson, 2006) thus deterring young people from trying to achieve educational goals and to participate in the labour market. Besides having an effect on young peoples employment opportunities, crime also influences indirectly educational and employment outcomes. Young people who come from areas with higher levels of deprivation are more likely not to go to university (Crawford et al [42], 2011) which limits their employment opportunities. This can be explained through the effect a deprived area has on parental practices, schools and interactions with peer group. This research is going to extend existing literature by testing the link between area crime and NEET status through the pathways which are specified below.

Individual characteristics and attitudes: This pathway relates to the role of environmental influences on individual characteristics and educational and occupational outcomes. The individual is considered as the recipient in the theoretical framework proposed by Jencks and Mayer. The individual has an active role in constructing experiences in the Microsystem of the Ecological Systems Theory. Additionally it relates to the human agency element of the Life Course approach as it describes decision making processes regardless of the constraints imposed by the social and cultural environment of a deprived neighbourhood.

The decision making processes and behaviour of young people in poor neighbourhoods with high crime and deprivation are very different compared to young people in more affluent areas. The presence of crime in young people's lives on a daily basis determines their sense of identity, social relations and cultural setting. When social relations and cultural settings are influenced by violence and crime it is easy for young people to deviate from socially accepted norms and behaviours. Poverty, unemployment, individual inequalities and limited opportunity contexts result in low occupational aspirations among young people (Furlong et al [66], 1996). Educational attainment is not appreciated and thus living in a deprived neighbourhood is associated with low educational attainment (Gibbons [72], 2002; Leventhal and Brooks-Gunn [110], 2000). Only a small portion of young people from low socio-economic backgrounds with high aspirations achieve to continue in higher education (Wolf [202], 2011). Low educational attainment increases the likelihood of entry in NEET status ((Britton et al [22], 2011; Rennison et al [148], 2006; Macmillan et al [120], 2012; Crawford et al [42], 2011; Bynner and Parsons [29], 2002).

Parental Characteristics and Relationships: This pathway maintains parallels a) with the microsystem as experiences in the family account for the child's immediate environment and the Mesosystem as the interaction between the structures of the microsystem, b) the concept of linked lives in relation to links between family members and c) the collective socialization model particularly in the areas of parental control and monitoring and the presence of routines in the family. The different settings of young peoples lives interact. The interaction of various settings may moderate the effect of crime deprivation on parental behaviours (Bronfenbrenner [23], 1979; Furstenberg et al. [67], 1993).

Concentrated poverty increases social stratification and social problems in disadvantaged communities such as single parent families and weakened family relations (Harding [82], 2010). An extension of disrupted family relations is parental behaviour which can be influenced by antisocial behaviour and crime when anomie is the social norm. For example living in a high crime area could invoke a range of parenting problems such as for example child abuse (Shaw and McKay [171], 1942) or less parental involvement (Wilson [199], 2012). Parents in deprived areas often follow parenting strategies such as monitoring or supervision to protect their children from potential neighbourhood dangers (Klebanov et al [105], 1994; Simons et al [172], 1996; Willis [196], 1977) and restricted social relations (Atkinson and Kintrea 2001, Musterd et al 2003). Parenting practices, in turn, are assumed to influence young peoples transitions. The parents of young people who are NEET were found to be less likely to be involved in education and career oriented activities of their children (Rennison [148], 2006) or to provide advice to their children (Macmillan and Britton [120], 2012) than parents of young people in education or work. Parental aspirations remain high since the majority young people experiencing NEET status had parents who wanted their children to continue in full time education, although the young people did not achieve educationally (Wolf [202], 2011).

School experiences and attitudes to schooling: This pathway is linked to the Microsystem because teachers have direct interaction and influence on young people and to the Mesosystem providing a connection between the young persons area and school level characteristics. This pathway overlaps to some extent to the institutional resource model since schools are institutional resources that could mediate the association between neighbourhood deprivation and educational and employment outcomes (Kauppinen [100], 2008). Schools are affected by the social and economic characteristics of young people and influence career destinations. Access to institutions is a pathway that mediates neighbourhood characteristics. Leventhal and Brooks-Gunns [110] (2000) argue that institutional resources such as schools and libraries offer parents the opportunity to stimulate young people and thus to influence educational outcomes. Additionally, as the collective socialisation model posits, parents can adopt monitoring role in these institutions to prevent negative behaviour of young people. Unlike well organized communities though, monitoring and control levels are very low in poor neighbourhoods. As social organization theory posits, poor neighbourhoods fail to control public behaviour.

The community context of a poor neighbourhood can shape the resources available to young people, the educational experiences and attitudes to schooling. Negative experiences of young people with their teachers and disruption caused by students in the classroom have a negative impact on young people engaging in further education (Spielhofer [180], 2009). Disaffection with school influences outcomes (Macmillan and Britton [120], 2012) and lack or insufficient advice from career teachers are associated with entry to NEET status (Rennison et al. [148], 2006). NEET status was also associated with characteristics such as proneness to being bullied (Stone et al. [183], 2009); truancy and school exclusion (Spielhofer [180], 2009; Coles et al. [38], 2002); and negative attitudes to schooling (Raffe [145], 2003).

Social Epidemics: This pathway is linked to the Microsystem (Bronfenbrenner [23], 1979) because the peer group belongs to the immediate environment of a child and to the Mesosystem because it refers to the connection between the child's neighbourhood and its peer group. The pathway relates to the Contagion/Epidemic model (Jencks and Mayer [95], 1990) in terms of how behaviour of neighbours is copied and spread on residents in a community. Finally it relates to the Relative Deprivation theory since residents judge their position in relation to the position of their neighbours and peer group.

A potential pathway that links area deprivation and young peoples outcomes is that deprived neighbourhoods lack the structure of a socially organized society and that negative behaviours spread like epidemics. Simons et al [172] (1996) found that living in a disadvantaged community increases the risk of behaviour problems and affiliation with deviant peers for young boys because of the inability of the community to supervise and control teenage peer groups. Lack of supervision and sparse local friendship networks in a deprived community can explain problematic behaviour in groups of young people (Sampson and Groves [162], 1989). Problematic behaviour such as criminal activity and substance use (Willis [196], 1977) can be copied by young people in deprived areas. In turn, problematic peer group behaviour can affect school behaviour and NEET status (Spielhofer [180], 2009; Stone et [183], 2000). Young people in the NEET group are more likely to say they have not received support from informal sources of advice such as their peer group (Rennison et al [148], 2006).

Another potential pathway that peer group influence can mediate neighbourhood characteristics on young people is through social isolation. People who live in deprived areas are more socially excluded compared to people in affluent areas and therefore have limited choice of friends and role models. As Garbarino [70] (1982) puts it, rich people can afford a weak neighbourhood better than poor people, who rely solely on the social resources of their neighbourhood. As a result, a poor neighbourhood becomes an influential social space for its residents. Young people in poor areas seek friendship to people in their community and form strong bonds with a restricted peer group thus allowing only local socialisation which has a negative effect on schooling and future employment aspirations. Socially excluded individuals can only observe and copy the behaviour of people in their community. Young people who are cut off from mainstream society, lack opportunities for development and positive role models develop sub-cultural norms and values which lead them to reject education and employment.

The epidemic theory (Jencks and Mayer [95], 1990) holds that the behaviour of adults and peers in a community such as crime and interaction with neighbours (Jamieson et al. [92], 2008) can be learned and copied by young people. Young people who live in areas with high crime rates have higher contact with the criminal justice system and the police even if they are not involved in criminal activities. These contacts can leave young people feeling that the police treats their peers and neighbours with violence and lack of respect. These feelings are often complemented by feelings of insecurity and mistrust to the police who cannot provide safety in their area of residence. Such feelings can produce negative attitudes to the criminal justice institution which can eventually spread to other institutions such as for example schools.

This section reviewed the pathways considered to mediate neighbourhood deprivation effects on young peoples educational and employment outcomes. The final section of this chapter presents the research hypothesis and the research questions that are going to be investigated in this thesis employing the Compositional Model of Neighbourhood Effects and the Longitudinal Study of Young People in England.

3.5 Research hypothesis

The Compositional Framework of neighbourhood effects presented in the previous section will be employed to investigate the neighbourhood economic conditions and the other interrelated factors associated with entry to NEET status. The research hypothesis that will be tested is the following. I expect that living in a neighbourhood characterized by high rates of crime deprivation increases the likelihood of a young person becoming NEET at the ages $18 - 19$. I assume that living in deprived areas with high crime affects school to work transitions over and above four pathways that mediate the effect of crime on young people's outcomes and help explain the likelihood of becoming NEET. The four mediating pathways are: a) individual characteristics and attitudes; b) parental characteristics and relationships; c) school experiences and attitudes to schooling, and; d) d social epidemics (peer group).

The research questions that will guide this study are presented below:

(1) Is there an association between crime in the neighbourhood a young person lives in and NEET status?

(2) Can the effect of living in a deprived area with high crime on NEET status be explained after controlling for family demographic characteristics, parental practices and aspirations?

(3) Is the effect of living in a deprived area with high crime on NEET status mediated by individual characteristics after controlling for family characteristics?

(4) Is the effect of living in a deprived area with high crime on NEET status mediated by attitudes to and experiences of school after controlling for family and individual characteristics?

(5) Is the effect of of living in a deprived area with high crime on NEET status mediated by peer group influence and antisocial behaviour after controlling for family, individual and school characteristics?

(6) Is the effect of deprivation different for young people who live in high crime areas compared to those who live in low crime areas?

3.6 Summary and Conclusions

This chapter developed a theoretical framework to explain and understand the influence of neighbourhood poverty and crime on young people's educational and employment outcomes, the Compositional Model of Neighbourhood Effects. This framework is going to provide the structure to support the current research and will form the basis on which the research hypothesis will be tested. The theoretical framework introduced draws upon existing theories and adapts their arguments in the context of neighbourhood effects on young people's trajectories. Two theoretical frameworks are employed to inform the Compositional Model of Neighbourhood Effects and to understand the mechanisms of influence on young people: theories on individual development and theories on neighbourhood effects.

The theoretical assumptions about young people's development are drawn from the Life Course approach (Elder [54], 1998) and the Ecological Systems theory (Bronfenbrenner [23], 1979). The life course developmental approach proposes human agency in making choices and contextualizes people's lives through the social dynamic of linked or independent lives. In the current study parents and young people's lives are linked. Young people make decisions for their future in relation to the context of deprived neighbourhoods depending and influenced by their families, peer group and cultural and social conditions. Closely related to the Life Course perspective is the Ecological Systems theory which provides a comprehensive contextual framework of six systems that explain individual development. There are bi-directional influences within and between the six systems. The Ecological Systems theory was selected to inform the theoretical framework of this study because it considers the interaction between the quality and context of the environment and the individual in a comprehensive way, and also it can help explain how the context from the immediate family environment to the community and the historical conditions can influence young people's trajectories.

To further explore the influence of context on young people's trajectories, the Compositional Model of Neighbourhood Effects is informed by neighbourhood effects theories. Theories such as the social disorganization theory (Shaw and McKay [171], 1942) and the Underclass (Murray [131], 1999) link the effect of neighbourhood context on individuals. These theoretical frameworks suggest that the neighbourhood constitutes an important context that influences social processes which determine the trajectories young people follow in their lives. The theories suggest that the main characteristics of poor neighbourhoods can be divided in economic, social, behavioural and spatial. High crime and delinquency, restricted social relations, and low incomes foster a culture of gangs and an accepted system of values that allows antisocial behaviour in deprived areas. This culture increases social problems such as single parent families, unemployment and crime. While scholarship on neighbourhood effects mainly described the characteristics of deprived communities, Jencks and Mayer [95] (1990) proposed the Neighbourhood Effects Theory, a framework including five models that describe the processes through which neighbourhood structural dimensions affect individuals. The neighbourhood Effects theory incorporates elements of previous theories such as the spread of illegal behaviour, the importance of local social norms and the attitudes and beliefs of people who grow up in disadvantaged areas.

Drawing on neighbourhood effects theories and on developmental theories, this study puts forward the Compositional Model of Neighbourhood Effects that considers both the effect of neighbourhood context on young people's outcomes and also the role of the individuals as active agents influencing their development. The model specifies four pathways of influence on young people's development in the context of deprived neighbourhoods which are individual characteristics and attitudes, parental characteristics and relationships, school experiences and attitudes to schooling and social epidemics. The model underlies that neighbourhoods exert a direct influence on young people and indirect one through the four proximal pathways. The model will be employed to investigate the research hypothesis of the current research which focuses on understanding the effects of neighbourhood context on young people becoming NEETs. It is assumed that crime in the neighbourhood affects school to work transitions over and above the four mediating pathways proposed by the Compositional Model of Neighbourhood Effects and helps understand and explain the likelihood of becoming NEET. The methodology that will be selected to study neighbourhood context effects in this study will be discussed in the Chapter 4 after reviewing the most important methodological approaches that have been adopted in the literature to measure and assess accurately neighbourhood characteristics.

Chapter 4

Methodological Issues in Assessing Neighbourhood Effects

4.1 Introduction

Previous chapters of this study reviewed the literature on neighbourhood effects and young people in NEET status (Chapter 2) and introduced the Ecological Model of Neighbourhood Effects that will be put forward in the current analysis (Chapter 3). The goal of the current chapter is to review the methodologies that have been adopted in studying neighbourhood effects and to explore the key advantages and limitations of each approach in order to inform the selection of the appropriate methodology for the current study. The first step in understanding the influence of neighbourhoods on young people's outcomes lies on defining neighbourhoods and measuring their boundaries. The fact that there are different perspectives on neighbourhood boundaries brings up the question of which approach would be the most appropriate to measure accurately neighbourhood effects. Chapter 2 discussed the definitions of neighbourhood provided in the literature and pointed that neighbourhoods are not only geographic units but also they form entities where social interaction takes place. Section 4.2 addresses the need to measure neighbourhoods in such a way that both spatial and social characteristics of neighbourhoods are captured in the analysis. A review of the approaches employed in past literature will be provided in light of investigating how a specific definition of neighbourhoods will be meaningful in understanding its effect on young people.

After a clear approach on defining the boundaries of neighbourhood context to understand its influence on young people is obtained, a second major issue in assessing neighbourhood impact is to choose an appropriate method to estimate neighbourhood effects. The fundamental problem in estimating neighbourhood effects is the selection bias issue that does not allow causal associations to be tested. The key question in neighbourhood effects research is whether unmeasured social capital and parental characteristics influence young people's outcomes over neighbourhood characteristics or whether neighbourhood characteristics affect young people's educational and employment outcomes either directly or through mediating mechanisms. Section 4.3 will investigate the most common approaches taken to measure neighbourhood effects and to reduce selection bias. Two key approaches will be explored, mobility experiments and observational studies. Studies of housing mobility programs in the US offer the advantage of random assignment of individuals to treatment group which removes the selection bias problem and provide evidence of negative consequences on the educational and employment outcomes of young people who live in deprived areas (Section 4.3.1). Despite the fact that mobility experiments are a useful tool in analysing neighbourhood effects, they are rare because they are difficult to implement, incur high costs and raise ethical concerns with regards to participants in the programs. Observational studies, both longitudinal and cross-sectional, are the most widely used approaches to estimate neighbourhood effects (Section 4.3.3). Longitudinal studies follow large cohorts of individuals for many years, include large samples that are rich in available information and are readily available to use. Cross-sectional designs are publicly available and often include large datasets but they reflect an observation of a population at a specific point in time and therefore are less popular in studying causal associations.

Once the research design is selected, the attention will be directed in Section 4.4 to which statistical approach will be employed to measure neighbourhood effects. Regression based approaches employ a wide range of variables to remove selection bias by controlling for family and individual characteristics related to neighbourhood selection. A key problem in regression based statistical approaches is that it is not possible to assign individuals to treatments at random as would be the case in experimental designs.The Instrumental Variables (IV) approach is used to estimate causal effects by employing an instrument that predicts the causal variable of interest but does not affect the outcome variable. Sibling fixed-effects models are a form of Instrumental Variables approach widely used in neighbourhood research when there is available data, allowing researchers to estimate the importance of family inputs. Disadvantages of this method include the fact that researchers cannot control for differential characteristics among siblings and that unobserved within-family heterogeneity can be a cause of omitted variables bias.

Section 4.4.3 introduces a statistical approach that uses the reasoning and structure of experiments in observational designs, Propensity Score Matching. Propensity score analysis matches individuals in treatment and control groups conditional on observed characteristics and is used to remove overt biases recorded in the data. However, adjustments made by the propensity score may not control for unmeasured covariates. To appraise sensitivity to hidden biases, Section 4.4.4 introduces Sensitivity Analysis, an approach that investigates how hidden biases caused by unobserved characteristics can change the conclusions of propensity score analysis.

4.2 Conceptualising neighbourhoods

A key issue in neighbourhood research has been the difficulty to operationalise neighbourhoods and define their boundaries. Defining neighbourhood boundaries is a complicated issue because neighbourhoods are not only physical entities, but also social spaces where interaction takes place (Lupton [114], 2003). The social interaction that occurs in neighbourhoods is an important parameter that presumably contributes to neighbourhood effects (Tienda [185], 1990). However, the data available for neighbourhood research do not provide compatible spatial and social boundaries and therefore the researcher faces a difficult dilemma. If one choses to focus only on spatial characteristics of neighbourhoods, they are in danger of omitting key social interactions. Alternatively, if they focus on the social designation of neighbourhoods, the research will be limited by poor availability of data and inappropriate spatial boundaries. The dilemma cannot be solved easily because social and spatial characteristics are not congruent in available data. Therefore, past literature has distinguished between structural and social organisation boundaries (Leventhal and Brooks Gunn [110], 2000). The key advantages and limitations of each approach are discussed in this section.

Structural characteristics of neighbourhoods may include indicators such as poverty and unemployment rate, house tenure condition, family composition, demographic characteristics and concentrated poverty among others. Structural features of neighbourhoods can be captured in administrative data sources based on bureaucratically defined neighbourhood units. Examples of administrative data used in the literature are electoral districts (Bell [10], 2003; McCulloch and Joshi [126], 2001) and education zones (Garner and Raudenbush [71], 1991). The majority of neighbourhood research uses administrative data sources as they offer data for entire countries available for researchers to use (Galster [68] 2001; Manley et al. [121] 2006). Neighbourhood research based on large sample sizes provided by administratively defined units can provide robust analyses to inform policy. The datasets are readily available and the analysis can be easily replicated. Aggregate statistical measures of neighbourhood characteristics have been a source of data helpful in understanding the relationship between structural area characteristics and young people's educational and employment outcomes. Despite the advantages offered by using administrative units to measure geographic areas, a number of problems may arise because administrative units are defined for different purposes than research. Electoral districts provide a useful ready-made framework for the purposes of neighbourhood analysis, however, a potential problem associated with information from electoral districts is that political boundaries do not necessarily coincide with the boundaries of local communities. Education zones, as a unit of neighbourhood measurement, offer the advantage that they capture the community of teachers and students, however a school unit may not correspond to a geographic unit or to the neighbourhood the family lives in. Additionally, administratively defined neighbourhoods may not capture residents' perceptions of neighbourhood boundaries and sometimes are not directly indicative of the social characteristics of neighbourhoods (Pebley and Sastry [143], 2004). Finally, different residents may define neighbourhood boundaries based on their own experience and exposure in their area of residence. For example residents who have a business in their neighbourhood may perceive and identify a different geographic area than residents who spend little time in their community.

It is important to capture how residents perceive the neighbourhood in which they live when studying neighbourhood deprivation effects. Residents' perceptions of neighbourhood can be captured by social characteristics as a measure to define neighbourhood boundaries. The perception residents have of their area's social characteristics can help explain the impact of neighbourhoods on outcomes for young people. Social characteristics may refer to neighbourhood quality and identity, facility availability, positive or negative change, disorder and criminal activity. Social characteristics are included in datasets like community surveys which involve interviews of residents (Sampson et al [165], 1997) and systematic social observations such as personal, video or audio observations (Barnes-McGuire and Reiss [7], 1993, Rice and Ezzy, 1999). Sampson and Raudenbush [164] (2004), argue that perceived social characteristics have a higher impact compared to structural characteristics. Drawing on the broken windows theory which argues that even minor signs of disorder can instigate criminal behaviour in a neighbourhood, the authors suggest that residents' perceptions of crime and disorder increase the chances of antisocial behaviour and subsequently negative neighbourhood effects. Thus, the authors argue that neighbourhood social structure is a more powerful indicator of residents' perceptions of disadvantaged neighbourhoods compared to observable structural neighbourhood characteristics. In a similary way, Borooah and Carcach [17] (1997) find that characteristics such as area incivility, low neighbourhood cohesion and high area crime are significant predictors of the risk of becoming a victim of housing crime as well as the probability of being afraid of housing crime.

Despite the importance of social characteristics, a lot of work remains to be done to measure residents' perceptions of their neighrbouhood. Coulton et al [40] (2001) attempt to capture area social aspects by identifying residents' perceptions of neighbourhoods, however this approach was limited because residents' perceptions are subjective and may result in omitting important neighbourhood characteristics and in unspecified geographic boundaries. A further limitation of contextual data drawn from non-administrative sources is that they substantially increase study costs (Duncan and Raudenbush [52], 1997), they produce small sample sizes and they are difficult to implement. Even if it has been possible to draw large representative samples, assessing perceptions of residents is not straightforward. Each resident might have a different personal sense of neighbourhood boundaries and a different judgment of community characteristics and danger.

Taking into account the difficulties and constraints encountered in defining structural and social neighbourhood boundaries in past research, I use the lower Layer Super Output Areas (LSOAs) to define neighbourhoods in this study (`http://neighbourhood.statistics.gov.uk`). The LSOAs are a set of geographical areas developed in the UK (apart from Scotland) as a measure to improve and facilitate small area statistics and are built up from groups of Output Areas (`http://www.ons.gov.uk/ons/guide-method/geography`). Groups of continuous Output Areas, as consistent in population size as possible, have been used to build LSOAs. One LSOA is typically built containing four to six Ou1tput Areas. LSOAs were first built using 2001 Census data and have been updated following the 2011 Census. England and Wales have been divided into 32,482 small areas of around 1,500 people, each of which forms a LSOA.

The LSOAs were built using both measures of proximity and social homogeneity and have been widely used to define neighbourhood boundaries in the literature (Ketende, McDonald and Joshi [104], 2010; Tunstall, Lupton, Kneale and Jenkins [187], 2011; Holden and Frankal [89], 2012; Fenton and Lupton [59], 2013; Bradshaw [21], 2013; Midouhas, Kuang and Flouri [128], 2014). LSOAs were selected for this study as they can capture both structural and social aspects of neighbourhoods. LSOAs were selected for this study as they can capture both structural and social aspects of neighbourhoods. Structural dimensions are captured because the LSOAs have constant / fixed geographic boundaries unlike other measures such as for example electoral districts used in past research. Additionally, LSOAs are statistically robust area measures that offer smaller scale measures compared to previous studies that used, for example, local authorities (Lupton [114], 2003) or wards. It is important that LSOAs capture social aspects of neighbourhoods as well, because they were developed to include areas that share similar social characteristics. As a result, LSOAs allow the researcher to study social interactions in consistent physical boundaries and subsequently provide a robust measure of studying neighbourhood effects.

To sum up, understanding the influence of neighbourhoods on young people's outcomes strongly relies on measuring and analysing accurately the neighbourhood characteristics in which they live. This section focused on neighbourhoods as a geographically bounded context in which families and young people live and focused on the concepts of structural and social characteristics of neighbourhoods and the approaches utilised to measure these constructs. Structural features refer to physical characteristics of neighbourhoods and are captured by administratively defined units. Social features refer to residents' perceptions of the communities in which they live and are drawn from community surveys, interviews and social observations.

4.3 Approaches to measuring neighbourhood effects

4.3.1 Selection bias

Neighbourhood effects research on young people's outcomes focuses fundamentally on the study of a causal relationship.The goal of this study is to investigate the following question: *To what extent can the educational and employment outcomes observed on young people who live in deprived areas be attributed to area characteristics given that all other characteristics are held constant?*

Causality in relation to this question refers to whether observed educational and employment outcomes can be attributed to neighbourhood characteristics or to other characteristics such as individual, family, school and peer group influences. Association between Crime Score in an area and poor educational and employment outcomes does not necessarily mean that one is the cause and the other the effect. To support the inference that there is a causal relationship between area deprivation and NEET status, a researcher must take into account factors that could potentially affect NEET status other than neighbourhood characteristics or the vector of covariates introduced by the Compositional Model of Neighbourhood effects. A possible threat to the inference about whether the observed association between neighbourhood effects and NEET status reflects a causal relationship is selection bias. When the selected observations in the analysis are not independent of the outcome variables in the study, this sample selection can lead to biased inferences about causal relations (Winship and Mare [200], 1992).

The key reason behind the selection bias problem is that neighbourhood context is not allocated randomly, but it is guided by parental selection and preferences (Tienda 1991; Duncan et al. 1997; Duncan and Raudenbush, 1999; Galster 2008; Hedman and van Ham, 2011). The question is whether unmeasured parental characteristics and social capital (Garner and Raudenbush [71], 1991) that affect neighbourhood selection influence young people's development over and above neighbourhood characteristics or whether neighbourhood deprivation has an effect on young people either directly or through mediating pathways (Small and Feldman [175], 2012; Durlauf [53], 2004). For example, failure to consider parental allocation of time could result in selection bias. Some parents may decide to have one paid job and live in a poor neighbourhood in order to profit from a mother spending more time with their children. Failure to take into account parental time may lead to downward bias as the effect of living in a poor neighbourhood will be possibly downsized by the parental time devoted to children. Conversely, in the case of parents who cannot avoid a poor neighbourhood because of financial constraints and at the same time are not able to devote higher amount of time to their children, negative neighbourhood effects could be overestimated (Brooks-Gunn et al [25], 1993).

The problem that emerges is whether observed differences in educational and employment outcomes can be causally attributed to neighbourhood context or if they are due to differences between individuals who live in different neighbourhoods. It has been difficult in the literature to separate genuine neighbourhood effects on young people's outcomes from the effects of specific family characteristics who decide to live in a certain neighbourhood (Tienda [185], 1990; Manski [122], 1993; Ginther et al [74], 2000, Hedman and Ham, [85] 2012). Failure to include certain family characteristics in the analysis could lead to omitted variables bias. Omitted variables could be a result of unobserved characteristics such as for example motivation or ability which are difficult to measure and include in the analysis. Omitted variables may also be the result of observable characteristics that might be unmeasured in a specific analysis.

Differences between families and individuals in deprived and rich neighbourhoods may result in overestimation or underestimation of neighbourhood effects on young people's outcomes and therefore it is necessary to control for such differences. The selection bias effect on causal inferences has been a major concern of social researchers. Due to the importance of drawing causal inferences in social science, various modeling techniques have been developed by researchers to correct for selection bias. The following section focuses on two approaches that have been used to estimate neighbourhood effects on young people's outcomes and reduce the selection bias problem; experimental and observational studies.

4.3.2 Experimental design studies

Mobility experiments

Experiments have not been widely used in neighbourhood effects research. A definition of experiments that makes a comparison between experimental and observational data is provided by Cox and Reid (2000).

Remark 4.3.1. The word experiment is used in a quite precise sense to mean an investigation where the system under study is under the control of the investigator. This means that the individuals or material investigated, the nature of the treatments or manipulations under study, and the measurement procedures used are all selected, in their important features at least, by the investigator. By contrast in an observational study some of these features, and in particular the allocation of individuals to treatment groups, are outside the investigator's control.

Experiments make use of random selection and random assignment. Random selection refers to any process that selects a sample of size n without replacement from a population of size $N > n$ such that each subject of the population is equally likely to be selected. Random selection refers to how a sample is drawn from a population for the purposes of a study. Simple random assignment refers to how a sample is assigned to different groups or treatments in a study. Randomisation or randomised experiments refer to both random selection and assignment in performing an experiment.

Experimental designs in neighbourhood effects research involve assigning families randomly to reside in poor and non-poor neighbourhoods. Experimental designs allow a better estimate of neighbourhood effects because researchers can control for family characteristics associated with neighbourhood selection and in this way reduce selection bias and avoid the omitted variables problem. An example of this design is housing mobility programs which involve relocating families from public housing in poor neighbourhoods to other housing in less poor neighbourhoods. The assignment is random because families are not choosing their area of residence based on socio-economic characteristics or personal motivation but they are selected by the programs to change housing. As a consequence, unmeasured characteristics associated with family choice cannot impact on neighbourhood effects and therefore experimental designs minimize selection bias problem and allow the estimation of true neighbourhood effects. They permit to examine how a change in neighbourhood context influences young people and their families. By doing so, experimental designs provide the context to examine potential mechanisms through which neighbourhood effects are transmitted and allow causal relationships to be tested. Despite the advantages they offer, randomised experiments are not common in research for practical and ethical reasons. Practical reasons relate to the fact that random experiments are difficult to implement and incur costs. In addition, they have to be clearly designed and they need to have the right type of data, and enough of it, available to answer the questions of interest as clearly and efficiently as possible. Ethical considerations refer to the selection of participating families, since only a number of families are offered the opportunity to move to less poor neighbourhoods while others are not.

A well documented housing mobility programme that provides evidence of the existence of neighbourhood effects is the Moving to Opportunity Programme (MTO; Leventhal and Brooks-Gunn [110], 2000, Goering and Feins, [75] 2003). The program was sponsored by the US Department of Housing and Urban Development and started in 1994. 4,600 families, who lived in public housing and had at least one child less than 18 years old, were given the opportunity to leave high poverty areas and to reside in lower poverty ones. These families were randomly assigned in one of three groups. The first group received a voucher that could be used to move to a low poverty neighbourhood only. The second group received a Section 8 housing voucher, which allowed them to move to any neighbourhood as long as they moved into private housing. The control group did not receive any voucher but was eligible for public housing. The key results of the Moving To Opportunity on young people were assessed $4-7$ years after its implementation. Results show higher educational attainment for children, higher employment and wages in families who moved to lower poverty neighbourhoods, better physical and mental health and less juvenile crime (Ladd and Ludwig [106], 1997; Katz et al [98], 2001; Ludwig, Ladd and Duncan [113], 2001).

Quasi-experimental studies

Closely related to random assignment in mobility experiments are quasi-experimental studies. Quasi-experimental studies are employed to define causal relations as a viable alternative when it is not possible to use randomised experiments to assign participants to poor and non-poor neighbourhoods at random. These studies attempt to support a counterfactual inference similar to randomised experiments to compare effects for a treatment with the effects in the absence of treatment. Assignment to conditions in these studies is not random, rather it is selected either by participants or administrators of the study (Shadish, Cook and Campbell [170], 2002).

Quasi-experimental studies have been carried out with both longitudinal and cross-sectional data. In the US literature, a well-known quasi-experiment was the Gautreaux project. The Gatreaux project was a US anti-poverty housing project which arranged private housing for 4,000 families who volunteered to move in a predominantly white section of the city of Chicago. Results from the Gatreaux intervention suggest that moving to middle-class neighbourhoods had positive implications for participants in the study. Relocation to middle class suburbs was associated with higher educational attainment, higher possibility to attend college, higher rates of employment and higher wages compared to those who moved to city neighbourhoods (Rosenbaum and Popkin [152], 1991; Rosenbaum [150], 1991). However, critiques on the effects of the Gatreaux intervention argue that only a small sample of the participants were selected to explore the effects of the programme and that participants were contacted four years after they moved to different neighbourhoods. The small sample studied and the considerable time that elapsed before the intervention was evaluated raise concerns about potential upward bias of the results (Katz et al [98], 2001).

Examples of quasi experimental designs in the UK are two studies conducted as part of the National Evaluation of Sure Start (NESS). The NESS is an evaluation of the effects of an area based initiative to improve services in disadvantaged areas in the UK for young people aged under five, their families and communities. In these studies, child and family outcomes are analyzed as a function of whether participants are in a Sure Start area or not, controlling for child, family and community characteristics (National Evaluation of Sure Start Research Team (Reading [147] 2006; Belsky, Melhuish, Barnes, Leyland, Romaniuk, [12] 2006). The studies compare families living in disadvantaged areas with improved services (treatment group) to families living in disadvantaged areas without these services (control group). Another study [11] compared the NESS sample to a control group drawn from the Millennium Cohort Study (MCS) children and their families. The MCS is a large scale longitudinal study of UK children born in 2000 2001 and their families. The criterion for selecting the comparison group was to identify children in areas with similar economic and demographic characteristics to those in which the Sure Start sample resided. This enabled a comparison of children and families from areas similar to the Sure Start impact areas. A potential cause of selection bias in this study was that family characteristics could still affect outcomes. The authors attempted to minimize selection bias by statistically matching many relevant covariates. However, unmeasured characteristics could not be completely discounted because in practice it would not be possible to control for all the characteristics that influence the decision of families to live in particular neighbourhoods.

Quasi-experimental designs allow the researcher to investigate whether a program has an effect after controlling for effects of individual, family and community characteristics. It is selected as the next best evaluation design when a randomised experiment is not possible. The limitation of this design compared to randomised experiments is that unmeasured differences such as for example family characteristics or genetic factors may nevertheless affect the results. However, quasi-experimental designs are more easily and frequently implemented than randomised designs.

4.3.3 Observational studies

Longitudinal studies

One of the most widely used approaches to studying neighbourhood effects on young people has been the use of longitudinal studies. The current thesis employs a longitudinal approach too. Longitudinal studies can be nationally representative, country representative or they can include data from particular cities or regions.

Nationally representative datasets that have been used to study neighbourhood effects include the Millennium Cohort Study (MCS), the National Child Development Study (NCDS), the Great Britain National Child Development Study (BNCDS) and the Longitudinal Study of Young People in England (LSYPE) which will be employed in the current study. US longitudinal datasets include the National Longitudinal Survey of Youth (NLSY), the Children of National Longitudinal Survey of Youth (CNLSY), the Panel Study of Income Dynamics - Child Development Supplement (PSID-CS), the Infant Health and Development Program (IHDP) and the Adolescent Pathways Project (APP). Other examples are the National Longitudinal Survey of Children and Youth (NLSCY) in Canada and the Longitudinal Study of Australian Children (LSAC). There are also smaller regional studies, such as the Project on Human Development in Chicago neighbourhoods (PHDCN), the Beginning School Study in Baltimore, Promoting Academic Competence in Atlanta, the Woodlawn Study in Chicago and the Ontario Child Health Study (OCHS), which have smaller samples and do not have extensive information available like larger datasets. Despite the fact that these datasets have not been designed specifically to study neighbourhood effects, they have formed the basis for neighbourhood effects research.

Nationally representative longitudinal studies facilitate research of neighbourhood effects for a number of reasons. They are rich datasets that offer large samples readily available to study. They include a wide range of variables for young people's educational and employment decisions and outcomes and for the characteristics of the families, schools and peer groups of those young people. They provide variables that describe the interactions of young people with their parents, teachers and peer group. Additionally, they follow large number of families for many years allowing the investigation of family characteristics that could affect young people's outcomes. Further to that, they can be linked with geographical data to allow the investigation of neighbourhood effects on young people's outcomes. On the contrary, smaller scale studies offer smaller samples and often do not include rich data on neighbourhood characteristics as larger studies do.

A longitudinal design was selected to investigate the association between neighbourhood deprivation and young people's outcomes in this study. Taking into account that it is not easy to establish causal relations in neighbourhood research using observational data, a longitudinal approach was considered the best alternative to experimental studies as it offers a large number of variables that permit neighbourhood effects to be investigated. In addition, the fact that outcomes and explanatory factors of interest are measured at different stages in life in longitudinal studies, allows the investigation of individual developmental trajectories more effectively (Duncan and Raudenbush [52], 1997). A longitudinal approach allows a researcher to explore for example the effect of living in an area characterized by high deprivation in early years of an individual's life on his or her later educational attainment and employment condition and to study the processes by which these outcomes occur.

Cross-sectional observational studies

Neighbourhood research has also employed cross-sectional observational designs. Cross-sectional studies involve observation of all of a population, or a representative subset, at one specific point in time. Data are often available from public administrative sources. In contrast to longitudinal and experimental studies, cross sectional are descriptive studies. Limited availability of variables may constrain research in neighbourhood effects with the use of cross-sectional data (Goering et al [75], 2003). An example is a study by Crane [41] (1991) who used data from a special linked family tract file from the 1970 American Community Survey (ACS) Census based Public Use Microdata Sample (PUMS) file. The PUMS files are a set of records about individual people and housing units. The study focused on out of wedlock birth rates and high school dropout rates. The research found that high dropout rates were more likely to occur among individuals living in neighbourhoods where less than 5% of workers held professional or managerial jobs.

Cross-sectional data are easy to find because they are usually publicly available through administrative sources allowing researcher to access data that often contain large samples and facilitate research. A major limitation of cross-sectional studies is that they can only observe characteristics at one specific point in time. In contrast to longitudinal studies, they do not allow researchers to investigate the dynamic nature of neighbourhoods and their effects on young people's development over time. For this reason, the results of studies like Crane's [41] (1991) cannot identify a causal relationship between neighbourhood characteristics and young people's outcomes. As Manski

[122] (1993) pointed out, studies based on cross-sectional data may suffer from the "reflection problem". This means that the association between neighbourhood characteristics and young people's outcomes reflects the fact that the characteristics observed are only an aggregation of family and individual level characteristics at the time the census was taken. Therefore, results in cross sectional studies only show associations but they cannot establish causal relationships. Longitudinal and experimental data may provide statistical leverage to solve this problem.

4.4 Statistical modelling approach

Longitudinal observational studies are the most common approach to investigate neighbourhood effects because of the difficulties and constraints in conducting experimental projects and the limitations of cross-sectional studies. This section is going to review the main statistical modeling approaches that have been adopted in longitudinal studies to study neighbourhood effects and reduce the selection bias problem.

4.4.1 Regression models

A common modeling approach to studying neighbourhood effects using observational data has been to use standard regression models with statistical controls for covariates. Most studies adopt linear regression analysis, ordinary least squares regression or multi-level regression modeling (Snijders [179], 2011). These statistical approaches are selected to investigate the relationship between neighbourhood characteristics and young people's outcomes and to define the effect of neighbourhood characteristics influence on young people. Control variables are included in relation to the model that is tested. If data are hierarchical in nature, relations of interest are studied in a multilevel framework allowing the simultaneous analysis of nested data. A wide range of individual and family variables known to influence parents' decision to live or stay in a specific neighbourhood have been included in neighbourhood studies such as income, demographics, parental education, ethnicity, family composition, and family size. Other variables used in the literature are health and disability, neighbourhood mobility and future aspirations. Estimates of neighbourhood effects on young people's outcomes based on standard regression models are very sensitive to individual and family level characteristics. Neighbourhood effects appear strong when few or no individual and family characteristics variables are included in the model. Conversely, neighbourhood effects tend to be weaker or insignificant when a broad list of family characteristics variables are included in the model as control variables (Ginther et al [74], 2000). If observed or unobserved characteristics are not available to be included in the analysis, then neighbourhood effects will not be estimated with accuracy. This problem can be overcome when a rich longitudinal data is employed which offers a wide range of variables to select. In such a case, the selection of covariates to be included in the analysis should be informed by the theory to avoid a large number of unnecessary variables in the analysis.

Neighbourhood effects estimates are not consistent across different studies depending on the different model specifications. Therefore, researchers come to different conclusions ranging from important to non-significant. For example, Brooks-Gunn et al [25] (1993) examine how neighbourhood and family characteristics influence outcomes at early childhood and late adolescence using data from the Infant Health and Development Program (IHDP) and the Panel Study of Income Dynamics (PSID). The modeling approach includes a wide range of variables controlling for area economic characteristics, parental socio-economic characteristics and behavior, school and peer group characteristics. The study finds strong neighbourhood effects, particularly in the presence of affluent neighbours on young people's outcomes. Conversely, a study by Evans et al [57] (1992) finds insignificant effects of neighbourhood peer group on teenage outcomes, drawing on data from the National Longitudinal Study of Youth (NLSY). The results are insignificant when family characteristics that could explain the decision of a young person to participate in a particular group of people are included in the model.

Taking into account the inconsistency of neighbourhood effects estimates in the literature, we reach the conclusion that a theoretically informed modeling approach that controls statistically for individual and family characteristics is required to measure neighbourhood effects. Unmeasured family characteristics that affect both neighbourhood choice and young people's outcomes could lead to omitted variables or selection bias problems which will subsequently lead to over or under estimates of neighbourhood effects. For example, suppose that two parents are highly interested in the welfare of their child. We could reasonably consider that this child would have high educational attainment as a result of a number of factors such as the time parents spend with their child, school choice , parental practices and monitoring to name a few. A model that would measure only the association between neighbourhood characteristics and educational attainment would mistakenly attribute high educational attainment to area characteristics while omitting important family characteristics.

4.4.2 Instrumental variables

In addition to regression models with statistical controls for covariates, the Instrumental Variables (IV) approach has been used to remove selection bias in neighbourhood studies from observational research settings. This approach is considered when neither regression, nor matching or any other type of conditioning technique can be used to estimate effectively a causal effect. The IV literature suggests that when there is an instrument that predicts the causal variable of interest but does not affect the outcome variable, then an IV estimator can be used to estimate effectively the causal effect. Certain problems arise in the IV approach. First, it is often difficult to support the assumption that an IV does not have a direct effect on the outcome variable. Second, even in cases that an IV does not have a direct effect on the outcome variable, IV estimators are biased in finite samples. This bias can be substantial when an instrument only weakly predicts the causal variable. Third, IVs tend to have large standard errors. And fourth, the IV approach is often based on arbitrary assumptions. For example, Duncan et al [52] (1997) use the instrumental variables approach to reduce selection bias by locating an instrument for the future neighbourhoods of the mother after all of her children will have left home. However the authors make the arbitrary assumption that parents will only change neighbourhood after their children leave home.

One form of the instrumental variable approach used frequently in the estimation of family inputs on young people's attainment is to factor out the effects of unobservable factors at the family level by comparing the educational outcomes across siblings (Galster [69], 2008, Flouri et al [65], 2010). By comparing the differences in the outcomes between siblings who have been subject to different levels of inputs (e.g. family income) at different ages, the approach allows the researcher to difference out the unobserved heterogeneity in the family fixed effects, such as parental ability. One of the advantages of this strategy, provided that it is successfully applied, is that it allows researchers to identify when family inputs matter most by comparing attainments between siblings at different ages. One of the central arguments against sibling studies is that siblings themselves may have differential unobserved characteristics (e.g. innate abilities) that cannot be eliminated by the sibling effects model. It is also likely that siblings will be close in age, and experience very similar levels of family inputs throughout their childhood (Blow et al [15], 2005). Additionally, unobserved within-family heterogeneity in IV models cause a problem of omitted variable bias.

4.4.3 Propensity score matching

An important limitation of longitudinal datasets is that they provide observational data which means that the datasets are not based on experiments. A relatively new statistical approach to correct for this limitation is propensity score matching (PSM), that attempts to design a randomised experiment using observational studies in cases where it is not feasible to conduct randomised trials and therefore it is challenging to draw causal inferences. PSM is employed for the current thesis. The overall process of propensity score matching analysis will be described in this section. Details of the statistical theories, the modelling principles and a step by step analysis will follow in Chapter 7.

The debate on neighbourhood effects on young people's outcomes centres on the question of whether differences observed in the outcome (NEET status at 18-19) between young people who live in high and low Crime Score areas are caused by neighbourhood characteristics or by the characteristics of the people who live in those areas. In other words, if being in NEET status is attributed to neighbourhood characteristics then this finding suggests that living in an area characterised by high Crime influences negatively young people's educational and employment outcomes. If however, differences in young people's outcomes are attributable to the people who live in specific areas, findings would suggest that specific people would become NEETs regardless of whether they live in high or low Crime Score areas. The best approach to study such a question would be to employ a randomised experiment. Because observational data, such as the LSYPE study employed in the current analysis, do offer the possibility to assign individuals to treatment and control groups at random a statistical procedure needs to be employed to balance the data and to create two comparable groups before assessing treatment effects. In the current study propensity score analysis is employed to assess the impact of Crime Score on young people becoming NEETs.

The aim of propensity score analysis is to balance data when treatment assignment is non-ignorable, to evaluate treatment effects in a non-randomised approach and to reduce multidimensional covariates to a one-dimensional score called the propensity score (Rosenbaum and Rubin [154], 1983). The propensity score analysis starts by finding the conditioning variables or covariates that are considered to affect the outcome and to cause an imbalance between the treatment and control groups. After the vector of covariates is defined, the modelling begins with an estimation of the conditional probability of receiving a treatment given the vector of observed covariates. The estimation of the conditional probability, ie the propensity score, is done by using a logistic regression model to analyze the effects on the treatment of the vector of covariates. The propensity score is a balancing score. The propensity score is estimated both for treated and control groups based on the values of specific covariates. The balancing scores (propensity scores) are employed to match treated participants to control participants. Matching based on propensity scores balances observed covariates and controls for selection bias. Matching data can be performed using one of three conventional methods, the ordinary least squares regression, matching and stratification. Matching, which will be selected in the current analysis, is performed by matching each treated participant to a non-treated participant based on a vector of matching covariates and employing the propensity score. The goal of matching is to create two groups of participants similar in terms of the propensity scores which can be compared on the observed covariates. Various algorithms for matching exist such as greedy match, the Mahalanobis matching and optimal matching. The main difference is the way they treat loss of participants in cases where the propensity scores cannot fulfil matching. Greedy matching will be employed in the current analysis and more specifically the nearest neighbour without replacement without caliper approach which will be presented analytically in Chapter 7. After the two comparable groups are created, post-matching analysis will be performed on the matched samples. Analysis initially estimates the Average Treatment Effect. Subsequently, multivariate analysis is performed on the matched samples as it would have been done as if a sample created by a randomised sample was used. Propensity score methods create a summary measure of the probability of receiving a treatment. The advantage of propensity score matching is that it approximates randomised trials and that after units are matched, the unmatched comparison units are discarded and consequently not used in the treatment impact (Dehejia and Wahba [46], 2002). However, bias may also arise in propensity score matching because the apparent difference between the two compared groups of units may result from characteristics that affected whether or not a unit received a treatment and not from the effect of the treatment per se. As Rosenbaum [153] (2002) noted what remains unknown when propensity score matching is employed is the extent to which matching adequately controls for bias and yields estimates of treatment effects that can be robust. The most important form of bias that can arise in propensity score analysis is the hidden bias which is created by the omission of unobserved characteristics which might affect the outcome of the analysis. A statistical approach to correct for hidden bias is sensitivity analysis.

4.4.4 Sensitivity analysis

The previous section introduced propensity score analysis, a method that was designed to address selection bias, a fundamental problem in observational studies where it is not possible to conduct a randomised experiment. Even after employing propensity score as a corrective method to handle selection bias, researchers still face the challenge of hidden bias which might be caused by unobserved characteristics that were not included in the analysis. Rosenbaum [153] (2002) distinguished between over and hidden bias. Bias in observational studies occurs when treated and control groups differ prior to treatment in ways that can influence the outcome of the study. An overt bias refers to bias that can be observed and included in the analysis such as for example prior to treatment subjects could be observed to have different educational attainment compared to the control group. A hidden bias refers to bias that cannot be observed or recorded despite the fact that it provides essential information for the outcome of the study such as for example individual ability or self-efficacy. Propensity score analysis corrects for overt bias as it balances data on observed characteristics prior to treatment and creates comparable groups through matching. The problem with propensity score analysis is that it can adjust only for the observed characteristics while unobserved covariates remain a problem in the analysis. Rosenbaum and Rubin [154] (1983), Rosenbaum [153] (2002) developed sensitivity analysis to deal with hidden bias caused by unobserved covariates.

For the purposes of the current analysis, after matching treated and control groups using propensity score analysis, sensitivity analysis will be carried out to control for hidden biases. Sensitivity analysis is an exploratory analysis conducted in observational studies to determine the level of bias and to explore how sensitive are the results to hidden biases. The approach taken in this analysis is to estimate the odds of receiving a particular treatment to explore how much the estimated treatment effects may vary. It attempts to explore what the unmeasured covariate would be like to alter the conclusions of the propensity score analysis. Sensitivity to hidden biases varies substantially in observational studies, some studies can be very sensitive to very small biases while others are insensitive to large biases. A simple sensitivity analysis model is based on a parameter γ that measures the degree of departure from random treatment assignment. A factor of γ denotes the different odds of receiving a treatment for two individuals. In the case of an experiment, random assignment ensures that both individuals have the same odds of receiving a treatment and therefore $\gamma = 1$ implying that sensitivity analysis is not required. If in an observational study $\gamma = 2$, this means that for two individuals that were matched on observed covariates one has twice possibilities compared to the other to receive the treatment because of unobserved covariates. Many different values of γ are estimated in sensitivity analysis to investigate how the conclusions drawn by propensity score analysis might be altered because of hidden bias.

Overall, propensity score matching and sensitivity analysis attempt to create the structure and robustness of experimental designs in an observational study to control for selection bias. Propensity score analysis adjusts for overt bias through matching. Overt bias refers to pre-treatment biases between the treatment and control group that can be controlled in observed covariates. Sensitivity analysis aims to identify hidden biases, which are biases that were not observed and included in the analysis. The goal of sensitivity analysis is to explore the magnitude of hidden bias that would need to be present to alter the conclusions drawn by propensity score analysis.

4.4.5 Conclusions

This chapter examined various approaches and methodologies that have been utilized in measuring neighbourhood effects. A fundamental issue in capturing neighbourhood effects is to define neighbourhood boundaries to capture both the dimension of the geographical entity and the dimension of the social space where interactions take place. The majority of data available for neighbourhood research such as electoral districts and educational authorities administratively define neighbourhoods and capture only spatial boundaries (Sloggett and Joshi, 1998; Garner and Raudenbush, 1991). Community surveys include social aspects of neighbourhoods but are difficult to implement and involve inconsistent boundaries. Taking into consideration the incongruence between spatial and social characteristics in delineating neighbourhood boundaries, special attention was paid in selecting a measure to define neighbourhoods in the current research. The study employs Lower Super Output Areas (LSOAs) to operationalize neighbourhoods. LSOAs have consistent geographic boundaries (32,482 small areas in England and Wales of around 1,500 people) and were developed to include areas that share similar social characteristics and thus capture both spatial and social neighbourhood characteristics.

After operationalizing neighbourhoods, it is important to decide whether an experimental or an observational methodological approach will be employed. Experimental designs involve random assignment of individuals to neighbourhoods and therefore permit the investigation of how a change in neighbourhood context influences young people's outcomes. Additionally, due to random assignment to treatment, experiments allow for causality of neighbourhood characteristics to be tested. Compared to the rest of the approaches, they provide a better estimate of true neighbourhood effects by minimizing selection bias as a problem. However, they are difficult to implement because of practical and ethical concerns. The next best solution is quasiexperimental designs which involve comparable groups of similar individuals or families. Quasi experimental designs allow selection biases to be reduced and causal relationships to be established. They are more easily implemented than randomised designs, however unmeasured differences may still affect the results. Observational data on the other hand, include longitudinal and cross-sectional studies. Longitudinal studies involve a large range of socio-economic status and income characteristics for families and neighbourhoods. Therefore, they allow causal relationships to be tested and selection bias to be reduced. Longitudinal studies permit the researcher to study changes in neighbourhood characteristics over time. Cross-sectional studies are the least preferred approach. Cross-sectional studies involve observations and examine correlations between characteristics of neighbourhoods, families and young people at one specific point in time. They reflect associations at the time the census was taken and therefore they do not permit causal relationships to be investigated.

Analysis based on observational data is the most common approach, however careful statistical modeling needs to be employed to address the selection bias issue. The most commonly used statistical approaches are regression models controlling for many variables considered to affect selection of neighbourhood and instrumental variables such as for example the sibling fixed-effects models. Regression models need to include a wide range of individual and family variables in the analysis to avoid omitting unmeasured family characteristics that affect both neighbourhood choice and young people's outcomes and could lead to omitted variables or selection bias problems which will subsequently lead to over or under estimates of neighbourhood effects. In the instrumental variables approach, an instrument is used to produce a consistent estimator of a parameter when the explanatory variables are correlated with the error terms. The instrumental variables technique is subject to large standard errors and IV estimators only capture the effect of the treatment on the subset of the sample that is on the margin. Siblings fixed-effects models allow the researcher to difference out the unobserved heterogeneity in the family fixed effects, such as parental ability however, the sibling fixed-effects models often have large standard errors and do not control for unobserved family characteristics that vary over time and are different between siblings. A relatively new approach in the social science literature is propensity score matching and sensitivity analysis. Propensity score matching approximates a randomised trial by comparing outcomes among units that received a treatment versus those that did not and aims to control for overt bias, that is, bias that can be seen and controlled for. Sensitivity analysis is employed to indicate the magnitude of hidden bias in propensity score analysis. Hidden bias refers to bias that is caused by unobserved characteristics that are not included in the analysis such as for example individual motivation or ability.

Chapter 5

Dataset Description

5.1 Introduction

This chapter introduces the dataset which will form the basis of the current analysis on neighbourhood effects on young people's outcomes. It is well established that a number of longitudinal studies offer rich and high quality data in the UK to inform and assess policy. Section 5.2 reviews the key goals and areas of interest covered by administrative datasets that investigate young people in their early teens in the UK. Four datasets will be examined and compared with the LSYPE study to explain the choice of dataset. The key criterion that will drive the final decision is to use a longitudinal dataset that will allow the research hypothesis of this study to be tested and causal associations to be investigated. In particular, a dataset is required with information on young people and their transitions as they move from compulsory education to further education or to economic activities, a dataset that will provide neighbourhood deprivation data and rich data to control for family, individual, school and peer group characteristics.

For the purposes of the current research, a large scale dataset was selected, the Longitudinal Study of Young People in England (LSYPE). The LSYPE follows the transitions of a representative cohort of young people in England into adulthood offering one of the most detailed and in-depth data sources on young people in the UK today. Section 5.3 will introduce the LSYPE and describe the uniqueness of the dataset in relation to the data provided and the goals of this thesis. Section 5.3.1 will investigate how the LSYPE content will provide an understanding of the trajectories of individual life histories and of the dynamic processes that affect young people in their area of residence. Sections 5.3.2 to 5.3.4 provide a description of the sampling approach, the data collection methods, the achieved sample of the study, the weights used to accurately represent the population of young people and their families, and the temporary or permanent loss of sample members due to attrition. Section 5.4 briefly introduces the two administrative datasets linked to the LSYPE (the National Pupil Database (NPD) and school level data) and describes in detail the geographical indicator that will be employed in the analysis, the IMD and its seven decomposed indices, that were linked to the Wave 1 of the study. Section 5.5 describes the analytic sample employed in the analysis to study the main activity of young people at $18-19$ and the missing value analysis that will be conducted as a method to investigate the patterns of missing data. Section 5.5.2 describes the statistical modeling approach that will be carried out to reduce the selection bias that plagues neighbourhood effects studies which will involve logistic regression analysis, propensity score matching and sensitivity analysis. Section 5.5.3 introduces the variables that will be used in the analysis employing the LSYPE and the decomposed IMD.

5.2 Datasets considered for the analysis

A number of datasets were examined before choosing the source that would be employed for the current thesis. The main dataset selection criteria were to employ a dataset in the analysis that would allow the research hypotheses to be tested following an observational approach. A rich longitudinal dataset with information on young people's transitions from secondary and tertiary education to economic roles in early adulthood combined with information on area deprivation was required for this study. The studies that were considered covered broadly similar topics, had similar aims and focused on a similar age range of young people as the LSYPE that was finally selected. The main studies investigated were Growing Up in Scotland (GUS), Families and Children Study (FACS), Understanding Society (US) and the Millennium Cohort Study (MCS) which will be briefly described in this section and compared with the LSYPE.

GUS is one of the largest longitudinal studies in Scotland that follows the lives of thousands of children and their families from the early years of their lives. It provides information on childcare, education, health and social inclusion. A common characteristic between the LSYPE and GUS is that both have a similar age group focus. However, unlike LSYPE, GUS focuses more on child development at early ages (until the age of 8) and additionally focuses only in Scotland and not on young people in England. ***The Families and Children Study (FACS)*** is a longitudinal study that investigates approximately 7,000 families in Britain. It was set up in 1999 and provides information on all households with dependent children at the ages of $11-15$. Six waves have been conducted until it was terminated. The main focus of FACS are the economic circumstances of the family and the children and not the young people and their development as in the LSYPE. In addition, FACS is a study that is currently complete and therefore it cannot provide information on young people's educational and employment outcomes. ***Understanding Society (US)*** is the largest longitudinal study in the UK and investigates circumstances and attitudes of 40,000 UK households and up to 100,000 individuals. The main focus of the US lies on socio-economic circumstances, social trends and how they develop such as for example duration of marriage and cohabitation, poverty persistence, health and wellbeing and financial circumstances. The study is funded by the Economic and Social Research Council (ESRC) and run by the Institute for Social and Economic Research (ISER) at the University of Essex. The US is a rich dataset, however it has got a broader focus than young people and their trajectories. Unlike the LSYPE, the US does not offer information for in depth analysis of young people and their educational and employment outcomes. ***The Millennium Cohort Study (MCS)*** is the most recent British longitudinal birth cohort study that follows the lives of approximately 19,000 children born in the UK in 2000/2001. The main focus of the study is child development, parenting, school choice and cognitive development, housing, social capital, parents employment, income and poverty. In comparison to the LSYPE the MCS is more focused on socio-economic data. Both studies can be linked to the geographical indicator, the Index of Multiple Deprivation (IMD) which allows neighbourhood characteristics and their effects on young people to be examined. However, the age group focus is different in the two studies. The oldest age at which data have so far been collected is 11 in the MCS. Conversely, in the LSYPE, the oldest age group of young people is at the age $19 - 20$. Both studies focus on approximately the same age of young people (when LSYPE participants aged 13/14 MCS participants aged 12/13). However, unlike the MCS in LSYPE students are clustered by school which allows researchers to investigate school characteristics and its effects on young people's outcomes. Additionally, the LSYPE is linked to a geographical indicator, the Index of Multiple Deprivation which allows neighbourhood characteristics and their effects on young people to be examined.

To sum up, the first three studies investigated (Growing Up in Scotland, Families and Children Study, Understanding Society) lack the focus that LSYPE provides on young people and the most important factors that are considered to influence their educational and employment outcomes that are investigated in the current thesis. LSYPE uses a cluster of young people in schools in contrast to other studies such as Understanding Society and FACS where young people are sampled at the household level and therefore LSYPE allows better estimation of the effect of different schools on young people. Additionally, LSYPE follows young people from early teenage years until adulthood and is nationally representative. In comparison to the MCS, the LSYPE offers the advantage that it focuses on young people after compulsory education. For all these reasons, LSYPE is in a better position to allow the investigation of neighbourhood effects on young people becoming NEETs and to form the basis to inform future policy. Despite the facts that there are homologous areas of investigation between the LSYPE and other major cohort studies, LSYPE is the only longitudinal study exploring in depth young people's attitudes and experiences and main activities after compulsory education, that covers the whole England and allows investigation at the school level. Thus, LSYPE was selected to examine the effect of parental, individual, school and peer group characteristics over and above neighbourhood deprivation on young people's outcomes at the ages $18 - 19$.

5.3 The Longitudinal Study of Young People in England

The Longitudinal Study of Young People in England (LSYPE), also known as Next Steps, is a large panel study of young people that was initiated by the former Department for Education and Skills (DfES) in 2004 (`http://www.esds.ac.uk/longitudinal/access/lsype/L5545.asp`). LSYPE was run by the DfES and co-funded by the Department for Business, Innovation and Skills (BIS) and the Department for Work and Pensions (DWP). The LSYPE is currently run by the Centre for Longitudinal Studies (CLS). The dataset is publicly available from the UK Data Archive and the iLSYPE (`https://www.education.gov.uk/ilsype/workspaces/public/wiki/Guide`) although special permission is required for some variables of the data. The main objectives of the LSYPE study are to collect evidence on the trajectories young people follow from secondary education through to further and higher education, training or employment in their early adulthood. Additionally, it aims to monitor and evaluate existing policy and thus to provide insights for future policy development. More specifically, by covering a wide range of information on young people, the LSYPE can prove a useful tool in analyzing the implementation of new policies in the context of young people's lives. Due to the fact that LSYPE can be used to evaluate and inform policy, a growing set of publications has emerged from the analysis of the LSYPE produced both by the DfE as well as academic researchers, charities and independent research organisations.

5.3.1 Questionnaire content

The LSYPE study covers a wide range of issues relating to young people's lives and their effect on transitions and pathways into adulthood. Additionally, every Wave contains household and demographic information collected on a yearly basis. Information on young people's activities after compulsory education is provided in Waves $4-6$ and collectively at Wave 7. Further information is collected at different Waves depending on the age of the young person and policy interest. The areas of information collected in each Wave relate to attitudes to school and education, extra-curricular activities, special education needs, family characteristics, parental involvement, family activities, parental aspirations, household responsibilities, parental relationship with the young person, risk factors and antisocial behaviour, friendship and socializing, views on local areas, community cohesion, higher education and employment. Detailed information on the survey content and the variables available in the dataset can be found using the following web link: `https://www.education.gov.uk/ilsype/workspaces/public/wiki/`. It is important to stress that the LSYPE provides detailed information on parental characteristics and behaviour. This information gives researchers the ability to think of young people in the context of their families and to investigate in depth the effect of parental characteristics on young people's experiences, decisions and outcomes. For example, information on parental educational level and socio-economic status are essential characteristics that drive social mobility, determine the choice of neighbourhood a family lives in and subsequently affect young people's outcomes. Even though parental characteristics are not the central point of the analysis, controlling for them is essential in studying neighbourhood effects to provide a picture of the context a young person lives in and its impact on other characteristics such as individual behaviour, school characteristics and relationships with the peer group. The detailed questionnaires of the LSYPE study that provide rich information both on young people and their parents allow researchers to thoroughly investigate the transitions young people make into adulthood. More specifically, for the purposes of the current research, detailed information is provided to allow in-depth investigation of the pathways proposed by the Compositional Model of Neighbourhood Effects considered to affect young people's educational and employment outcomes.

5.3.2 Sampling

The LSYPE is a large scale longitudinal survey of young people. The sample members were born between 1st September 1989 and 31st August 1990 and started to be interviewed when they were in Year 9 (age 13/14) or equivalent. The sample was drawn from those attending maintained schools, independent schools and pupil referral units in England. Pupils were sampled using a two-stage probability proportional to size (PPS) sampling procedure with disproportionate allocation. At the first stage, schools were the primary sampling units (PSUs). Maintained schools were stratified into those in deprived and non-deprived areas. Deprived schools were over-sampled by a factor of 1.5. The second stage involved sampling pupils from each of the selected schools. The two stage design of the study was a useful step as it allows analysts to conduct multilevel modeling in estimating school effects on young people's outcomes which would not be possible otherwise. The sample was boosted with regards to ethnic minorities and pupils eligible for Free School Meal. Ethnic minority pupils were oversampled to achieve 1,000 pupils in each group and to ensure all pupils within an ethnic group had an equal chance of being selected and to increase sample sizes to allow subgroup analyses. Because selection probabilities differed within maintained schools, schools were oversampled based on their deprivation status as this was identified by Free School Meal Eligibility. Excluded from the sample were children educated at home and boarders, children residing in the UK solely for educational purposes, pupils in schools with a very low number of year 9 pupils (schools for fewer than 10 pupils in the maintained sector and fewer than 6 pupils in the independent sector).

5.3.3 Data collection and survey design

All the respondents gave voluntary informed consent to the DfE to participate in the study. Young people in the study were first interviewed in 2004 and then participated in annual interviews until 2010. Young people from English secondary schools at the ages of 13 and 14 were interviewed for the first time in 2004. The LSYPE cohort was designed as a face to face survey but after Wave 5 a mixed mode design was adopted. The LSYPE comprises seven interviews to the young person, the main and the second parent. From Wave 5 all members were given the choice to submit an online questionnaire and those who did not respond had the option to complete a telephone interview or a face to face interview. A mixed mode approach is considered more appropriate in longitudinal studies to correspond to different preferences of participants. For example if certain sample members are more likely to respond to web questionnaire than others, then a mixed mode approach would ensure that responses will be maximized and the responding sample will be in closer correspondence to the sample that the study is trying to capture. For these reasons, a choice of response modes was provided to LSYPE participants. Overall, evidence from experimental studies shows that a mixed design in longitudinal studies improves the response rates (Dillman et al [47], 1995). Despite the fact that response rates are not increased, a choice of participation mode can potentially be a factor to improve the attitudes of participants in a survey which could be favourable for a longitudinal study (de Leeuw et al [44], 2008).

More analytically, in the first four waves of the LSYPE data was collected through face to face interviews using computer assisted personal interviewing (CAPI). The process started in the first wave with letters sent to all head teachers of sampled schools providing introductory information about the study. Subsequently, contact was made by interviewers to collect information for the sampled pupils. Next, letters were sent to young people and their parents. The letters provided information about the survey, and described the interview process. Young people were offered a £5 voucher as an incentive to participate in the interview in Waves two to four. When it was possible, the interviewers were assigned the same households they were assigned in Wave 1. The interviews consisted of five modules; the young person interview, household information, main parent interview, second parent interview and child history. Special attention was given to cases where the young person was not living in the parental home in Waves 4 to 7. The interviewers made a special effort to follow young people who moved to another house, to the college, in the armed forces, in prison or young offenders institution.

The data collection approach and the survey design changed from Wave 5 onwards. In Waves $5-7$ only the young person was interviewed and not the main and/or second parent. The Wave 7 sample constituted of young people who participated in Wave 6. Waves $5-7$ include information on the household and the young person only. From Wave 5 onwards the young person had the option to complete the interview online, over the telephone or face to face with an interviewer in their home. Advance letters were still sent to the respondents but email contact was preferred as a more direct and easier access to the respondents.

Some longitudinal studies adopt a monetary incentive to ensure response rates remain high throughout the years. For example, British studies such as the British Household Panel Study (BHPS), and the English Longitudinal Study of Ageing (ELSA) have used monetary incentives. It is considered that the incentives need to keep up with the increasing cost of living and to provide for the time spent to attend the interview or to complete the questionnaire. A monetary incentive was given to LSYPE participants. All the participants of Wave 1 were given a £5 high street voucher. Subsequently, in

Waves 2 and 3 an unconditional £5 voucher was sent to cohort members with their advance letter at the beginning of each Wave. The value of the voucher increased to £8 in Wave 4. In Wave 7 it further increased to 10. Increasing the amount of money provided by incentives is considered rewarding for participants who remain in the study in the long-term. Additionally, a small increase in the incentive provided to participants is found to have a positive psychological effect on participants irrespectively of the value of the increase (Laurie and Lynn [107], 2009).

5.3.4 Response, weighting and attrition

The achieved sample for Wave 1, when young people were aged $13 - 14$ was 15,779. However, because LSYPE is a longitudinal survey, respondents who took part in the first wave of data collection did not necessarily participate in any or all of the subsequent interviews. Therefore, the final sample for Wave 7, when young people were at the age of $18 - 19$ was 9,791. The latest wave includes information on young people at ages $18 - 19$, which means that three years of post-compulsory education data are available (see Table 5.1: 'Sample and Response Rates in the Longitudinal Study of Young People in England, Waves $1-4$' and Table 5.2: 'Sample and Response Rates in the Longitudinal Study of Young People in England Waves $5 - 7$)'. Partial interviews in Table 5.1 in Waves 1-4 and Wave 4 ethnic boost refer to cases where either the main parent, or the second adult, or the young person were not interviewed.

Weights have been created for the LSYPE data to ensure that subsequent analysis of the data would account for the survey design for each wave. In Wave 1 a two stage weighting process was adopted. Pupils from maintained and from non-maintained schools were weighted separately. Data was weighted in subsequent Waves using a design weight provided by the fieldwork consortium. Initially data was weighted to account for non-response between Waves 1 and 2. Some of the pupils who responded in Wave 1 did not respond in Wave 2. The characteristics of young people who did not respond could be different from those who responded. Missing responses could lead to bias in estimates of population quintiles. Therefore, non-response weights were applied to reduce bias. In a similar way, weights were applied in Wave 3 to account for non-response between Waves 2 and 3. In Wave 4 weighting was conducted at three stages; the main survey, the boost survey and a combined main and boost survey. Weighting included two stages in Wave 5. In the first stage, final weights from Wave 4 were used to account for the probability of being in the sample. In the second stage, respondents from main and boost cohorts were considered separately. The two stage weighting approach that was conducted in Wave 5 was also conducted in Waves 6 and 7. Wave 7 weight, which will be used for this analysis, was created to ensure analysis can account for the survey design and therefore involves unequal sampling probabilities for schools, pupils and sample boosts. In addition, the Wave 7 weight is longitudinal since it adjusts for non-response between successive waves (see LSYPE User Guide, Section 2: Sampling and Section 6: Weighting, http://www.esds.ac.uk/).

Table 5.1: Sample and Response Rates in the Longitudinal Study of Young People in England (LSYPE) Waves 1 – 4

	Issued Sample	**Achieved Sample**	**Response Rate**	**Full Interviews**	**Partial Interviews**
Wave 1	21,000	15,770	74%	13,914 (66%)	1,856 (9%)
Wave 2	15,678	13,539	86%	11,952 (76%)	1,587 (10%)
Wave 3	13,525	12,439	92%	12,148 (90%)	291 (2%)
Wave 4	12,468	11,449	92%	11,053 (89%)	396 (3%)
Wave 4 *Ethnic Boost*	600	352	59%	309 (52%)	43 (7%)

Note1: The survey interviews the young person and their parents in Waves 1 – 3.

Table 5.2: Sample and Response Rates in the Longitudinal Study of Young People in England (LSYPE) Waves 5 – 7

	Issued Sample	**Achieved Sample**	**Response Rate**	**Online Interview**	**Telephone Interview**	**Face to Face Interviews**
Wave 5	11,793	10,430	88%	3,832 (32%)	5,140 (44%)	1,458 (12%)
Wave 6	11,225	9,799	87%	3,803 (39%)	4,705 (48%)	1,291 (13%)
Wave 7	9,791	8,682	90%	3,965 (40%)	3,942 (40%)	1,715 (18%)

Note: Only the Young Person completes the interview in Waves 5 – 7.

5.4 Data linkage. The English Indices of Multiple Deprivation (IMD) 2010

Three types of administrative data were linked to the LSYPE. First, the National Pupil Database (NPD) which provides pupil information about examination results and pupil and school characteristics about all pupils in state or partially state-funded schools in England. The NPD includes data on attainment, such as Key Stage 2, 3 and 4 and pupil characteristics data such as free school meal eligibility and Special Education Needs (SEN) status. Second, school level data drawn from PLASC (Pupil Annual School Census) which indicate information about the school each sample member attended and information about primary school attended by the young person at Key Stage 2. And third, a geographical indicator, which is disclosive if a secure service is used, the Indices of Multiple Deprivation.

The Indices of Multiple Deprivation are published by the Department for Communities and Local Government every three years (`https://www.gov.uk/government/organisations/department-for-communities-and-local-government`) and identify the most deprived areas across the country using a number of indicators. The IMD 2010 is the latest set of indices that has been published. The Indices are official measure of deprivation in England and their purpose is to identify small areas across England which experience multiple aspects of deprivation. Area deprivation is typically measured by income but the IMD is an advance of this approach combining multiple dimensions to look beyond income to detailed measures of deprivation. The IMD has been used in the literature in neighbourhood effects in the past (Flouri, Mavroveli, and Tzavidis [64], 2010; Flouri, Tzavidis and Kallis [65] 2009; Flouri, Mavroveli, and Midouhas [63], 2012). The general IMD index comprises seven domains each of which reflects a different aspect of deprivation. The seven domains are income, employment, health, education, crime, access to services and living environment. The domains are formed of 38 separate indicators and have their own scores and ranks allowing examination of specific aspects of deprivation. Most of the indicators used in the IMD 2010 are from 2008 however there are some indicators from other time points. The Indices measure deprivation at small areas across England. England has been divided in 32,482 areas with roughly the same number of people. Those areas are known as the Lower Super Output Areas (LSOAs) and are a way to divide up England and Wales. Each LSOA in England has got a deprivation score. The Indices allow the researcher to investigate deprivation across both small and large areas, and to calculate the number of people who are income or employment deprived. The LSOAs in England are ranked according to their Index of Multiple Deprivation score. The LSOAs which have the highest rank of 1 are those areas which are considered most deprived. The LSOAs with the rank of 32,482 are the areas which are least deprived. Due to the exponential transfomration of the ranking system, it is possible to compare the level of deprivation in different LSOAs ordinally but it is not possible to estimate the magnitude of the difference between them.

In the past, a number of different area deprivation measures were used. Nolan and Whelan [135] (1996) defined deprivation as: 'exclusion from the life of society owing to lack of resources'. This definition though does not provide a clear measure of deprivation. A commonly used approach to measure deprivation is by using income or money based measures. Townsend [186] (1987) constructed an index of deprivation that incorporates four components: a) unemployment; b) non-car ownership; c) non-home ownership; and d) household overcrowding. Borooah [16] (2007), uses data for Northerh Ireland, and extends the range of deprivation measures associated with lack of possessions and constructs two indices: a) one index based on possession of outcomes; and b) one index based on economising on, or postponing of, the purchase of items. The advantage offered by measuring deprivation through economising and possession captures both the number of deprived persons as well as the depth of their deprivation. The IMD was selected to study neighbourhood deprivation effects on NEETs in this study as it provides a powerful measure of neighbourhood deprivation and can be used to compare deprivation in different areas in England at the LSOA level. Given the constraints in defining neighbourhoods described in Chapter 4 , the use of the LSOAs allows both structural and social neighbourhood characteristics to be defined in the current study. The consistent geographic boundaries of small areas reflect the physical dimension of neighbourhoods and allow structural dimensions to be captured. It is a statistically robust area measure because it offers a smaller scale measure compared to previous studies that used, for example, local authorities and electoral wards (Lupton [114] 2003). At the same time LSOAs boundaries were developed to include areas with similar social characteristics and thus to allow social interactions of residents and their impact on young people's outcomes to be examined. In the current study I use the Crime Score of the decomposed IMD. Special permission has been gained to access the decomposed IMD index and to link it with the LSYPE dataset in Wave 1. The seven Indices of Deprivation are briefly summarised below.

The ***Income Deprivation Domain*** measures the proportion of the population in LSOAs facing income deprivation. It is composed of five indicators: adults and children in Income Support families; adults and children in Income-Based Jobseekers Allowance families; adults and children in Pension Credit (Guarantee) families; adults and children in Child Tax Credit families (not in receipt of Income Support, Income-Based Jobseekers Allowance or Pension Credit) whose equivalised income (excluding housing benefits) is below 60 per cent of the median before housing costs; and asylum seekers.

The ***Employment Deprivation Domain*** measures the proportion of the population in LSOAs who are at working age and unemployed despite their intention to work. This measure is composed of seven indicators: Jobseekers Allowance; Incapacity Benefit; Severe Disablement Allowance; Employment Support Allowance; Participants in New Deal for the 18−24s who are not in receipt of Jobseekers Allowance; Participants in New Deal for 25+ who are not in receipt of Jobseekers Allowance; and Participants in New Deal for Lone Parents aged over 18. The first two Indices, Income and Employment, are different compared to the other Indices as they measure the proportion of the people who are on at least one of a range of income/employment benefits or programmes.

The ***Health Deprivation and Disability*** Domain measures poor health and its effects on quality of life, illness and disability and premature death. It is composed of four indicators: Years of Potential Life Lost; Comparative Illness and Disability Ratio; Measures of acute morbidity; and Proportion of adults under 60 suffering from mood or anxiety disorders.

The ***Education, Skills and Training Deprivation Domain*** measures the extent of deprivation in education, skills and training in LSOAs. The indicators included in this domain are: average points score of pupils taking English, Maths and Science Key Stage 2 and 3 exams; average capped points score of pupils taking Key Stage 4 (GCSE or equivalent) exams; Proportion of young people not staying on in school or non-advanced education above age 16; Secondary school absence rate; Proportion of those aged under 21 not entering Higher Education; and Proportion of adults aged $25-54$ with no or low qualifications.

The ***Barriers to Housing and Services Domain*** measures housing conditions, homelessness, financial resources to obtain a house and geographical proximity to services. The domain is composed of seven indicators: Household overcrowding; Homelessness; Difficulty of access to owner-occupation (local authority district level); Road distance to a GP surgery; Road distance to a supermarket or convenience store; Road distance to a primary school; and Road distance to a Post Office.

The ***Crime Domain*** measures the rate of recorded crime at the small area level. It consists of four crime indicators: burglary, theft, criminal damage and violence that represent the risk of personal and material victimisation at a small area level. The indicators are constructed by using Police Force Data for the recorded four different crime offence types.

The last index of the IMD is the ***Living Environment Deprivation Domain*** which measures the quality of living conditions in and outside the home environment. The indicators measure indoors housing quality and outdoors living environment. The indoors living environment consists of two indicators: Social and private housing in poor condition; and Houses without central heating. The outdoors living environment consists of two indicators: Air quality; and Road traffic accidents.

The Crime Score was selected to study neighbourhood effects and to test the Compositional Model of Neighbourhood Effects that is put forward in the current study and was informed by sociological theories of neighbourhood effects and theories focusing on young people's development. Based on previous sociological approaches the current study suggests that high crime score has a negative influence on the neighbourhoods' social dimensions and affects young people's behaviour and decisions and subsequently their educational and employment outcomes. The pathways that connect the Crime Domain and young people's outcomes are proposed by the sociological approaches that informed the Compositional Model of Neighbourhood Effects discussed in Chapter 3. The social disorganization theory (Shaw and McKay [171], 1942) suggests that high crime and delinquency in deprived neighbourhoods increases fear among residents, disrupts social cohesion and reinforces a culture of antisocial behaviour among young people. A key characteristic in areas characterized by high crime scores is socio-economic disadvantage, a culture of gangs and high rates of unemployment (the theory of Underclass, Wilson [199], 2012). Social problems in areas characterized by high crime rates spread like epidemics and influence the behaviour of their residents (the epidemic hypothesis, Crane [41], 1991). Additionally, the neighbourhood effects theory by Jencks and Mayer [95] (1990) provides an analytical approach of five different models to help explain the processes by which neighbourhood effects are mediated to its residents and impact young people's development. Given the associations between neighbourhood crime and young people's outcomes described in previous sociological theories, the Crime Score was selected in the current study to depict areas with high Crime Score and to examine their effect on young people becoming NEET.

5.5 Data analysis employing LSYPE and the IMD

5.5.1 Analytic sample and missing data

The previous sections described the dataset that will be used in the current analysis, the LSYPE, and the general IMD index and its component indices that were linked to the LSYPE for the purposes of this study. The focus now turns to the analytic sample that will be employed in the analysis, how missing data will be handled and thereafter the statistical modeling approach of this thesis.

Special permission was granted to gain access to the secure full monthly activity files of the LSYPE, which are used to estimate the main activity of young people at ages $18-19$ (Wave 7, see Chapter 6). The analytic sample in this report comprises of young people at the ages $18-19$, who gave valid information on their main activity in the LSYPE study for two years ($N = 8,931$). As already mentioned, a specific weight is provided for each LSYPE wave to ensure correct weighting in data analysis. Careful weighting selection was required because the outcome variable comes from Wave 7 and the independent variables come from Wave 1. The weight from the most recent Wave a variable has been taken from was used to ensure that the changing cohort structure is accounted for in the analysis since not all Wave 1 respondents remained in the study until Wave 7. The sample design was specified to ensure robust analysis using complex samples in SPSS before applying logistic regression analysis in Chapter 6. Additionally, because the analysis in the current thesis employs variables from two different files, surveyid, a serial number unique to the cohort member and therefore each family, was used to link variables from different Waves of the dataset. Surveyid was also used to sort each of the files prior to merging.

Missing data and the criteria by which missing data procedures should be evaluated have been a challenge among researchers (Schafer and Graham [167], 2002). Partial or full loss information might be the result of unfortunate events such as for example mortality, imperfectly measured data or data coarcening (Heitjan and Rubin [86], 1991). Different missing data patterns have been identified in research (Srndal, Swensson and Wretman [166], 2003). Unit non-response occurs when a sampled unit is contacted but fails to respond (eg they are inaccessible or not at home). Item non-response occurs when the sampled unit participates incompletely to a questionnaire. Attrition may occur when subjects miss a particular measurement and then return at the next wave, or when subjects completely drop out of the study. The missing values problem needs to be addressed in order to avoid invalid conclusions as a result of problems with internal and external validity (Jelicic, Phelps and Lerner [94], 2009). Understanding why data are missing is very important in order for the sample to be representative of the population and the analysis to produce robust results. In order to deal with subjects with incomplete data in this study, a missing value analysis was conducted to identify the patterns of missing data in the analytic sample (see Chapter 6).

5.5.2 Statistical modeling

Several stages are involved in data analysis. Initially, descriptive statistics are conducted to explore binary relationships between the indices of deprivation and young people in NEET status at the ages $18-19$ and the main independent variable, neighbourhood deprivation Crime Score. In the analysis of factors associated with NEET status the outcome variable, "NEET at $18-19$ " is a nominal binary variable that consists of two categories, "young person in education, employment or training at $18-19$" and "young person in NEET status at $18-19$" with "NEET at $18-19$" as the reference category. The IMD ranks of each deprivation index were used as a measure of area deprivation. Initial analysis tests for the association between the general IMD index and each one of its component indices, but further analysis focuses on the relation between the Crime Score and young people's outcomes.

The statistical modelling involves two stages and is designed to address one of the key methodological issues in neighbourhood effects studies, the difficulty to causally attribute neighbourhood context effects on young people's outcomes and to remove selection bias. The underlying concept in neighbourhood effects studies is the idea that living in a deprived neighbourhood has a negative effect on residents' life chances over and above the effect of their individual and family characteristics. However, differences between individual and family characteristics in high poverty and low poverty areas may bias neighbourhood effects estimates and therefore these characteristics need to be taken into consideration in the statistical modelling approach. This problem is often referred in the literature as selection bias or omitted variable bias. It refers to the fact that omitted family and individual characteristics, such as parental education or ability that may influence the selection of neighbourhoods, need to be considered in the analysis to obtain robust results about the true effect of neighbourhoods on young people.

Various approaches have been used to address the selection bias issue in neighbourhood analysis (see Chapter 4). Those include social experiments such as housing mobility programmes. Research based on observational data has used regression models with statistical controls for covariates, siblings fixed-effects models, instrumental variables and a relatively new method, propensity score matching. Following past research on neighbourhood effects, the first stage of the statistical modelling in this study involves logistic regression models with statistical controls for covariates. The models address selection bias by controlling extensively for family and individual attributes. An investigation of the factors associated with NEET status at ages $18-19$, using multivariate logistic regression follows a descriptive exploration. Predictor variables, as these have been defined by previous studies and proposed by the Compositional Model of Neighbourhood Effects, are added to test neighbourhood Crime effects. A series of models are produced to control the association of NEET status with other factors. The first model involves "NEET at $18-19$" and the deprivation index. The second model controls for factors such as for example parental education level, benefits claimants, single parent families and parental practices. Thereafter individual characteristics are added in the model such as ethnicity, educational attainment and aspirations for the future. Next, attitudes to school and perceptions of educational ability are added. Finally, variables that denote relationships with the peer group and antisocial behaviour are included in the model. The model examines successively the mechanisms that mediate the effect of neighbourhoods on young people's main activity. The final model tested tests the full combination of predictor variables.

The second approach to the statistical modeling involves propensity score matching estimators of the effect of neighbourhood crime by comparing outcomes for individuals who grow up in deprived and non-deprived neighbourhoods. The modeling approach involves five steps. First, a logit model is estimated with all covariates predicting whether an individual receives the treatment (ie living in a high crime area or not). Covariates are selected according to previous research and the model that is put forward in this thesis. Second, propensity scores are calculated, i.e. the predicted probabilities of receiving the treatment. Third, treated subjects are matched to controls according to their propensity scores. Fourth, observed covariates are checked for balance. And fifth, treated and control groups are compared on the outcomes. Propensity score matching allows reasonable comparisons between treatment and control groups and is more efficient, in terms of smaller standard errors, because fewer parameters are estimated (Winship and Sobel [201], 2004). Further analysis is carried out, sensitivity analysis, to check for biases caused by unobserved characteristics such as for example individual ability or self-efficacy.

5.5.3 Variables in the analysis

The outcome variable is young person's main activity at the ages $18 - 19$ and the main independent variable is the Crime Score of the IMD index. The LSYPE dataset offers detailed histories of individuals' monthly main economic activity after compulsory education, between September 2006 and May 2010 in Wave 7. Monthly main activity files report employment activity of 11,821 respondents. Fourteen different activity categories were summarised into four main categories: Education; Employment; Training; and Unemployed / Inactive (NEET). Following previous studies methodology (Payne [141], 2001; Bynner and Parsons [29], 2002; Yates et al [203] 2011) "NEET status" in this study refers to young people who are unemployed or inactive without participating in any form of education or training for a period of six months.

The main independent variable, neighbourhood deprivation, is measured with the Crime Score of the decomposed IMD index. Neighbourhood disadvantage is associated with a number of correlated variables such as for example ethnicity, parental socio-economic status and parental educational level and individual characteristics which could have an effect on young people becoming NEETs. In area analysis it is difficult to isolate neighbourhood effects and to draw causal conclusions. Therefore, these correlated characteristics will be used as controls in the analysis to investigate the mechanisms through which neighbourhoods influence educational and employment outcomes of young people.

5.6 Summary and Conclusions

The UK has developed a tradition for producing high quality longitudinal datasets which are used by analysts across the world. Despite the time and cost required to undertake longitudinal studies, these studies make a significant contribution to inform policy and understand the impact of policy interventions. A number of longitudinal surveys were considered prior to deciding a dataset for the current analysis. In comparison to the other studies investigated, LSYPE was chosen because it offers the biggest sample at the appropriate age. Additionally, it investigates thoroughly young people and provides insightful information on the factors that are considered to have significant impact on young people's development and the trajectories they follow after compulsory education. The LSYPE questionnaires report a broad range of important characteristics and look at the key issues that affect the lives of young people, the pathways through which they move into adulthood and their educational and employment outcomes. The LSYPE covers demographic and household information; young people's educational attainment, attitudes to schooling, risk factors encountered, ambitions for the future, friendships, higher education and employment and; parental attitudes, practices and aspirations. Due to the fact that the LSYPE questionnaires take many different directions and involve a wide range of different but related information, they allow the current analysis to focus on the factors associated with and influencing the transitions young people make and the different paths they follow at the ages $18-19$.

The LSYPE response rates remain relatively high throughout the study and do not differ from response rates from other longitudinal studies and in relation to the original sample (Lynn [117], 2005). About 7% of respondents drop out in each Wave. Low drop rates reflect a good representation of respondents in the study. Given the young age of respondents in the study, the danger of attrition was highly likely. For this reason, unconditional incentives were adopted to increase willingness to participate and to minimize levels of attrition.

A strength of the LSYPE data is that it has incorporated data from the National Pupil Database (NPD) and the Pupil Annual School Census (PLASC) which add information on students' academic achievement and offer school level data allowing the investigation of educational outcomes. Additionally, the LSYPE has included geographic information through the linkage with the IMD index of area deprivation. Geographic information is essential for the neighbourhood focus of the present study. The IMD index and its seven constituent domains provide important contextual information with regards to the neighbourhood where the young people live.

After reviewing the dataset that will be employed in the current analysis, it becomes clear that the key benefit of using the LSYPE study is that it enables the Compositional Model of Neighbourhood Effects to be tested. In addition, the LSYPE allows the application of statistical techniques to reduce selection bias and to identify the effect of area deprivation in combination with different spheres of young peoples lives to their development.

The next step involves selecting the vector of covariates that depict family, individual, school and peer group characteristics in order to address the first five research questions and to estimate the probability of a young person becoming NEET if they live in a high Crime area. The following Chapter employs multivariate logistic regression analysis to test the Compositional Model of Neighbourhood Effects taking into account that the outcome variable, NEET, is a dichotomous variable. The goal will be to estimate the probability that a young person will become NEET based on the values of the set of independent covariates proposed by the Ecological model of Neighbourhood effects that is put forward in this thesis.

Chapter 6

Controlling for Family and Individual Characteristics

6.1 Introduction

This thesis started with defining young people Not in Education, Employment or Training and describing the factors associated with entry to NEET status. Subsequent chapters presented theories that have been used to study neighbourhood effects and theories on individual development to help explain the pathways through which area deprivation influences young people's trajectories at the ages $18-19$. These theoretical frameworks have informed the Compositional Framework of Neighbourhood Effects that will be tested in this thesis. This chapter, investigates the first five research questions proposed by the Compositional Framework of Neighbourhood Effects.

Section 6.2 of Chapter 6 presents the research questions that are going to be addressed, the data that will be employed to investigate each question and how attrition and non-response are going to be taken into consideration in the analysis. Section 6.2 also describes the method of data analysis that will be followed throughout the analysis to test the association between NEETs and the set of selected covariates. The analysis will begin with descriptive statistics and subsequently continue with logistic regression analysis. Binary logistic regression is selected because the outcome of interest is a dichotomous variable, NEET status which is classified as “yes” or “no”. This section identifies the properties of the logistic function and explains how the logistic formula will be applied in this study. Section 6.3 presents descriptively the key measures that will be employed in the analysis. The first key measure that will be employed is the main activity of young people, described by the main activity files in the LSYPE study. The second key measure is the indicator of area deprivation, which is measured by the Index of Multiple Deprivation 2010 (IMD) average score and its seven sub-indices. Finally, a summary of all the measures that will be employed to test the Compositional model of neighbourhood effects is presented. Section 6.4 includes the statistical analysis to address the first four research questions. The analysis will begin with descriptive statistics of the data and the Pearson chi-square measure of association to measure the strength of the relationship between NEET and each covariate. Further analysis will be carried out, using a binary logistic regression model, to estimate the probability that a young person will become NEET or not based on the values of the set of independent variables. Section 6.4 includes the discussion and analysis of results presented in Section 6.3.

6.2 Research questions

This chapter addresses the first five research questions of the Compositional Model of Neighbourhood Effects:

(1) Is there an association between crime in the neighbourhood a young person lives in and NEET status?

(2) Can the effect of living in a deprived area with high crime on NEET status be explained after controlling for family demographic characteristics, parental

practices and aspirations?

(3) Is the effect of living in a deprived area with high crime on NEET status mediated by individual characteristics after controlling for family characteristics?

(4) Is the effect of living in a deprived area with high crime on NEET status mediated by attitudes to and experiences of school after controlling for family and individual characteristics?

(5) Is the effect of of living in a deprived area with high crime on NEET status mediated by peer group influence and antisocial behaviour after controlling for family, individual and school characteristics?

6.3 Data

The research questions will be addressed using data from the LSYPE dataset.

The first research question *Is there an association between neighbourhood deprivation and NEET status?* aims to explore the relationship between area deprivation and being in NEET status at the age of 18. The following two measures were employed to address the first research question. Area deprivation characteristics are captured by the general Index of Multiple Deprivation 2010 and its seven sub-indices. Past research in area deprivation has used the general IMD index only. For the purposes of this thesis, secure access has been granted by the Department of Communities and Local Government to the seven sub-indices of deprivation. The sub-indices were linked with Wave 1 data of the LSYPE study by the Department for Education. The advantage of using the sub-indices is that the general IMD index is a measure of deprivation of multiple kinds in each local authority whereas the sub-indices allow for an in-depth analysis of the specific dimensions of deprivation on young people's educational and employment outcomes. In addition, the indicators used in the Indices of Deprivation 2010 are measured in 2008, a time period which coincides with the time that the respondents in the LSYPE study were at the age of 18. NEET status of young people at the ages $18 - 19$ is measured using the 48 main activity files of young people that provide detailed information on educational and employment activities for four years after compulsory education. Secure access has been granted from the Department for Education to access the full four year monthly main activity files of young people. The main activity files are linked with Wave 7 data and the sample size consists of 8,931 young people.

To address the research questions $2 - 5$, data have been taken from Wave 1, when young people were at the age $13 - 14$. The sample size in Wave 1 of the LSYPE study consists of $15,770$ people. Wave 1 was selected because it involves the largest sample of respondents and therefore it lends itself to an accurate analysis of the influence of early age characteristics on future educational and employment outcomes. Wave 1 includes a wide range of parental and demographic characteristics and at the same time provides an in-depth exploration of young people's attitudes, aspirations, social relations, attitudes to school and educational attainment. Young people are at schooling age, they start making decisions about their future, they get more involved with their area of residence and are affected by its characteristics as they develop.

Research question 2 introduces parental characteristics and demographics in an attempt to reduce the selection bias issue associated with living in a specific area (see Chapter 3). The neighbourhood context is not allocated randomly, but it is the result of parental selection, preferences and mobility (Duncan and Raudenbush, 1999). This study controls for parental characteristics and demographics before exploring factors that might affect young people's educational and employment outcomes over and above area deprivation. The family demographic characteristics, parental socio-economic status, family type and receiving benefits usually remain stable over time and therefore are likely to be good predictors of becoming NEET at a later stage. Research question 2 also employs Wave 1 variables to investigate the effect of parental practices and aspirations when the young person was at age 14 on their outcomes at $18 - 19$.

Research questions $3 - 5$ introduce individual, school and peer group characteristics using Wave 1 variables. Educational attainment of young people at Key Stage 2 is provided by the Pupil Level Annual School Census (PLASC) school-level data that were merged with the LSYPE Wave 1.

A note on missing data

While one of the most important benefits of using the LSYPE study is the wide range of data available to control for family and individual background characteristics, some of the data are missing in some Waves. The LSYPE was designed to be representative of all young people in England, however not all respondents took part in every year of the study. Respondents from the first wave of data were not necessarily present in any or all of the subsequent waves. Other respondents dropped out for one or more waves and participated in the study at a later point. Temporary or permanent drop-out is a common problem in longitudinal analyses, referred to as attrition. In longitudinal studies, sample attrition is the cumulative effect of non-response over repeated waves of data collection (Laurie and Lynn [107], 2008).

Attrition can become a problem because respondents who participated in one or more Waves and were contacted to participate again, declined to complete questionnaires or to be interviewed in subsequent Waves. The factors influencing attrition and non-response may relate to technical reasons, such as for example long questionnaires, or to concerns over personal information, privacy and confidentiality. Laurie and Lynn [107] (2008) also propose that the importance respondents place on the content of the questionnaire is related to the way the questionnaire is introduced by researchers and interviewers. The authors propose that when the respondents are interested in a topic or believe that a group might be advantaged by it, they enjoy the opportunity to participate in the study. Attrition can cause a problem in the analysis because participants who represent particular population characteristics may drop out more frequently compared to others. Additionally, attrition in longitudinal datasets reduces the sample size causing a loss of statistical power in the analysis. What is most important is that if dropout from a wave is selective, attrition may bias the analysis estimates. Two common methods are proposed to overcome the attrition problem, imputations of missing data and weighting. In this study the sample size in Wave 1 is $15,660$ while the sample is reduced at $8,862$ at Wave 7 denoting a considerable reduction in the number of participants in the study (see Chapter 5, Section 5.3.4 for a detailed description of the sample and missing data in the LSYPE). To account for the sampling design and attrition initially a missing value analysis was conducted which indicated that values were missing completely at random (MCAR). Further to that, weighting of the data was conducted prior to the analysis, following recommendations from the LSYPE user guide to the Datasets, Wave 1 to Wave 7. Every LSYPE wave has an accompanying weight which is appropriate for analysis within each wave. When variables from multiple waves are used in the analysis, the user guide recommends always to use the weight from the most recent wave that variables have been taken from. Using the weight from the most recent Wave compensates for the changing pattern of non-response over time. In this thesis, the dependent variable, NEET, comes from Wave 7 and all the independent variables from Wave 1. Weighted estimates were obtained using the most recent weight, the Wave 7 weight, in the analysis. To ensure robust analysis, the complex sample design procedure in SPSS was used.

6.4 Method of Data analysis

The statistical analysis will involve descriptive statistics and logistic regression analysis. The analysis begins with examination of the data that includes tables of frequencies and graphs for the main activity of young people, the indices of deprivation and the variables in the analysis. Cross-tabulations are used to describe the relationship between NEET status and the variables in the model. The observed percentages given in cross-tabulations only offer a description of the relationship between NEETs and the other variables and therefore additional steps are taken to draw further conclusions about the relationship of the variables. It is of interest to further explore the relationship between area deprivation and being in NEET status or not at the ages $18-19$. The Pearson chi-square measure of association is used to measure the strength of the relationships. The chi-square is used to test the null hypothesis that NEETs are not related with the variables in the model, in other words that the two variables are independent. The observed significance level ($p < 0.5, **p < .01, ***p < 0.001$) for the chi-square statistics determines if the null hypothesis can be rejected and if there is a significant association between NEETs and other variables in the model.

After summarising the strength of the relationship between NEETs and the other variables in the analysis, the use of a regression model will allow a clearer picture of the relationship between NEETs and the variables in the model to emerge. The logistic regression model was selected for this analysis to model the probability that a young person will become NEET or not. When the outcome variable is dichotomous, it is not possible to use multiple linear regression to study the relationship between the outcome (NEET) and the independent variables because it is impossible for such data to satisfy the required assumptions of linear regression. That is because it is impossible for a binary variable to be normally distributed with a constant variance. The logistic regression model is a flexible option to study the relationship between a binary variable and a set of variables that are continuous or categorical.

There are two main differences between a linear regression and a logistic regression model. The first difference lies in the choice of parametric models and the assumptions (Hosmer and Lemeshow [91], 2000). This difference is related to the nature of the relationship between the outcome (NEET) and the independent variables. In linear regression analysis, the key measure is the conditional mean, which is the mean value of the outcome variable given the value of the independent variable. It is expressed as $E(Y \mid x)$ where Y denotes the outcome variable and x denotes the value of the independent variable. This equation shows the expected value of Y given the value of x. A linear equation

$$E(Y \mid x) = \beta_0 + \beta_{1x}$$

implies that it is possible for $E(Y \mid x)$ to take any value as x ranges between $-\infty$ and $+\infty$. With dichotomous data, the conditional mean must be greater than or equal to zero and less than or equal to 1 $[0 \leq E(Y \mid x) \leq 1]$. The fact that the logistic function ranges between 0 and 1 allows the researcher to estimate the probability of a young person being NEET given their characteristics. This probability allows to estimate that one of two events will occur, a young person will be NEET or not, based on the values of the set of independent variables of the Compositional Model of Neighbourhood Effects. Thus, for the logistic model, we can never get an estimated probability either above 1 or below 0. In addition, the change in $E(Y \mid x)$ per unit change in x becomes progressively smaller as the conditional mean gets closer to 0 or 1. This results in an elongated S-shaped curve. The S-shape indicates that the effect of x variables on becoming NEET is minimal for low x values until some threshold is reached. The probability then increases over intermediate $x$values and remains extremely high around 1.

Remark 6.4.1. In this thesis the logistic regression model is used to estimate the probability of a young person being NEET at the age $18 - 19$. The analysis begins with a binary logistic regression model, given by

$$L = \ln(o) = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X + \varepsilon, \tag{6.1}$$

where p is the probability of an event taking place, o is the odds of the event, β_0 and β_1 are the Y-intercept and the slope respectively, and ε is the random error. Y is the binary outcome (being NEET or not), and X represents area deprivation characteristics.

At the second stage of the analysis, multiple logistic regression analysis is employed to represent a model with more than one independent variables. More precisely, a vector of covariates representing each of the four pathways introduced by the Compositional Model of Neighbourhood Effects is included in the analysis. Recall that the multiple logistic regression function is given by

$$L = \ln(o) = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon, \tag{6.2}$$

where X_i for $i \in \{1, \ldots, n\}$ are the independent variables.

The second difference between linear and logistic regression models is related to the conditional distribution of the outcome variable. In a linear regression, an observation of the outcome variable can be expressed as $y = E(Y \mid x) + \varepsilon$, where ε is called the error term and denotes an observations deviation from a conditional mean. The conditional distribution of the outcome variable (NEET) given x will be normal with mean $E(Y \mid x)$ and a constant variance. With a dichotomous outcome variable, the conditional distribution of the outcome variable follows a binomial distribution with probability given by the conditional mean.

There are also differences between the linear and logistic regression models, In terms of how they are estimated. In linear regression, the likelihood equations are obtained by the difference of the squared deviations function and are linear. In logistic regression, the likelihood equations are not linear and can be obtained using an iterative weighted least squares procedure (McCullagh and Nelder [118], 1989). Maximum likelihood and least squares estimation are different approaches that give the same results in regression analyses when the dependent variable is normally distributed. Under the linear regression assumptions, we estimate parameters of the model using the principle of least squares. The idea of least squares is that we chose parameter estimates that minimize the average squared difference between observed and predicted values. We maximise the fit of the model to the data by choosing the model that is closest to the data. The principle of least squares cannot be used as an estimation method for logistic regression analysis, and instead the maximum likelihood method provides the basis of estimation in logistic regression models. The maximum likelihood method finds the set of values for the parameters of the model that are most likely to have resulted in the data that were observed. The maximum likelihood method finds the parameters of the model that best explain the data, in the sense that they maximise the probability of obtaining the observed data. The maximum likelihood estimation has not been widely used for many years due to the fact that software programs were not available to carry out complex calculations. In the last years, new programs have made the maximum likelihood estimation more popular. The advantage of the maximum likelihood method is, that in comparison to the least squares method, it can be applied in the estimation of complex non-linear models and therefore it is a preferred estimation method in logistic regression.

6.5 Variable selection and model building in logistic regression

Having described the logistic function and the estimation of the logistic regression model, the focus now turns to the strategy that was developed to include variables in the model and the logistic regression model building that was employed. A variable selection strategy was adopted to investigate the hypothesized pathways of neighbourhood effects on young people's outcomes introduced in Section 3.4. This process involved two steps. The first step was to plan the selection of variables that would be included in the model and the second to assess the adequacy of the model in terms of the specific variables selected and the overall fit of the model. The LSYPE study offers a wide range of independent variables that could potentially be included in the model and for this reason numerous analyses were carried out before selecting the final variables that would be introduced in each step of the model. Initial selection of variables that could be important predictors of entering NEET status was guided by past research (Chowdry et al [33], 2009, Britton et al [22], 2011) and careful consideration of the Compositional Model of Neighbourhood Effects. The selection process began with careful univariable analysis of each variable and NEET status. For this process, the Pearson chi-square test (which is asymptomatically equivalent to the likelihood ratio chi-square test) was used. Results are provided in descriptive analysis tables. After the completion of the univariable analyses, variables were tested in the model using logistic regression analysis. There are two methods of mechanical selection of variables in the logistic regression model; first, the stepwise (forward and backward) method in which variables are selected in a particular order to be introduced in the model and second the "best subsets selection" in which a number of models with different numbers of variables (two, three or more each time) are examined to select the most adequate based on specific criteria. The "best subsets selection" has not been used extensively in logistic regression analysis. Variable selection was driven by the Compositional Model of Neighbourhood Effects, the theoretical framework introduced in Chapter 3, to help understand the pathways through which neighbourhoods influence young people's outcomes. The variables that were selected for each of the four pathways of the model were included in the analysis using the stepwise method with forward selection. The stepwise approach was selected because it offers the advantage that models are built in a successive mode and thus it is possible to examine different models adding control factors in each sequence and examining the fit of the model and whether the introduction of new covariates improves the model or not. After fitting each multivariable model, the estimated coefficients of the model were assessed.The importance of each variable was defined in terms of a measure of the statistical significance of the coefficient for the variable. Further to that, the odds ratios and the overall fit of each successive model were verified.

6.6 Key measures

The independent variable is NEET and derives from the main activity files of the LSYPE study. The key independent variable is the IMD (2010) average score and its seven sub-indices which describes area deprivation characteristics of the residence at Wave 1. A set of control variables are used to predict NEET status at the ages $18-19$ at Wave 7.

6.6.1 Main activity of young people

The LSYPE dataset has collected information on all the activities of young people on a monthly basis in the four years after compulsory education. The activities of 11,821 young people are explored in detail from September 2006 to October 2010 and form the monthly activity history for each respondent. LSYPE respondents have been asked a series of questions to identify their main activity each month. Young people were asked when these activities started and finished and whether a different activity was pursued before this time. This history provides a full picture of the activities of each young person after compulsory education and forms the main activity history files for each respondent. The 2007 survey (Wave 4 in LSYPE) was used to calculate all activities from September 2006 to August 2007. The same procedure was followed in subsequent years / waves. In a minority of cases where the activities from consecutive surveys do not meet, a random generation was enabled to avoid gaps in monthly activities and to allow a continuous timeline creation. The history files initially constituted of fourteen different activity categories that were summarized into four main categories listed in Table 6.1: 'Main activity of young people, definitions'.

Table 6.1: Main activity of young people, definitions

Education	Main activity is education, which may or may not be full-time
Employment	In paid employment, with or without training
GST	Government Supported Training, this consists mainly of Apprenticeships, but also Entry to Employment and other training courses
NEET	Not in Education, Employment or Training

The focus of this study is the LSYPE data examining young people's activities during the 2008-2010 academic year, when respondents were at the age of $18-19$ (academic age) (see Table 6.2: 'Age of young people in the LSYPE and YCS'). This is the age they will be referred to in this thesis. The actual age of most respondents at the time of the interviews will have been $18-19$ and $19-20$ due to the fact that birthdays fall across a year.

Table 6.2: Age of young people in the LSYPE and YCS

Wave	Year Inteviewed	Academic Year	Actual Age (Years)	Academic Age	School Year
1	2004	2003/04	13/14	13	Year 9
2	2005	2004/05	14/15	14	Year 10
3	2006	2005/06	15/16	15	Year 11
4	2007	2006/07	16/17	16	Post-compulsory (Year 12)
5	2008	2007/08	17/18	17	Post-compulsory (Year 13)
6	2009	2008/09	18/19	18	Post-compulsory (1st Year HE)
7	2010	2009/10	19/20	19	Post-compulsory (2nd Year HE)

The analysis starts by describing and identifying young people in NEET status in the LSYPE study in the four years after compulsory education. Figures 6.1: ‘Main activity of young people at 16’, 6.2: ‘Main activity of young people at 17’, 6.3: ‘Main activity of young people at 18’, and 6.4: ‘Main activity of young people at 19’ show young people’s main activities from September 2006 (first September after compulsory education, beginning of year 12 at school) when young people were at age 16 until October 2010 when young people were at age 19 (equivalent to second year at university for those who continue to higher education). The figures show that the majority of young people remain in education after the age of 16 and for two years after compulsory education. The number of young people in education drops in years 2009 and 2010 (ages 18 and 19). Analytic tables that describe monthly main activity of young people for the four year period are given in Appendix 1.

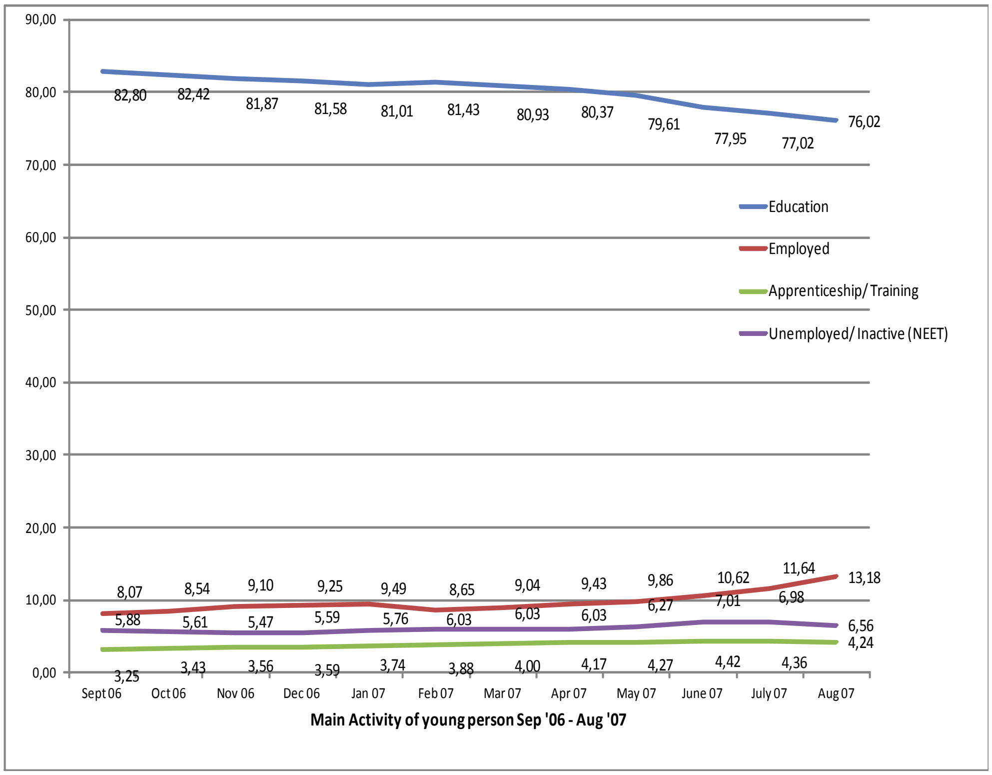


Figure 6.1: Main activity of young people at 16 (source LSYPE)

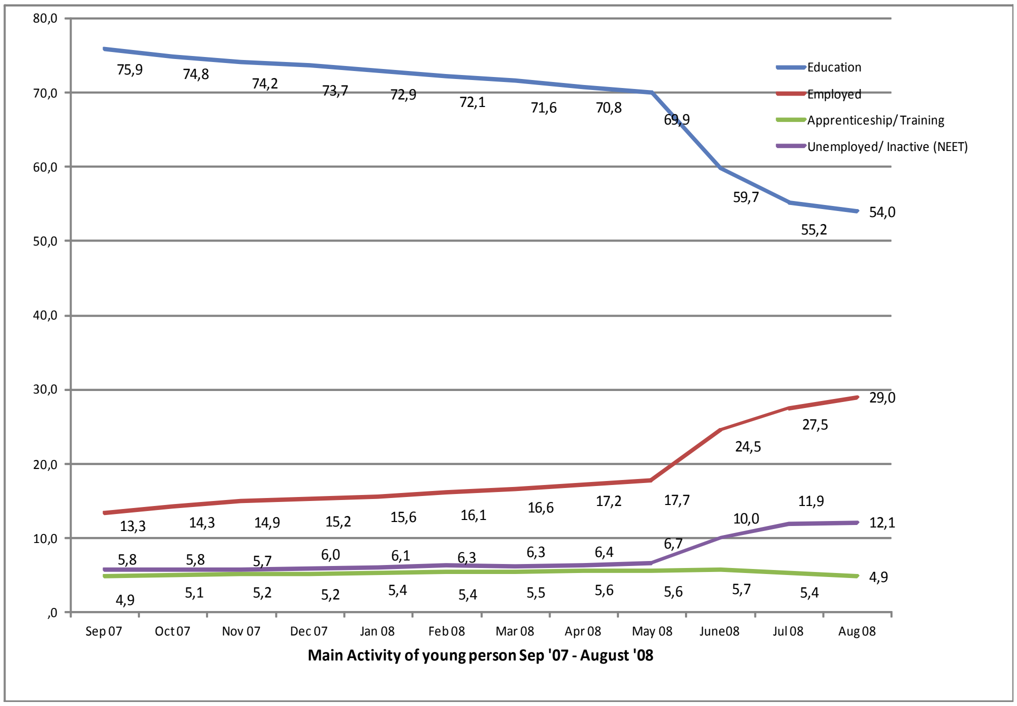


Figure 6.2: Main activity of young people at 17 (source LSYPE)

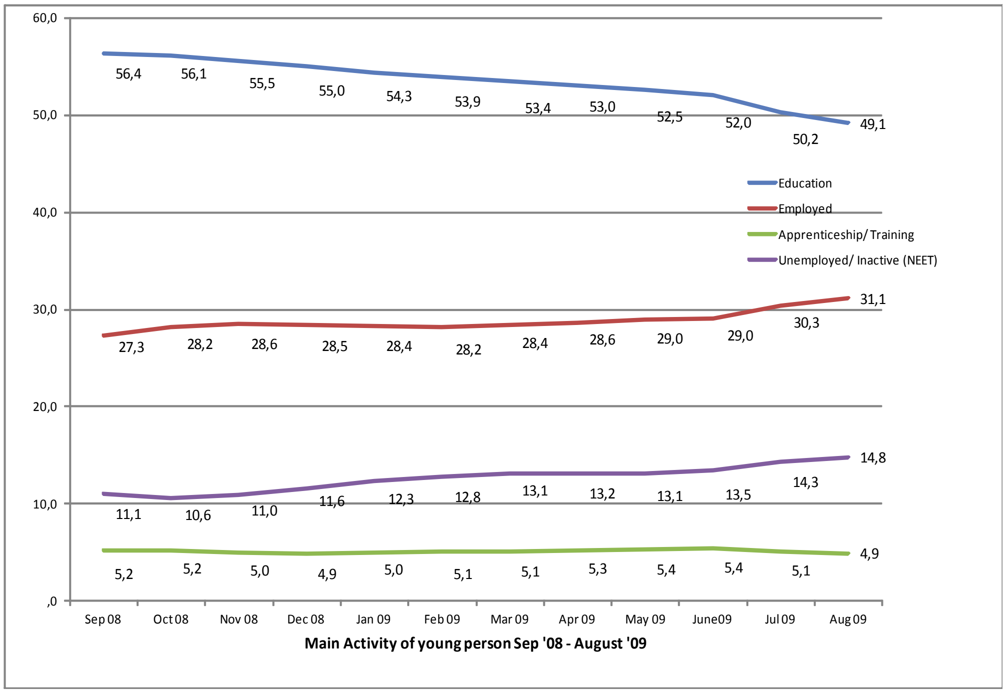


Figure 6.3: Main activity of young people at 18 (source LSYPE)

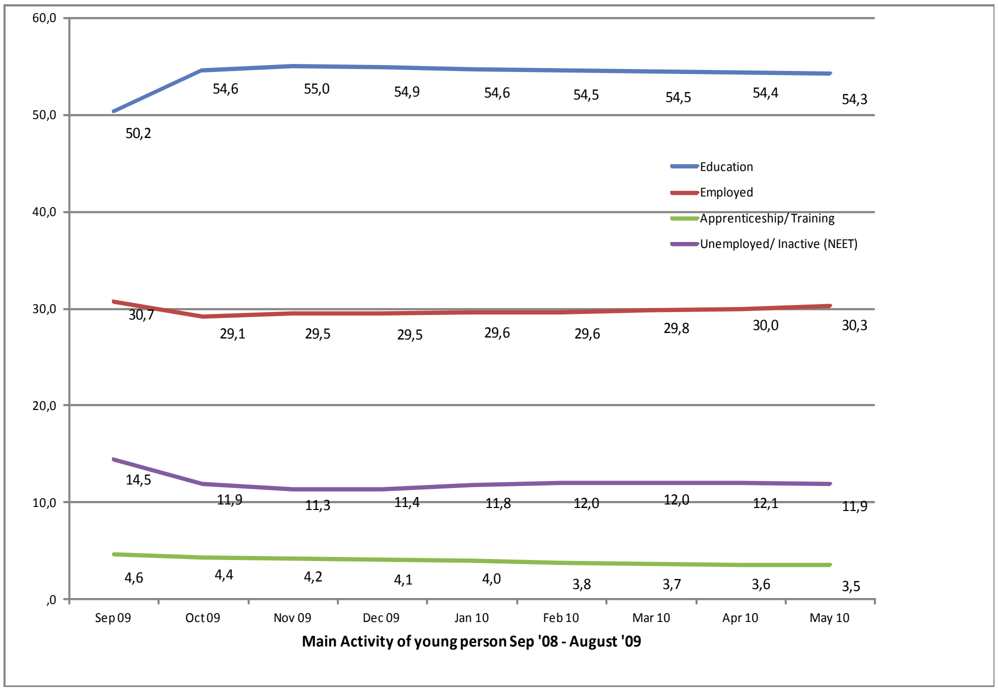


Figure 6.4: Main activity of young people at 19 (source LSYPE)

6.6.2 Defining NEETs

The way that NEET status is defined in the literature is not consistent due to the fact that young people's lives are dynamic, characterized by change and progress. Many young people leave full time education in summer (June / July) after the age of 16, they work over the summer period and then return back to education in September. NEET status reflects a changing condition of young people's lives and therefore it needs to represent a minimum time out of education, employment or training. Previous studies have defined NEET as being out of education, employment or training for six months or more during the ages 16-18. Bynner and Parsons [28] (2002) use a subsample of the 1970 British Cohort Study and define NEETs as young people out of education, employment or training for any six months the period from January 1987 to December 1988. Yates et al (2010) use the British Youth Cohort Study and define NEETs as young people who spend a combined total of six months outside of work, education or training for a 24 month period and excluding those in part time employment.

Numerous exploratory analyses were carried out in the data to determine how young people would be defined in this study. Information of monthly main activity after compulsory education was drawn by the LSYPE dataset in combination with the YCS. The datasets report detailed monthly activity of 11.821 young people for four years. Analysis indicates that the group of young people who struggle to make the transition from education to employment is not constant over the four year period. Initially, the number of NEETs was estimated on a yearly basis followed by a combined percentage of NEETs for the whole four year period. Table 6.3: 'Young People in NEET status aged $16-19$' shows the number and percentage of young people in NEET status for four subsequent years, $2007-2010$. At the ages of 16 and 17 the majority of young people are absorbed in education and therefore NEET rates are low. The lowest number of NEETs appears at 16 when 6.90% of young people were in NEET status for six months or more. At the age of 17 the number of NEETs increases to 10.10%. It appears that the largest number of young people in NEET status was at 2009 when young people were at the age of 18 and constituted 13.70%. The proportion of young people in NEET status decreases at 19 to 12.80%. The combined percentage of young people who were NEETs for six months or more during the whole period from 2006 to 2009 is 20.39%. The combined percentage presents a worrying situation, however, we should take into consideration that it refers to a total of six, not necessarily consecutive, months in a four year period. For many young people, the period after compulsory educatioon is characterised by churning between different activities. Some decide to stay out of education for a few months or for a whole term and then go back to education while others move between education, training and unemployment.

Table 6.3: Young People in NEET status aged 16 – 19 (source LSYPE)

Year	Age of young person	NEET (6 months or more)	Total Number of young people	Percent
2007	16	684	11821	6.90%
2008	17	676	11821	10.10%
2009	18	1242	11821	13.70%
2010	19	988	11821	12.80%
2007/2008	16 – 17	1160	11821	9.80%
2008/2009	18 – 19	1698	11821	14.40%
2006/2009	16 – 19	2411	11821	20.39%

Following methodology from previous studies (Bynner and Parsons, 2002; Yates et al, 2010) NEET status in this study refers to young people who are unemployed or inactive without participating in any form of education or training for a period of six months (excluding summer months) for the ages 18 – 19. Young people with caring responsibilities were excluded from the analysis. As it has already been discussed in Chapter 2, research shows that young women's trajectories are more likely to be interrupted after compulsory education as there is a chance that they become mothers (Wolf, 2011; OECD, 2009; Macmillan et al, 2012, Coles, 2002). Young women with caring responsibilities are more likely to become disengaged from both education and the labour market even though they might return to the labour market after their children grow up. Following this definition and excluding carers, the proportion of NEETs is 13.20%.

6.6.3 Indicator of area deprivation

Area deprivation in each LSOA is measured using the Index of Multiple Deprivation 2010 (IMD) average score. The IMD is a weighted area level aggregation of specific dimensions of deprivation. The overall index is composed of seven separate indices, each representing a different dimension of deprivation. The dimensions of deprivation are a) Income; b) Employment, c) Health and disability, d) Education and training, e) Barriers to housing, f) Crime, g) Living environment. The seven indices have been originally formed by assigning a score of deprivation to 32,482 super output areas (LSOAs) across

Table 6.4: The seven indices of multiple deprivation (IMD 2010), descriptive statistics

	N	Minimum	Maximum	Mean	Standard Deviation
Index of Multiple Deprivation Score	15754	0.70	84.02	26.04	17.86
Rank of Income Score	15754	1	32480	13740.91	9904.02
Rank of Employment Score	15754	2	32480	14356.06	9461.93
Health Deprivation and Disability Score	15754	1	32482	14304.70	9504.22
Rank of Education Skills and Training Score	15754	5	32482	14708.24	9525.05
Rank of Barriers to Housing and Services Score	15754	2	32477	15382.88	9331.05
Rank of Crime Score	15754	5	32472	14644.53	9296.64
Rank of Living Environment Score	15754	2	32478	14551.73	9590.25
Valid N (listwise)	15754				

Source: Department for Communities and Local Goverment

England. A rank of 1 (minimum value = highest deprivation) was assigned to the most deprived LSOA and a rank of 32,482 (maximum value = lowest deprivation) to the least deprived LSOA. The combination of these scores has led to the creation of the seven indices of deprivation and subsequently the general IMD (see Chapter 4). Table 6.4: 'The seven indices of multiple deprivation, descriptive statistics' presents descriptive statistics of the ranks of the seven indices. The table includes number of observations, mean, standard deviation, minimum and maximum values (total sample at Wave 1 is $15,774$ people.

Control variables

The relationship between area deprivation and NEET status will be examined using control variables to test each step of the Compositional model of neighbourhood effects. The control variables employed in the analysis to predict NEET status, are characteristics observed at ages 13 and 14 (Wave 1). A summary of each variable and its coding scheme is provided in Table 6.5: 'Variables to be included in the model'. Following Section 3.4, the analysis includes family demographic characteristics, parental socio-economic status, family type and receiving benefits, as well as individual characteristics, attitudes to schooling and peer group relationships.

Table 6.5: Variables to be included in the model

Model I: Family Characteristics, Parental practices and Aspirations	
Variable	Coding description
Highest qualification of main parent	1. Degree or equivalent; 2. Higher education below degree level; 3. GCE A Level or equivalent; 4. GCSE grades A – C or equivalent; 5. Qualification at level 1 and below; 6. Other qualifications
Whether main parent or partner currently receive benefits for people on low incomes (IFS definition)	1 = Yes, receiving income benefits; 0 = No
Family type	1 = Single parent household; 0 = No
Mother's (natural only) age at birth of YP	1 = under 20; 2 = 20 – 24; 3 = 25 – 29; 4 = 30 = 34; 5 = 35+
How often the main parent knows where is the young person when he/she goes out in the evening	1. Always; 2. Usually; 3. Sometimes; 4. Rarely or hardly ever; 5. Never; 6. The young person does not go out in the evening
What main parent would like young person to do when reach school leavinig age	1. Continue in full time education; 2. Start learning a trade/get a place on a training course; 3. Start an apprenticeship; 4. Get a full-time job
Model II: Individual Characteristics and Aspirations at Wave 1 in addition to model I	
Variable	Coding description
Young person's ethnicity	1. White; 2. Mixed 3. Indian; 4. Pakistani; 5. Bangladeshi; 6. Black Caribbean; 7. Black African; 8. Other
Key Stage 2 average point score	1 = Bottom quartile; 2 = Second quartile; 3 = Third quartile; 4 = Fourth quartile
Model III: Peer Group Influence and Antisocial Behaviour at Wave 1 in addition to models I and II	
Variable	Coding description
Young person excluded from a group of friends	1 = excluded; 0 = No
Police got in touch because young person has done something	1 = Police got in touch; 0 = No
Model IV: School Experience and Attitudes to Schooling at Wave 1 in addition to models I, II and III	
Variable	Coding description
Young person played truant	1 = Yes, played truant; 0 = No
Feelings about school - Count minutes in a lesson until ends	1 = Strongly agree; 2 = Agree; 3 = Disagree; 4 = Strongly disagree
How good or bad young person is at maths	1 = Very good; 2 = Fairly good; 3 = Not very good; 4 = No good at all

6.7 Neighbourhood deprivation and NEET status

This section aims to investigate the first research question *Is there an association between crime in the neighbourhood a young person lives in and NEET status?* The analysis will begin by exploring the broader relationship between the general IMD and each of the seven sub-indices of deprivation to NEET status at ages 18-19. It will go on to further explore and evaluate the extent to which exposure to area deprivation is associated with NEET status or not by employing the logistic regression modelling procedure.

6.7.1 IMD and NEET status; Descriptive Statistics

The relationship between the general IMD score at $13 - 14$ and each one of the sub-Indices of Deprivation and NEET status at the age of $18 - 19$ are explored in this section using cross-tabulations. The general IMD and its sub-Indices have been coded as quartiles. The highest rank is rank 1 and stands for the most deprived areas and 4 for the less deprived ones. NEET is a binary variable (1=NEET, 2 = Education / Employment / Training). The observed percentages in Table 6.6: 'Deprivation Indices and NEET' describe the relationship between the two variables (n unweighted = 9,523, n weighted = 4,995). The percentage of NEETs is higher in areas with high general IMD index (first quartile). Gradually, as the area deprivation becomes lower, ie the area becomes more affluent, the percentage of NEETs decreases. As table 6 shows, the same pattern follows for the seven sub-indices of deprivation except for the Barriers to Housing index which mixes housing factors with rurality; the percentage of NEETs is higher in the areas which experience the highest rank of multiple aspects of deprivation.The percentage of young people in NEET status decreases when the measurement of relative deprivation is lower.

Table 6.6: Deprivation Indices and NEET

	Ranking	**Education/Employment/Training (%)**	**NEET/Main activity at 18 (%)**	**Total (%)**
Rank of Index if Multiple Deprivation	First quartile	81.5%	18.5%	100.0%
	Second quartile	86.7%	13.3%	100.0%
	Third quartile	90.1%	9.9%	100.0%
	Fourth quartile	90.9%	9.1%	100.0%
	Ranking	**Education/Employment/Training (%)**	**NEET/Main activity at 18 (%)**	**Total (%)**
Rank of Income Score	First quartile	82.0%	18.0%	100.0%
	Second quartile	86.6%	13.4%	100.0%
	Third quartile	89.4%	10.6%	100.0%
	Fourth quartile	91.5%	8.5%	100.0%
	Ranking	**Education/Employment/Training (%)**	**NEET/Main activity at 18 (%)**	**Total (%)**
Rank of Employment Score	First quartile	81.4%	18.6%	100.0%
	Second quartile	87.5%	12.5%	100.0%
	Third quartile	89.0%	11.0%	100.0%
	Fourth quartile	90.9%	9.1%	100.0%
	Ranking	**Education/Employment/Training (%)**	**NEET/Main activity at 18 (%)**	**Total (%)**
Rank of Health Deprivation and Disability	First quartile	81.5%	18.5%	100.0%
	Second quartile	86.4%	13.6%	100.0%
	Third quartile	90.7%	9.3%	100.0%
	Fourth quartile	90.3%	9.7%	100.0%
	Ranking	**Education/Employment/Training (%)**	**NEET/Main activity at 18 (%)**	**Total (%)**
Rank of Education Skills and Training	First quartile	81.2%	18.8%	100.0%
	Second quartile	87.4%	12.6%	100.0%
	Third quartile	89.4%	10.6%	100.0%
	Fourth quartile	90.5%	9.5%	100.0%
	Ranking	**Education/Employment/Training (%)**	**NEET/Main activity at 18 (%)**	**Total (%)**
Rank of Barriers to Housing and Services	First quartile	87.7%	12.3%	100.0%
	Second quartile	86.5%	13.5%	100.0%
	Third quartile	85.9%	14.1%	100.0%
	Fourth quartile	87.2%	12.8%	100.0%
	Ranking	**Education/Employment/Training (%)**	**NEET/Main activity at 18 (%)**	**Total (%)**
Rank of Crime Score	First quartile	82.6%	17.4%	100.0%
	Second quartile	86.6%	13.4%	100.0%
	Third quartile	88.4%	11.6%	100.0%
	Fourth quartile	90.5%	9.5%	100.0%
	Ranking	**Education/Employment/Training (%)**	**NEET/Main activity at 18 (%)**	**Total (%)**
Rank of Living Enviroment	First quartile	84.1%	15.9%	100.0%
	Second quartile	86.3%	13.7%	100.0%
	Third quartile	88.7%	11.3%	100.0%
	Fourth quartile	89.1%	10.9%	100.0%

6.7.2 Predicting NEET status based on area deprivation

In this section, data from the IMD and its seven sub-indices are used to predict whether living in a deprived area predicts NEET status or not. Descriptive statistics, which were provided in the previous section, describe only the relationship between the two variables. To draw conclusions about the relationships between the data, logistic regression analysis is carried out. The question explored is to predict the values of a binary variable, NEET, from a categorical variable, IMD and subsequently from its seven sub-indices. Logistic regression estimates the probability of an event occurring. Binary logistic regression is used in the analysis to model the probability of being NEET based on area deprivation. The goal is to predict whether the nodes are positive for NEET status based on high deprivation. Indicator variable coding scheme has been used to represent the categories of the general IMD and its seven sub-indices. With this method, categorical variables with four categories (quartiles) have been computed. The reference category is the highest value, the fourth quartile, which represents the lowest deprivation areas. With this coding, the effect of each category will be interpreted in comparison to the fourth quartile. Respectively, the coefficients of each category will be compared to the reference category. Forward logistic method is selected.

In this section, the analysis begins by fitting a univariable logistic model for a single independent variable, IMD and its seven sub-indices separately. Multivariable tests will be carried out in the next sections including control variables to address the subsequent research questions. For both univariable and multivariable models, a series of steps will be used to assess the model. This approach will involve an examination of the coefficients of the model in Tables and graphically, discussion of statistically significant variables, examination of odds ratios and evaluation of measures of fit. The analysis begins by presenting the estimated coefficients for the fitted model in Table 7. The fitted model tests the statistical hypothesis presented by research question 1, to determine whether the independent variable in the model, IMD, is significantly related to the outcome variable NEET. The P-value for the chi-square distribution associated with this test shows that $P < 0.001$ for the first quartile of the following scores: the general IMD Score, the Income Score, the Employment Score, the Health and Disability Score, the Education, Skills and Training Score and the Crime Score. This shows convincing evidence that the first quartile (highest deprivation) of all Scores (except for the Barriers to Housing) is a significant variable in predicting NEET status.

In multiple regression, R^2 which is the proportion of the variance in the dependent variable explained by the independent variables, is used to measure how well the model predicts the values of the independent variable. In logistic regression analysis, there is not such a measure that can be easily interpreted. Two measures attempt to quantify the proportion of explained variation in the logistic regression model, the Cox and Snell R^2 and the Nagelkerke R^2 [91]. These two measures in practice have the same purpose as the R^2 although the variation in a logistic regression model is defined differently. The problem with the Cox and Snell R^2 measure for logistic regression is that it cannot achieve a maximum value of 1. Nagelkerke R^2 proposed a modification of the Cox and Snell R^2 so that the value of 1 could be achieved. It is important to note that the values of logistic summary measures are typically much smaller than the values usually observed in a linear regression model. In subsequent steps, when more variables will be added in the model, both the Cox and Snell R^2 and the Nagelkerke R^2 measures will be presented. However, the focus of attention will lie on P-values and on odds ratios. i.e. the significance and magnitude of estimated effects.

Table 6.7: 'Estimated coefficients of a univariate logistic regression model using NEET and the Indices of Deprivation' presents graphically the odds ratio results. Odds ratios describe the ratio of the odds of being NEET for a particular factor (area deprivation) to the odds of not being NEET for the reference category (lowest deprivation). The odds ratio (B) provides the estimated probability that a young person will be in NEET status and is given by the following equation:

Table 6.7: Estimated coefficients of a univariate logistic regression model using NEET and the Indices of Deprivation

NEET **Reference category:** **Education,** **Employment or** **Training**	**Quartiles**	**B**	**Standard Error**	**Significance**	**Exp(B)**
Overall IMD Score	First quartile Second quartile Third quartile	0.836 0.420 0.057	0.176 0.185 0.201	0.000*** 0.023 0.776	2.307 1.522 1.059
Cox and Snell: 0.013					
Nagelkerke: 0.024					
Income Deprivation Score	First quartile Second quartile Third quartile	0.924 0.518 0.187	0.172 0.182 0.187	0.000*** 0.005*** 0.316	2.520 1.678 1.206
Cox and Snell: 0.013					
Nagelkerke: 0.025					
Employment Deprivation Score	First quartile Second quartile Third quartile	0.716 0.280 −0.004	0.161 0.175 0.192	0.000*** 0.110 0.983	2.047 1.323 0.996
Cox and Snell: 0.011					
Nagelkerke: 0.02					
Health, Deprivation and Disability Deprivation Score	First quartile Second quartile Third quartile	0.760 0.341 0.143	0.160 0.171 0.178	0.000*** 0.046 0.423	2.138 1.407 1.154
Cox and Snell: 0.01					
Nagelkerke: 0.019					
Education, Skills and Training Deprivation Score	First quartile Second quartile Third quartile	0.895 0.361 0.177	0.152 0.160 0.172	0.000*** 0.024 0.305	2.446 1.435 1.194
Cox and Snell: 0.015					
Nagelkerke: 0.026					
Barriers to Housing and Services Deprivation Score	First quartile Second quartile Third quartile	0.034 0.194 0.183	0.147 0.141 0.151	0.816 0.170 0.226	1.035 1.214 1.201
Cox and Snell: 0.001					
Nagelkerke: 0.002					
Crime Deprivation Score	First quartile Second quartile Third quartile	0.759 0.309 0.175	0.154 0.167 0.172	0.000*** 0.065 0.309	2.137 1.362 1.191
Cox and Snell: 0.001					
Nagelkerke: 0.019					
Living Environment Deprivation Score	First quartile Second quartile Third quartile	0.436 0.250 0.068	0.151 0.154 0.162	0.004** 0.106 0.674	1.547 1.284 1.070
Cox and Snell: 0.003					
Nagelkerke: 0.0106					
*reference category: Education, Employment or Training					
$p < 0.5$, $^{**}p < 2.01$, $^{***}p < 0.001$					

$$\text{Odds} = \frac{\text{Prob(event)}}{\text{Prob(no-event)}} \tag{6.3}$$

The exponent of B provides the estimated odds ratio. If B is positive, the odds ratio is greater than 1, which denotes that the odds of an event occurring are increased. If B is negative, the odds ratio is less than 1, which means that the odds are decreased. Finally if B is 0, the odds do not change. An odds ratio greater than 1 indicates an increased chance of being NEET and odds ratio less than 1 indicates a decreased chance. Figure 6.5: 'Area deprivation and NEET status, logistic regression analysis' presents the change in log odds when we have a low value in area deprivation compared with a high value. In Figure 6.5 bars to the right of the central line indicate that young people who live in areas with the denoted deprivation level were more likely to be NEETs compared to young people who live in low deprivation areas (reference category). Bars to the left of the central line indicate that young people who live in areas with these characteristics were less likely to be NEETs compared to young people who live in low deprivation areas. The bars in dark colour represent statistically significant results whereas the bars in light blue represent results which are not statistically significant. A common pattern emerges from the logistic analysis results for the coefficients of the general IMD and six of its seven components. The coefficient for the first quartile (highest deprivation) is always positive and higher compared to the second and third quartile. This means that compared to low deprivation (fourth quartile), high and medium values are associated with increased log odds of young people being NEET. The third quartile decreases the log odds more than the medium category.

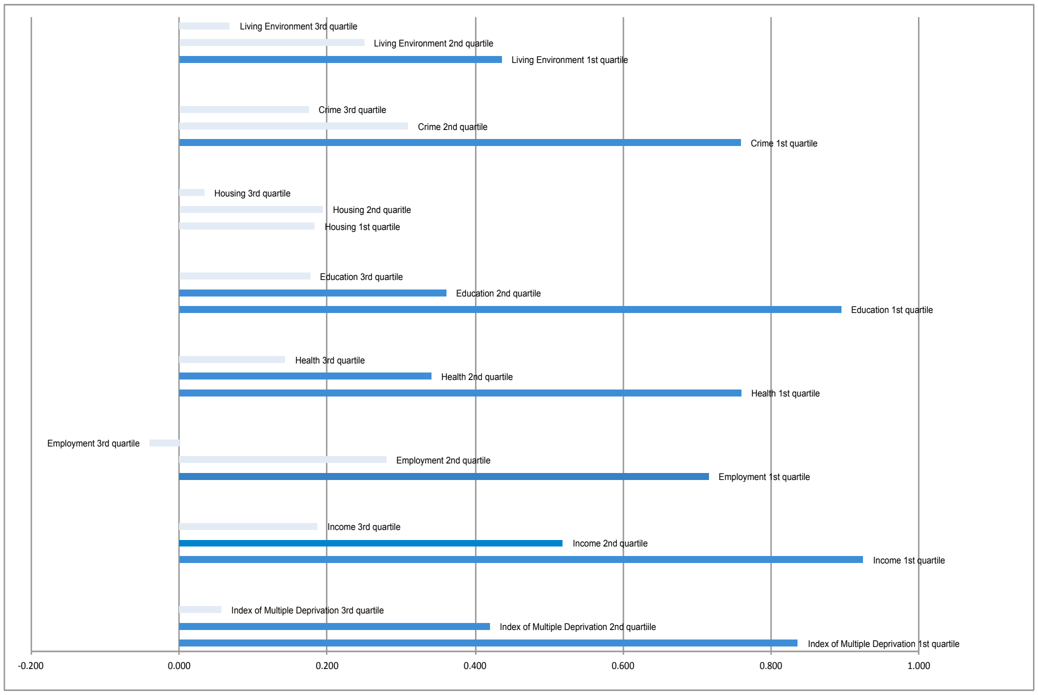


Figure 6.5: The Indices of Multiple Deprivation and young people in NEET status, logistic regression analysis results

This section has focused on the first research question and explored the relationship between the general IMD and the seven sub-indices and NEET status by employing descriptive statistics and logistic regression analysis. Reflecting on the associations studied in this part, we can conclude that living in an area characterised by high deprivation is associated with higher number of young people in NEET status. Additionally, living in a deprived area at $13 - 14$ increases the probability of a young person becoming NEET at the age $18 - 19$. After exploring the broad relationship between IMD and NEET status, subsequent analysis will focus on the experience of living in an area characterised by high criminal behaviour and its effects on young people's trajectories. Within the discourse of area deprivation and young people's trajectories, discussed in the Literature Review of this thesis, sociologists support that living in an area characterised by high crime is associated with poor educational and employment outcomes for young people. Research questions 2 to 6 aim to investigate whether high crime score in an area increases the likelihood of a young person becoming NEET after controlling for family, individual, school and peer group characteristics.

6.8 The effect of family demographics, parental practices and aspirations

This section investigates the second research question: Can the effect of living in a deprived area with high crime on NEET status be explained after controlling for family demographic characteristics, parental practices and aspirations?

The previous section focused on the broad association between IMD and its seven sub-indices and NEET status. Bivariate analysis provided statistical evidence that Crime deprivation is a significant variable in predicting NEET status. Before concluding that this variable is significant, the inclusion of other important variables in the analysis is required. The covariates that are added in this section denote family characteristics, parental practices and aspirations to investigate the differences between those who are in NEET status and those who are not. The main independent variable is area deprivation as this is defined by the Crime Score index. Parental socioeconomic characteristics are indicated by whether the main parent or their partner currently receive benefits for people on low income and by the highest qualification held by the main parent. Demographic characteristics are captured by whether single parent household and the age of the mother at birth of the young person. Parental practices are depicted by monitoring practices that the parents follow when the young person goes out with their friends. Finally, parental aspirations are given by what the main parent believes the young person will do when they reach school leaving age. The analysis starts with descriptive statistics to explore the relationship between NEETs, area deprivation and family characteristics. Additional steps are taken to draw conclusions about the variables in the analysis using logistic regression analysis.

Receiving low income benefits and NEETs

The analysis begins by exploring NEETs and families that receive benefits for people on low income. Here, and in most of the subsequent figures, the focus is on two groups, those who are in NEET status and those who are in Education, Employment or Training. Figure 6.6: 'Family receiving low income benefits and NEETs' presents the association between young people in NEET status and belonging in a family that receives benefits for people on low income (n unweighted = 9,428, n weighted = 4,939). The figure shows the number of young people in NEET status is higher in families that received benefits for people on low incomes compared to those who did not. 57% of NEETs come from families that receive low income benefits, whereas 43% come from families that do not receive benefits.

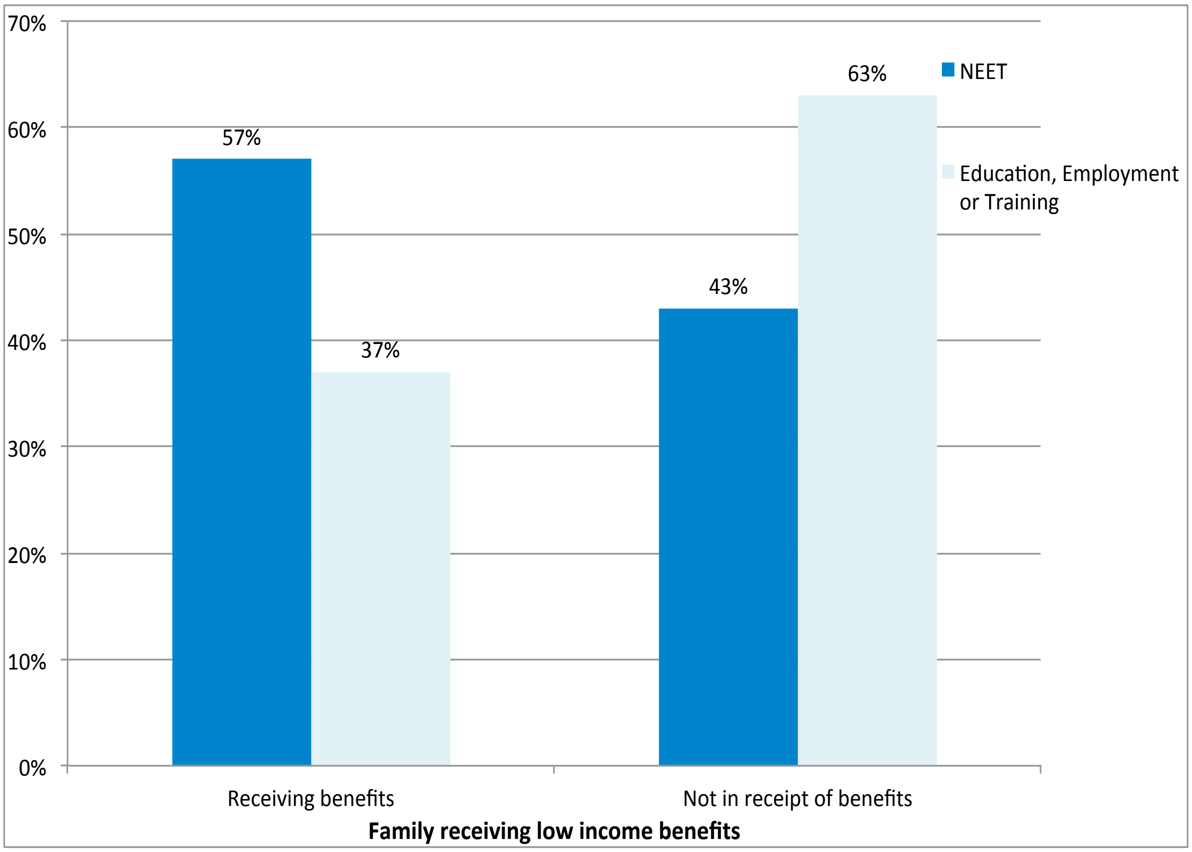


Figure 6.6: Family receiving low income benefits and NEETs (source LSYPE, weighted count)

NEETs by highest qualification of Main Parent

Figure 6.7: 'NEET by main parents highest qualification' shows that the highest proportion of NEETs, 35%, comes from parents with no qualifications (n unweighted = 9,135, n weighted = 4,796). The proportion of NEETs decreases as the educational level of the parents increases. This is disproportionate to young people in Education, Employment or Training. The highest proportion of young people in Education, Employment or Training comes from parents who have a degree or have complete Higher Education below degree.

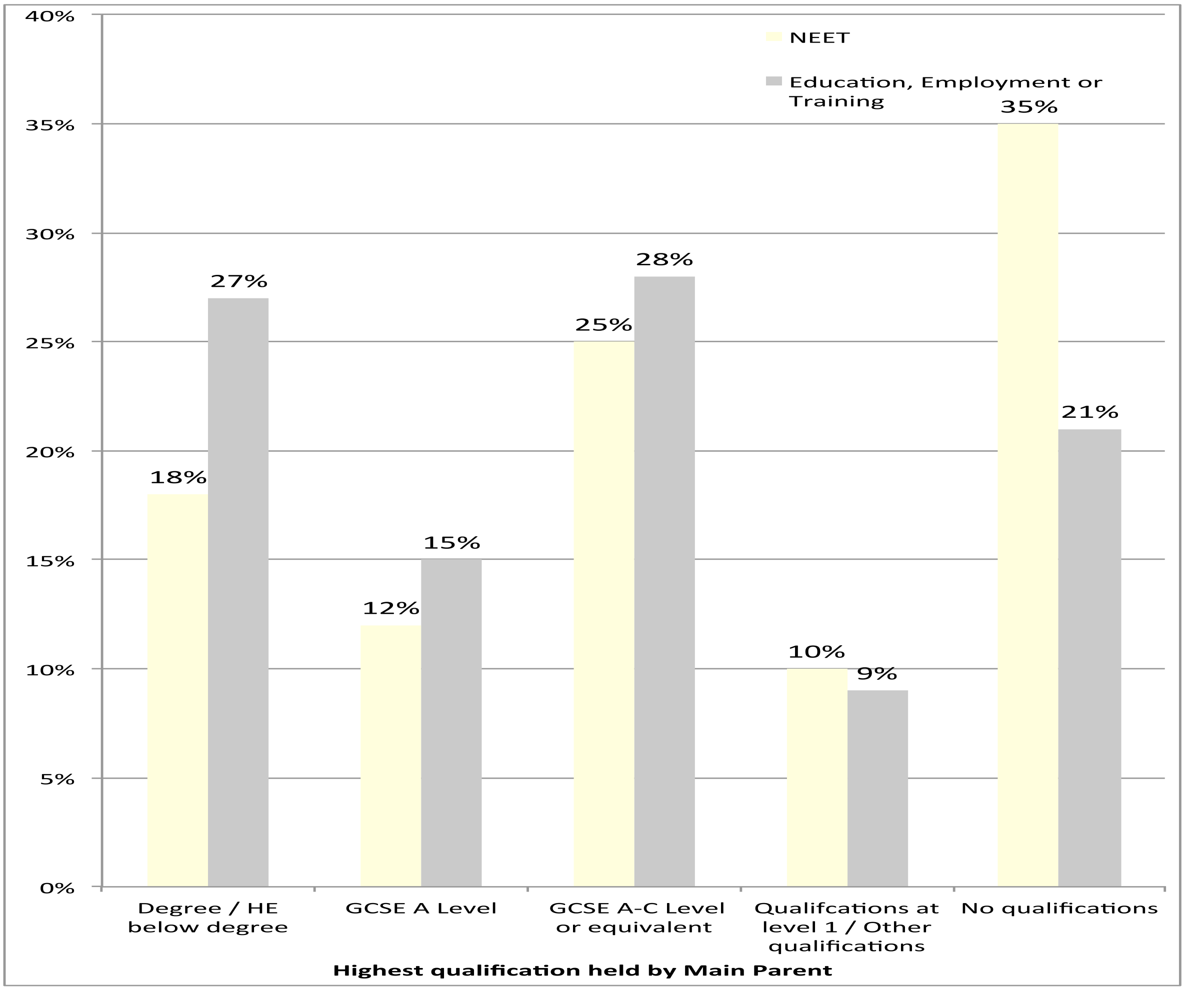


Figure 6.7: Main parent's highest qualification and young people in NEET status, descriptive statistics (source LSYPE, weighted count)

Parental aspirations

Figure 6.8: 'Parental aspirations by NEET status' presents NEET status by what the main parent would like the young person to do when they reach school leaving age (n unweighted = 8,902, n weighted = 4,647). The proportion of parents who would like their children to remain in full time education was higher in young people in Education, Employment or Training (87%) compared to young people in NEET status (81%). This shows that high parental aspirations can have a positive influence on young people remaining in education, employment or training.

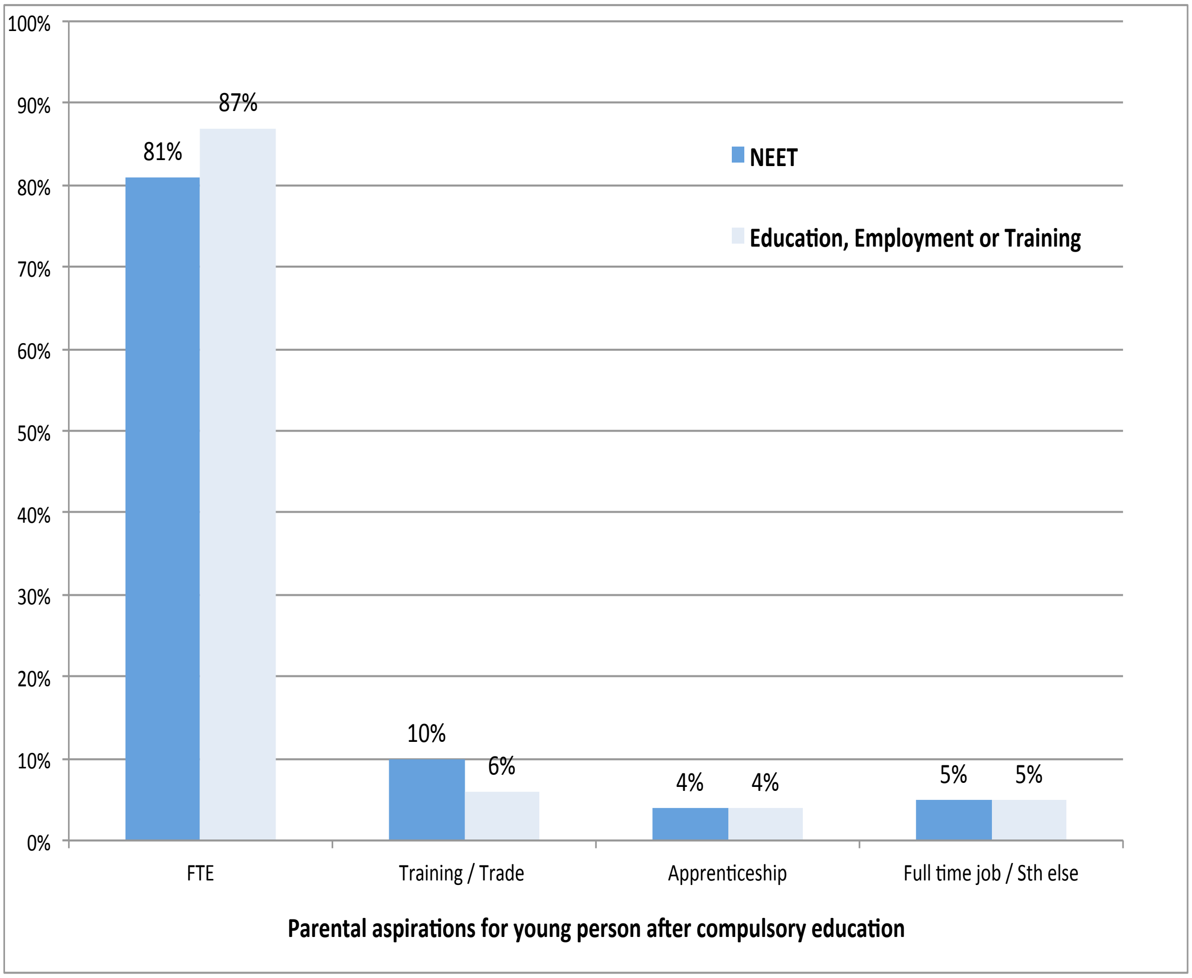


Figure 6.8: Parental aspirations by NEET status (source LSYPE, weighted count)

6.8.1 Family characteristics; descriptive statistics

Table 6.8: 'Control variables and NEET status at $18-19$' presents descriptive statistics of NEETs with family demographics, parental characteristics and aspirations. The goal is to explore and describe what characteristics of NEETs are related to parental characteristics. Cases of young people in Education, Employment or Training and NEET status are classified based on the values of the selected categorical variables. To test whether the variables that make up the columns and the rows are independent, I calculate how many cases are expected in each cell if the variables are independent, and compare the expected values to those actually observed using the chi-square statistic. The null hypothesis that is explored is that NEETs are not related to demographic characteristics and parental practices, or that they are independent. Independent in this case refers to the absence of a relationship between two variables. It means that the probability that a case falls into a particular cell of the table is the probability that the case falls into that row and the probability that the case falls into that column. Table 6.8: 'Control variables and NEET status at $18 - 19$' presents cross-tabulations and the Pearson chi-square test of significance to test if two variables are independent. From the calculated chi-square value it is possible to estimate how often in a sample it would be possible to see a chi-square value at least as large as the one observed if the independent hypothesis in the population is true. If the observed significance level is small enough, we can reject the null hypothesis that the two variables are independent. The nature and strength of the relationship between the variables can be given by various statistical indices. In this study, the null hypothesis is rejected if the two variables are significant under the following categories: $*p < 0.5, **p < .01, ***p < 0.001$. From Table 8 below, we can reject the null hypothesis for a range of variables. Being NEET is related to belonging in a low income family, mother's age at birth under 20, low educational qualifications of parents, single parent families, low parental monitoring and parental aspirations. Further investigation will be carried

out in the next section to directly estimate the probability of young people becoming NEETs based on the independent variables.

Table 6.8: Control variables and NEET status at $18 - 19$ (source: LSYPE, weighted count)

Control Variables - Chi Square Tests				
		Education/Employment/Training (%)	**NEET** (%)	**Significance**
Income	Family receiving low income benefits	80%	20%	0.000***
Demographics	Mother's age at birth of YP under 20	76%	24%	0.000***
	Mother's age at birth of YP $20 - 24$	83%	17%	0.002***
	Mother's age at birth of YP $25 - 29$	89%	11%	0.007**
	Mother's age at birth of YP $30 - 34$	90%	10%	0.007**
	Mother's age at birth of YP 35+	86%	14%	0.580
NS-SEC/Qualifications	Highest Qualificationof MP: Degree/HE below degree	90%	10%	0.168
	GCSE A Level equivalent/GCSE A-C	88.8%	11.2%	0.161
	HiQualMP-Level 1 oe below/Other Qualifications	87%	13%	0.169
	HiQualMP-No Qualifications	79%	21%	0.000***
Family Composition	Single parent family	79%	21%	0.000***
Practices/Monitoring	MP always knows where YP is when out	32.8%	67.2%	0.004
	MP usually knows where YP is when out	85.9%	14.1%	0.006
	MP sometimes knows where YP is when out	96.6%	3.4%	0.000*
	MP rarely knows where YP is when out	98.4%	1.6%	0.000*
	MP never knows where YP is when out	98.2%	1.8%	0.000*
Parental Aspirations	What would like YP to do at school leaving age. 1-Continue FTE	87%	13%	0.000*
	What would like YP to do at school leaving age. 2-Trade/Training	81%	19%	0.006**
	What would like YP to do at school leaving age. 3-Apprenticeship	86%	14%	0.920
	What would like YP to do at school leaving age. 4-FT job	68%	32%	0.001**
	What would like YP to do at school leaving age. 5-STH else	80%	32%	0.310

$^{*}p < 0.5$, $^{**}p < 0.01$, $^{***}p < 0.001$

6.8.2 Predicting NEET status; The effect of family characteristics

In this section, a binary logistic regression model estimates the probability that a young person is NEET, or not, based on area deprivation and family characteristics. When the first research question was addressed, a logistic regression model was introduced in the univariate context. In a similar way to linear regression, the strength of the linear regression modelling technique lies in its ability to model many variables. In this part, the logistic regression model will be generalised to include more than one independent variables. A set of independent categorical values are included in the model to estimate the probability that a young person will be NEET or not. Some of the independent variables in the analysis such as for example Highest Qualification of Main Parent and Mother's age at birth of young person cannot be included in the analysis as if they were interval scale variables. The method of choice in this situation is to use a collection of dummy variables. Most software packages generate design variables automatically. In this analysis, sampling design variables have been computed prior to including them in logistic regression analysis.

Table 6.9: 'Estimated coefficients for a multiple logistic regression model using NEET, Crime Score and family characteristics' presents the estimated coefficients from fitting the multiple logistic regression model to the data. Maximum likelihood, which is the method of estimation used in the univariate case will remain the same as in the multivariate situation. The interpretation of logistic regression coefficients is not as straightforward as in linear regression. In linear regression, we pay attention to the estimated change in the dependent variable for a one unit change in the independent variable, assuming that the values of the other independent variables remain constant. This means that the value of the coefficient depends on the other independent variables in the model. This also holds in logistic regression, as the value of a coefficient depends on the other independent variables in the model. However, in logistic regression it is also important to calculate odds and interpret the meaning of odds ratios.

Once the multiple logistic regression model has been fitted, the model assessment process begins. The total sample size in the multiple logistic regression model is 4,724 (weighted count). When trying to determine a sample size for logistic regression, it is important to take into account both the total sample size and the number of events. The number of events is the smaller of the counts for the values of the binary variable. Peduzzi et al (1996) suggest that at least 10 events are needed for each parameter that needs to be estimated. The first step in model assessment is to check the significance of the variables in the model. Table 6.9: 'Estimated coefficients for a multiple logistic regression model using NEET, Crime Score and family characteristics' presents the estimated coefficients and the levels of significance of the variables of the fitted model. We can see that we can reject the null hypothesis for $P < 0.001$ for the highest qualification of main parent, families that claim benefits for low income and parents who believe that their children will continue in full time education after 16. For $P < 0.01$ the first quartile of Crime Score remains significant in the analysis. Finally, variables that remain significant for $P < 0.05$ are mothers age at birth of young person under 20 and parents who sometimes know where the young person is when they go out at night. For these variables, we reject the null hypothesis and conclude that they are associated with NEET status at $18 - 19$.

Additionally, the observed coefficients show that the Nagelkerke R^2 has increased in comparison to the base models (NEET and area deprivation) tested in the previous section. This means that Model II has improved and that the addition of family characteristics variables results in predicting the values of the dependent variable in a better way. The observed values in the level of significance show that all the variables in the model are significant. However, the level of significance of the Crime Score has decreased in comparison to Model I.

Table 6.9: Estimated coefficients for a multiple logistic regression model using NEET, Crime Score and family characteristics

NEET (ref. category: Not NEET)	**B**	**Standard Error**	**Significance**	**Exp(B)**
Crime Deprivation 1st quart (ref. category: 4th quart)	0.432	0.176	0.014	1.541
Crime Deprivation 2nd quart (ref. category: 4th quart)	0.159	0.181	0.380	1.172
Crime Deprivation 3rd quart (ref. category: 4th quart)	0.064	0.198	0.748	1.066
Highest qualification of main parent: No qualification (ref. category: Degree)	0.413	0.119	0.001	1.511
Benefit claimants (ref. category: Not receiving benefits)	0.393	0.122	0.001	1.481
Mother's birth age under 20 (ref. category: 35+)	0.453	0.198	0.023	1.574
Single parent family (ref. category: Not single parent family)	0.504	0.122	0.000	1.656
How often the main parent knows where the young person is when he/she goes out in the evening: Sometimes (ref. category: Always)	0.740	0.354	0.037	2.095
Parental aspirations: Full-time education (ref. category: get a full time job)	−0.728	0.121	0.000	0.483
Cox and Snell: 0.035				
Nagelkerke: 0.024				
$p < 0.5$, $^{**}p < 0.01$, $^{***}p < 0.001$				

Figure 6.9: 'Area deprivation and NEET status including family characteristics, logistic regression analysis' presents graphically the odds ratios of being NEET for the multiple logistic regression analysis based on Crime Score and controlling for family demographic characteristics and parental practices. The analysis suggests that the factors that remain significant increase the odds that young people will become NEETs. The horizontal axis represents estimated B coefficients. Bars to the right of the axis indicate that young people from families with the denoted characteristics were more likely to become NEETs and bars to the left indicate that families with the denoted characteristics were less likely to be NEETs. The bars in dark blue colour indicate statistically significant variables whereas the variables in light blue colour indicate variables that are not statistically significant.

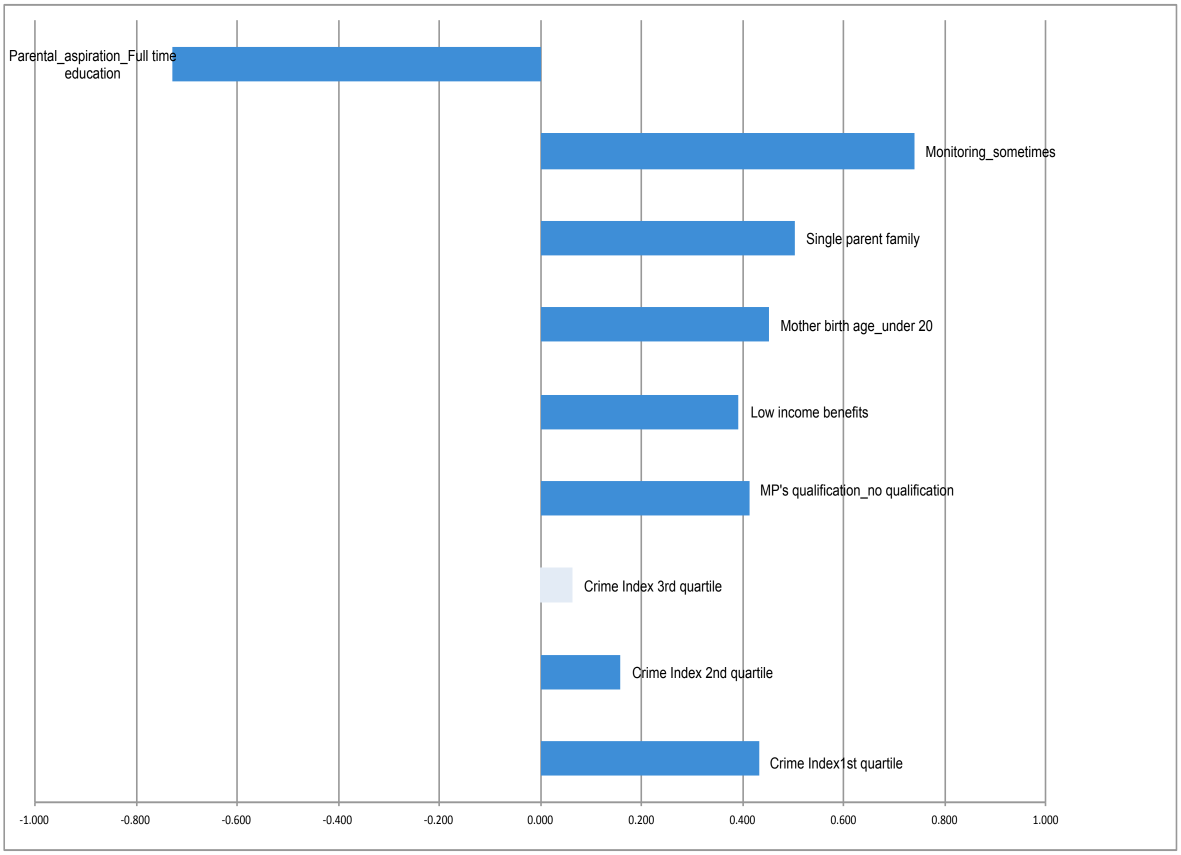


Figure 6.9: Area deprivation and NEET status including family characteristics, logistic regression analysis

6.9 The effect of individual characteristics

This section investigates research question 3: Is the effect of living in a deprived area with high crime on NEET status mediated by individual characteristics after controlling for family characteristics?

To address research question 3, variables that indicate individual characteristics are added in model II. All of the variables that were included in the analysis in model I remain in the model. The key independent variable is Crime Score (split in quartiles). Two variables are added to control for individual characteristics over and above family demographics and parental characteristics. Individual demographic characteristics are described by ethnicity of the young person. Educational attainment is given by the KS2 average point score (using fine grading) for contextual value added [1]. This variable includes an average of KS2 English, Maths and Science average point scores. The educational attainment variable is split in quartiles to represent different levels of educational attainment.

KS2 and NEET

Figure 6.10: 'NEET status by educational attainment at KS2' presents the proportion of young people in NEET status by educational attainment as this is described by Key Stage 2 attainment (n unweighted = 9,775, n weighted = 4,998). Key Stage 2 attainment was divided in quartiles. The first quartile presents lowest educational attainment whereas the fourth quartile presents higher educational attainment. The graph shows that high educational attainment is inversely associated with NEET status. The proportion of young people in NEET status is higher in the lowest educational attainment group. The observed proportions are different for young people in Education / Employment / Training. The lowest number of young people in Education, Employment or Training appears in the low educational attainment group. The number of young people in Education, Employment or Training increases as the educational attainment increases.

[1] Contextual value added (CVA) is a statistical measure of the relative effectiveness of a school or measuring pupil progress (http://www.education.gov.uk). CVA explains variation in attainment by taking into consideration pupils prior attainment in combination with the progress made by pupils from one key stage to the other. In addition, nine factors are considered including gender, ethnicity, deprivation and first language of pupils. The CVA model is developed using actual test and exam results of a specific year group. Average point score at Key Stage 2 is used as input. For point scores at KS2, fine grades are used. National average results are calculated for each category of pupils, which are subsequently compared with individual pupils results. The statistical power of CVA lies on the fact that it provides a good relative measure of effectiveness of a school and pupil progress and a basis for comparisons.

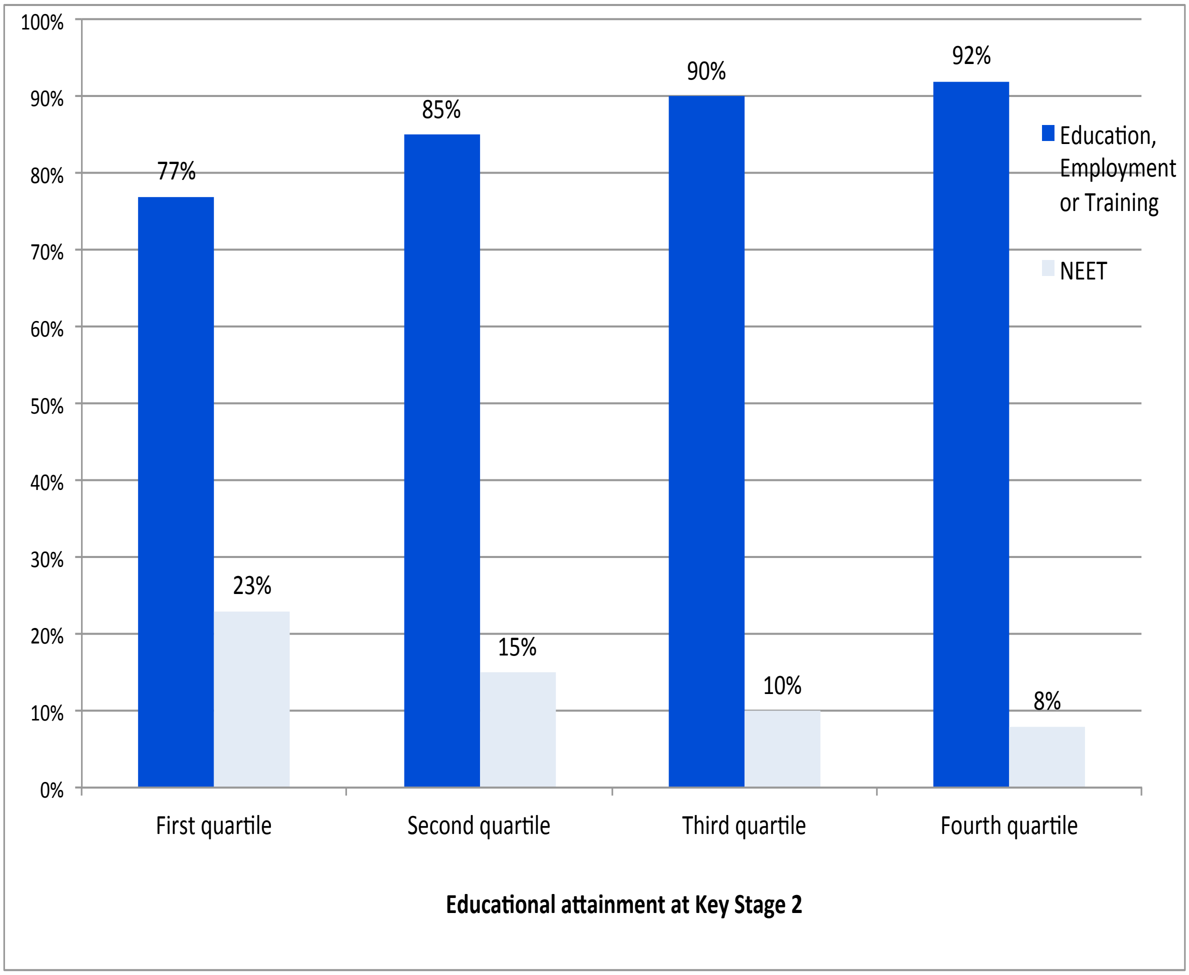


Figure 6.10: NEET status by educational attainment at KS2

6.9.1 Individual characteristics; Descriptive statistics

Figure 6.10: 'Individual characteristics variables and NEET' presents descriptive statistics of NEETs and individual characteristics of young people. Descriptive statistics include cross-tabulations and the Pearson chi-square test of significance. The goal is to explore and describe what characteristics of NEETs are related to specific individual characteristics; ethnicity and educational attainment. The null hypothesis that will be tested is that NEET status is independent of individual characteristics, in other words that we observe absence of a relationship between the variables. To measure

the associations between the variables, the chi-square measure of association was computed. The chi-square test compares two counts; the observed number of cases in a cell and the expected number of cases in a cell if two variables are independent. From the calculated chi-square value, the observed significance level is small enough to reject the null hypothesis for young people who are Indians and Black African and for young people whose educational attainment falls in the lowest attainment quartile (first quartile). This means, that according to the observed significance level for the Pearson chi-square, young people who belong to Indian and Black African ethnic group as well as young people with low educational attainment are more likely to become NEETs.

Table 6.10: Individual characteristics variables and NEET (source: LSYPE, weighted count)

Control Variables - Chi Square Tests				
		Education/Employment/Training (%)	**NEET** (%)	**Significance**
Demographics	Y.P's ethnicity - White	86%	14%	
	Y.P's ethnicity - Mixed	84%	16%	
	Y.P's ethnicity - Indian	80%	20%	
	Y.P's ethnicity - Pakistani	83%	17%	
	Y.P's ethnicity - Bangladeshi	81%	19%	
	Y.P's ethnicity - Black Carribean	88%	12%	0.000***
Educational Attainment	KS2 First quartile	78%	22%	
	KS2 Second quartile	85%	15%	
	KS2 Third quartile	90%	10%	
	KS2 Fourth quartile	91%	9%	0.000***
$^{*}p < 0.5$, $^{**}p < 0.01$, $^{***}p < 0.001$				

6.9.2 Predicting NEET status; The mediating effect of individual characteristics

This section focuses on predicting the values of NEET, a binary dependent variable, from a set of independent variables that focus on area deprivation, family and individual characteristics. A multiple logistic regression model is fitted to model the probability of young people becoming NEETs or not. The logistic regression model that was employed to address research question 2 will now be generalised to include more independent variables and to control for individual characteristics.

After the multiple logistic regression model has been fitted it is important to assess the model (see Table 6.11: 'Estimated coefficients for a multiple logistic regression model using NEET, Crime Score, family and individual characteristics'. The total sample size is 4,453 people (weighted counts).In comparison to the previous model, the sample size has reduced slightly (sample size in the previous model: 4,724). As Table 11 shows, the P-value for the chi-square distribution associated with this test shows that the variables that remain significant for $P < 0.001$ are parents with no qualifications, belonging to single parent family, parents that aspire their children to continue in full time education, and young people with low educational attainment. Variables that remain significant for $P < 0.01$ are the first quartile of Crime deprivation, belonging to a family that claims benefits for low income and, in the opposite direction, young person's ethnicity 'Indian'. For $P < 0.05$ variables that remain significant are parents who sometimes know where the young person is when they go out at night and young person's ethnicity 'Black African'. In comparison to the previous model, the observed values in the level of significance show that all the variables from the previous model remain significant. The significance of the first quartile of Crime Score increases in comparison to the previous model (0.007 in comparison to 0.018). The second quartile of the Crime Score is no longer significant. The only exception is 'mother's age at the birth of the young person under 20' which is no longer significant ($p = 0.060$).

Table 6.11: Estimated coefficients for a multiple logistic regression model using NEET, Crime Score, family and individual characteristics

NEET	**B**	**Standard Error**	**Significance**	**Exp(B)**
Crime Deprivation 1st quart	0.506	0.178	0.005	1.659
Crime Deprivation 2nd quart	0.239	0.183	0.192	1.270
Crime Deprivation 3rd quart	0.105	0.197	0.595	1.111
Highest qualification of main parent: No qualification	0.433	0.130	0.001	1.543
Benefit claimants	0.372	0.126	0.003	1.451
Mother birth age under 20	0.379	0.201	0.060	1.460
Single parent family	0.515	0.129	0.000	1.673
Parenting monitoring: Sometimes	0.753	0.347	0.031	2.123
Parental aspirations: Full-time education	−0.525	0.137	0.000	0.591
KS2 **1st quart (low attainment)**	0.517	0.116	0.000	1.677
Mixed Ethnicity	−0.053	0.235	0.821	0.948
Indian	−0.723	0.243	0.003	0.485
Pakistani	−0.089	0.225	0.694	0.915
Bangladeshi	−0.302	0.231	0.191	0.739
Black Carribean	−0.559	0.407	0.170	0.572
Black African	−0.930	0.419	0.027	0.395
Other Ethnicity	−0.763	0.436	0.081	0.466
Cox and Snell: 0.057				
Nagelkerke: 0.104				
$p < 0.5$, $^{**}p < 0.01$, $^{***}p < 0.001$				

Once the model has been estimated, it is now important to determine how well it fits the data. The observed coefficients show that the Nagelkerke R2 has increased in comparison to the previous model. The Nagelkerke R^2 is now 0.104 compared to 0.024 in the previous model. This means that the new model specification fits the data better than the previous model and the addition of new variables results in a better prediction of the dependent variable (NEET).

Figure 6.11: 'Area deprivation and NEET status including individual characteristics, logistic regression analysis' presents graphically the odds ratios coefficients. The horizontal axis represents estimated B coefficients. The bars to the right of the horizontal axis indicate young people with parental and individual characteristics that increase the probability of becoming NEET. The bars to the left of the horizontal axis indicate that young people with the denoted characteristics were less likely to become NEETs. The bars in dark blue colour indicate statistically significant variables whereas the variables in light blue colour indicate variables that are not statistically significant.

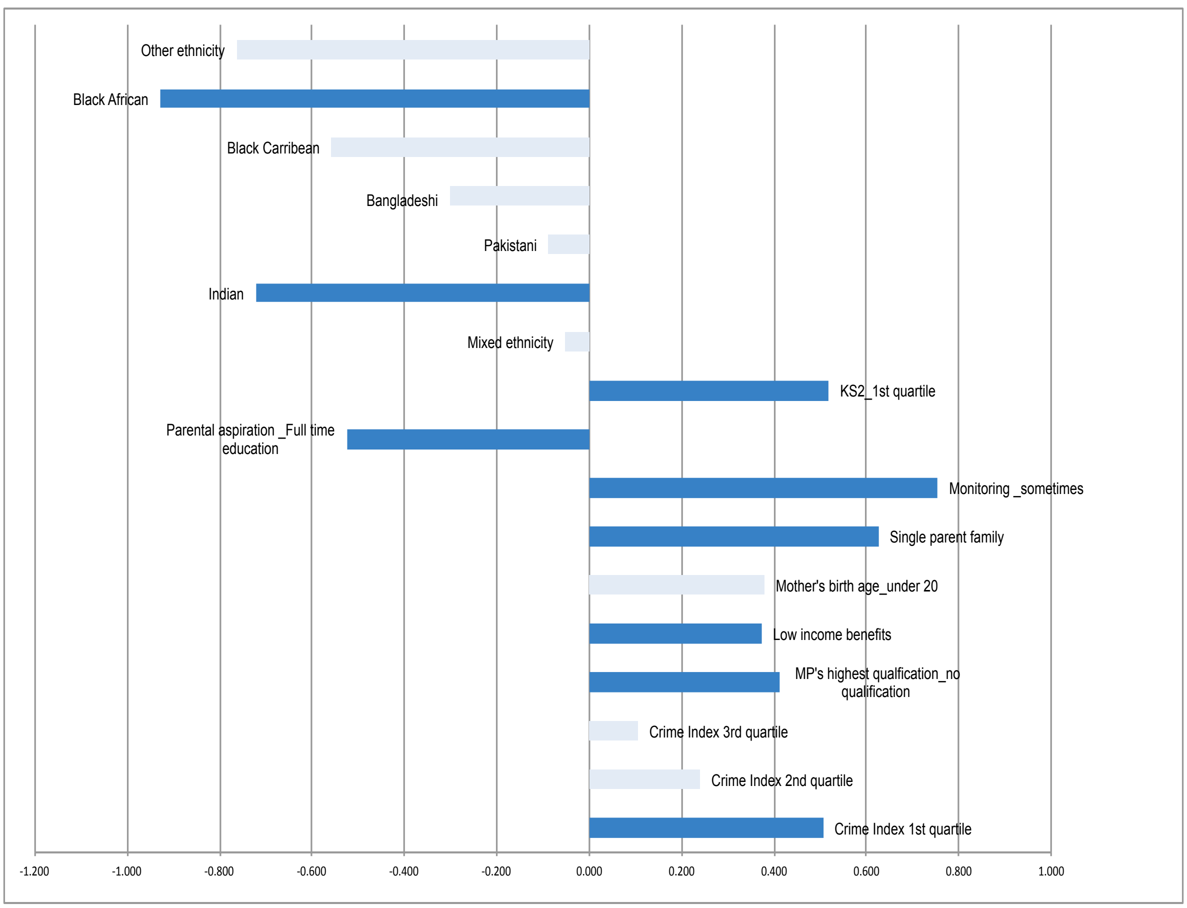


Figure 6.11: Area deprivation and NEET status including individual characteristics, logistic regression analysis

6.10 The effect of attitudes to and experiences of school

This section investigates research question 4: Is the effect of living in a deprived area with high crime on NEET status mediated by attitudes to and experiences of school after controlling for family and individual characteristics?

Research question 4 is addressed by exploring the attitudes and experiences to school over individual and family characteristics and whether there are differences between those who are NEETs and those who are in Education, Employment or Training. The variables that were used in the previous models are included in this model too. The key independent variable is area deprivation as this is depicted by Crime Score. A range of characteristics on feelings about school, attitudes and perceptions are used to help understand those most at risk of becoming NEETs. Attitudes to school are described by whether the young person played truant over the last 12 months. The feelings the young person has about school are given by whether the young person counts minutes in a lesson until it ends. Finally, the perception the young person has of their educational attainment is given by how good or bad the young person feels they are at maths. The analysis will begin with descriptive statistics to show the association between NEETs and attitudes to and experiences of school.

YP played truant

Figure 6.12: 'NEET by young person playing truant' presents the proportion of young people in NEET status by whether they played truant over the last 12 months (n unweighted = 8,893, n weighted = 4,653). Two main categories are displayed, young people in NEET status and young people in Education, Employment or Training. The graph shows that playing truant is associated with NEET status. The proportion of young people in NEET status is higher (21%) in the group who played truant compared to a much lower percentage (11%) in the group of people who remain in education / employment / training.

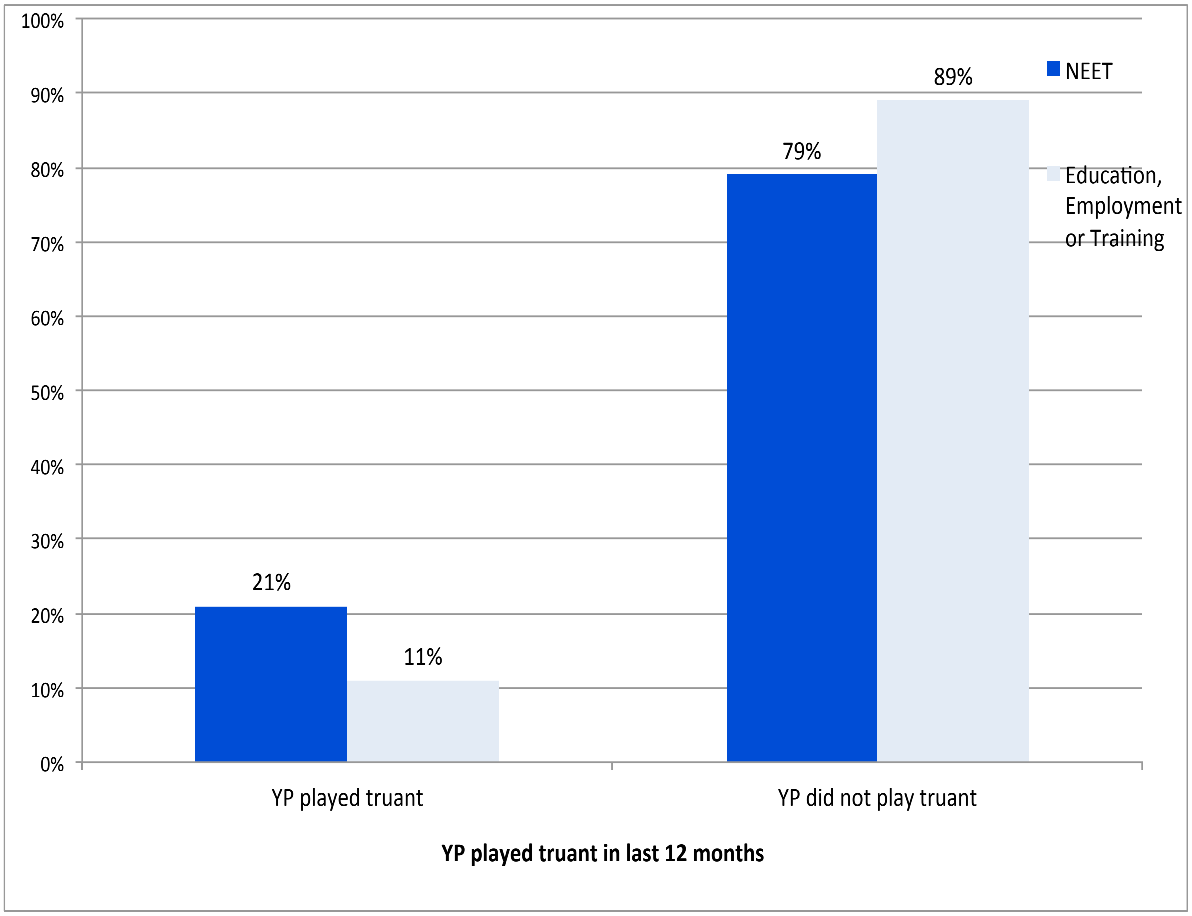


Figure 6.12: NEET by young person playing truant (source: LSYPE)

Count minutes

Figure 6.13: 'In a lesson I count minutes till it ends' shows that strong negative feelings about school are associated with increased rates in NEET status (n unweighted = 9,045, n weighted = 4,729). As can be seen from Figure 6 there are four different categories of feelings about school and variation in rates of NEETs across the four groups. Rates of NEETs are highest in the group that strongly agrees that in a lesson they count minutes till it ends.

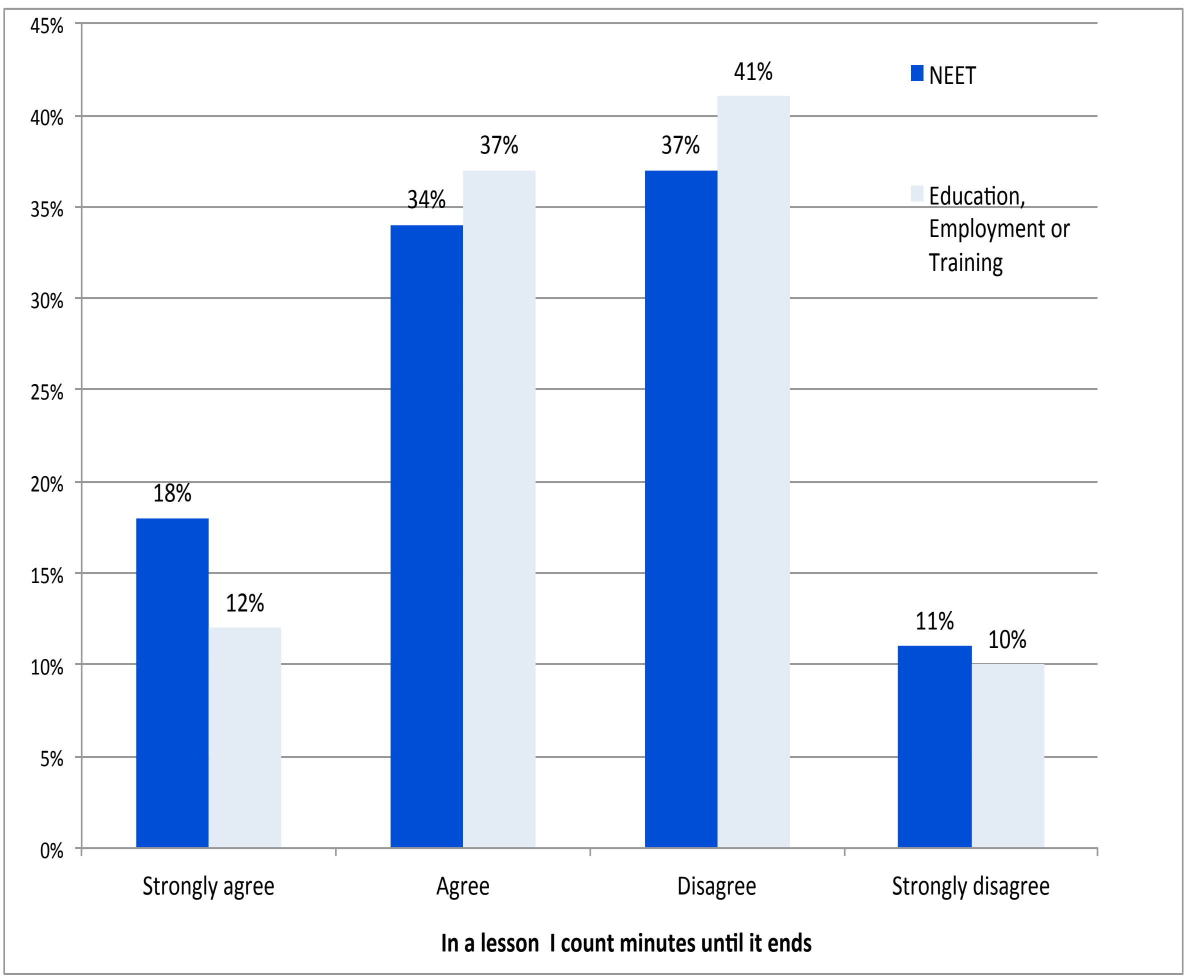


Figure 6.13: NEET by "In a lesson I count minutes till it ends"(source: LSYPE)

How good or bad at maths

Figure 6.14: 'How good or bad young person feels they are at maths' shows how NEETs vary according to their perception of educational ability and more specifically, how good or bad they feel they are at maths (n unweighted = 9,429, n weighted = 4,947). Four groups of different perception of ability are studied; Very good, Fairly good, Not very good, Not good at all. The observed figures show that when young people have positive feelings about their attainment the rates of NEETs are lower compared to those in Education, Employment or Training. The opposite is true for negative perceptions of educational attainment. NEETs percentages are higher for those who feel that their attainment is not good. We see that the highest percentage of NEETs falls in the third category and relates to young people who feel that they are "not very good at maths".

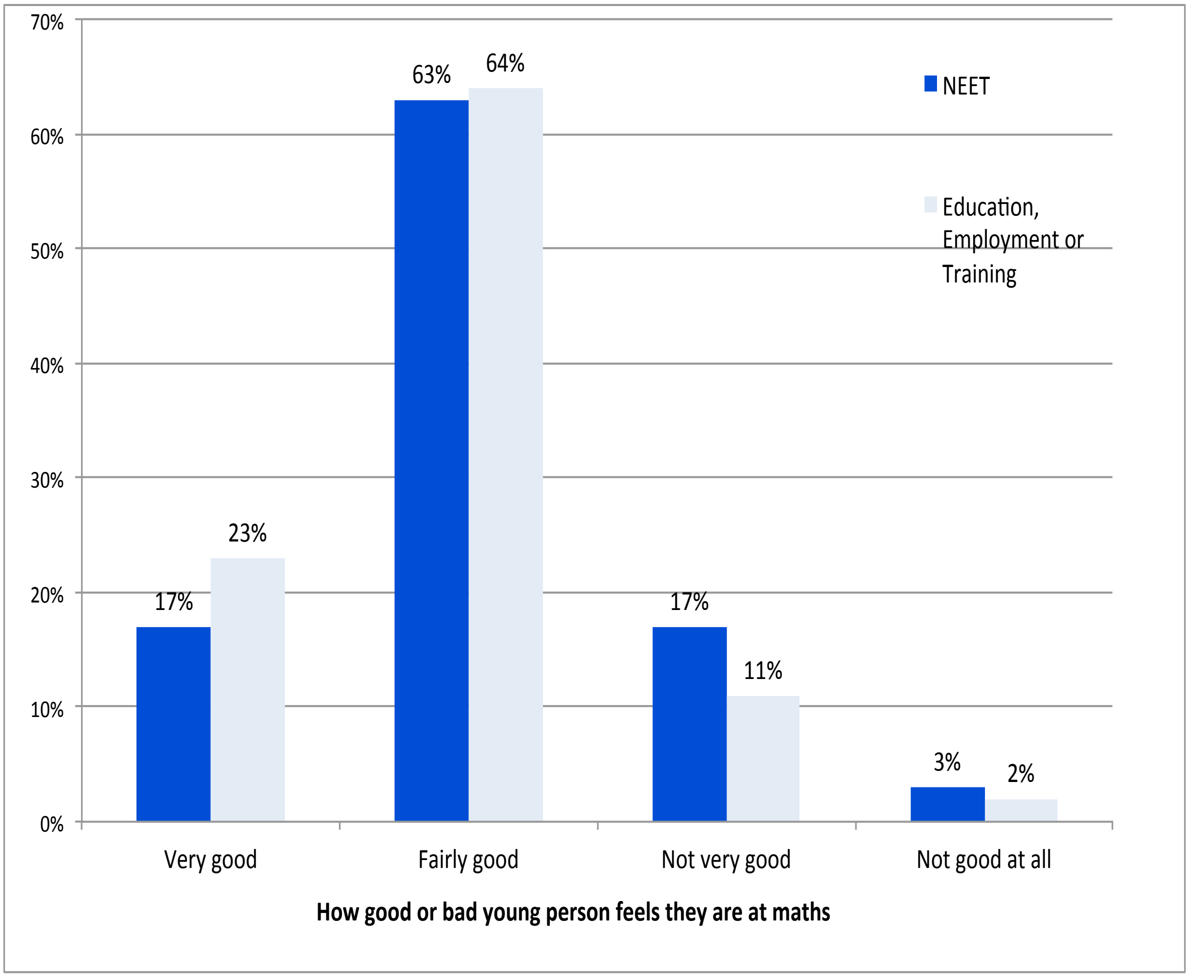


Figure 6.14: NEET by "How good or bad young person feels they are at maths"(source: LSYPE)

6.10.1 Attitudes and experiences of school; Descriptive statistics

Table 6.12: 'School characteristics variables and NEET status' presents a classification of values of NEETs with attitudes and feelings about school and perceptions of educational ability. The observed cross-tabulations show the proportions of NEETs based on school characteristics. The highest proportion of NEETs is observed in young people who feel that they are not at all good at maths (25%) and the lowest proportion of NEETs is among those who feel that they are very good at maths (10%). To summarize the strength of the relationship between NEETs and the independent variables,

the chi-square statistic is used. The null hypothesis can be rejected for young people who played truant over the last 12 months, those who feel that they are very good / not very good / not good at all at maths (19% / 25%), and those who strongly agree that in a lesson they often count minutes till it ends.

Table 6.12: School characteristics variables and NEET status (source: LSYPE, weighted count)

Control Variables - Chi Square Exact Tests				
		Education/Employment/Training (%)	**NEET** (%)	**Significance**
Attitudes to school	Young person played truant in last 12 months	79%	21%	0.000***
Perceptions of educational attainment	How good or bad young person feels they are at maths - Very good	90%	10%	0.000***
	How good or bad young person feels they are at maths - Fairly good	87%	13%	
	How good or bad young person feels they are at maths - Not very good	81%	19%	
	How good or bad young person feels they are at maths - Not good at all	75%	25%	0.000***
Feelings about school	In a lesson I often count minutes till it ends - Strongly agree	80%	20%	
	In a lesson I often count minutes till it ends - Agree	87%	13%	
	In a lesson I often count minutes till it ends - Disagree	88%	12%	
	In a lesson I often count minutes till it ends - Strongly disagree	86%	14%	0.000***
$^{*}p < 0.5$, $^{**}p < 0.01$, $^{***}p < 0.001$				

6.10.2 Predicting NEET status; The mediating effect of attitudes and experiences of school

So far we have highlighted some of the associations between the linked risks and NEET status by looking at descriptive statistics of attitudes and perceptions to school to explore these associations. In this section, regression analysis is used to identify associations that hold when a range of factors are taken into account. Table 6.13: 'Estimated coefficients for a multiple logistic regression model using NEET, Crime Score, family, individual and school characteristics' presents the estimated coefficients for the fitted multiple logistic regression model. The total sample size is 4,009 people (weighted counts) which is reduced compared to the previous sample size (4,453) after the introduction of new variables in the model. Once the model has been fitted, we can begin the process of model assessment. The first step in this process is to assess the significance of the variables in the model.

The factors presented descriptively in the previous section, attitudes to school and perception of educational attainment, are still associated with NEET status when controlling for other factors. The P-value for the chi-square distribution associated with this test shows that the variables that remain significant for $P < 0.001$ are belonging to a single parent family, young person having low educational attainment and young person having played truant in the last 12 months. Variables that remain significant for $P < 0.01$ are the first quartile of crime score, main parent having no qualifications, family claiming benefits for low income, parents aspiring their children to continue to full time education, young person's ethnicity "Indian" and young person strongly agreeing that in a lesson they count minutes until it ends. Finally, for $P < 0.05$ variables that remain significant are young person's ethnicity "Black Carribean" and young person strongly agreeing that they are not very good at maths. The observed values in the level of significance show that all the variables from the previous model remain significant. The significance of the first quartile of crime score decreases in comparison

Table 6.13: Estimated coefficients for a multiple logistic regression model using NEET, Crime Score, family, individual and school characteristics

NEET	**B**	**Standard Error**	**Significance**	**Exp(B)**
Crime Deprivation 1st quart	0.464	0.192	0.016	1.591
Crime Deprivation 2nd quart	0.251	0.194	0.198	1.285
Crime Deprivation 3rd quart	0.067	0.209	0.748	1.070
Highest qualification of main parent: No qualification	0.400	0.140	0.004	1.491
Benefit claimants	0.339	0.132	0.011	1.403
Mother birth age under 20	0.367	0.222	0.099	1.444
Single parent family	0.467	0.141	0.001	1.595
Parenting monitoring: Sometimes	0.676	0.382	0.078	1.967
Parental aspirations: Full-time education	−0.378	0.143	0.008	0.685
KS2 **1st quart (low attainment)**	0.408	0.127	0.001	1.503
Mixed Ethnicity	−0.034	0.238	0.885	0.966
Indian	−0.717	0.281	0.011	0.488
Pakistani	−0.124	0.246	0.614	0.883
Bangladeshi	−0.251	0.257	0.329	0.778
Black Carribean	−0.411	0.411	0.318	0.663
Black African	−0.826	0.417	0.048	0.438
Other Ethnicity	−0.641	0.440	0.145	0.527
Young person played truant	0.480	0.141	0.001	1.615
In a lesson count minutes till it ends	0.383	0.157	0.015	1.467
Young person feels not very good at maths	0.365	0.162	0.025	1.441
Cox and Snell: 0.057				
Nagelkerke: 0.107				
$p < 0.5$, $^{**}p < 0.01$, $^{***}p < 0.001$				

to the previous model (0.027 in comparison to 0.007). Low educational attainment remains a highly significant variable ($p = 0.001$). The ethnic groups that are significantly associated with absence of NEET status are the same, Indian and Black African. The newly added variables in model IV that denote attitudes to school and perceptions, are significantly associated with NEET status. Playing truant appears to be the factor that increases the most the probability of a young person becoming NEET. Finally, the observed coefficients show that the Nagelkerke R2 has slightly increased in comparison to the previous model. The Nagelkerke R^2 is now 0.107 compared to 0.104 in the previous model. This means that the new model specification fits the data in a slightly better way than the previous model.

Figure 6.15: 'Area deprivation and NEET status including school characteristics, logistic regression analysis' graphically represents odds ratios of the fitted model. The bars on the horizontal axis show the odds ratio (B coefficient) linking risk factors to NEET status. Shaded bars show statistically significant associations. A bar greater than 0 (positive B coefficient), indicates that the odds ratio is greater than 1, which means that the odds of being NEET are increased for a certain factor. The higher the bar, the greater the association. From figure 16, we can see that factors that increase the risk of being NEET are high Crime Score, parents with no qualifications, mothers age at birth of young person under 20, single parent family, low monitoring of young person, low educational attainment, playing truant, counting minutes in a lesson until it ends and not being very good at maths. The bars on the left of the horizontal axis represent young people with a reduced risk of being NEET. If the bar is less than 0 (negative B coefficient), the odds ratio is less than 1, which means that the odds of being NEET are decreased. The factors that are significantly associated with a decreased probability of a young person being NEET are parents who would like the young person to remain in full time education after 16, and ethnicity of young person being Indian and Black African.

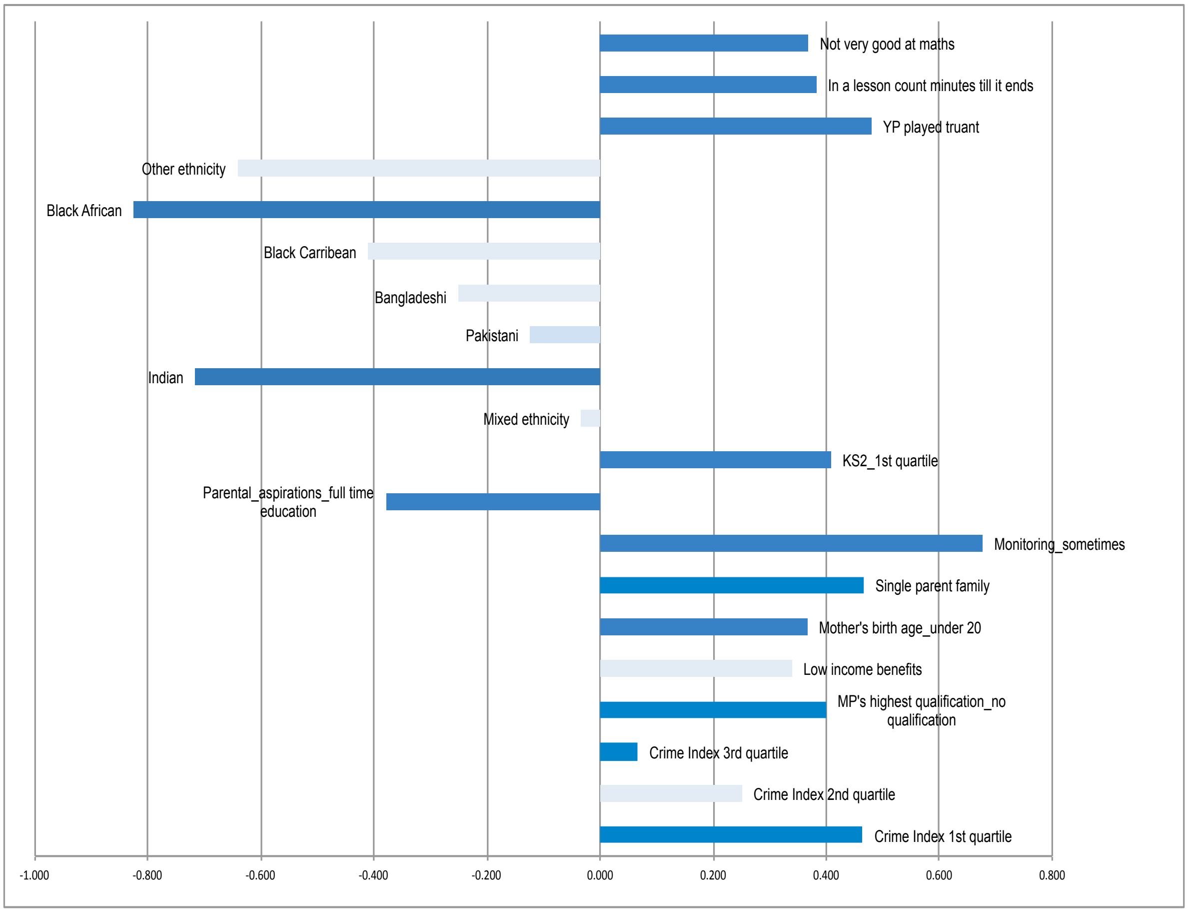


Figure 6.15: Area deprivation and NEET status including school characteristics, logistic regression analysis

6.11 The effect of peer group influence and antisocial behaviour

This section addresses research question 5: Is the effect of of living in a deprived area with high crime on NEET status mediated by peer group influence and antisocial behaviour after controlling for family, individual and school characteristics?

Having addressed family, individual and school characteristics, a range of characteristics will be explored now by including peer group effects and antisocial behaviour. Two variables thought to be of importance are added in the model. The first variable that will be included refers to peer group effects and bullying and describes whether the young person has been excluded from a group of friends over the last 12 months. The second variable describes anti-social behaviour and refers to whether the police has got in touch with the young persons parents because of something the young person has done. The analysis will begin with describing graphically the association between NEET status at $18 - 19$ and the new variables that are added in the model.

Excluded

The analysis begins by looking at how NEETs vary according to whether a young person was excluded from a group of friends over the last 12 months in Figure 6.16: 'young person excluded from a group of friends over the last 12 months' (n unweighted = 9,030, n weighted = 4,745). The proportion of young people in NEET status is higher (22%) in the group who experienced exclusion from a group of friends compared to a lower proportion (15%) in the group of people who remained in education / employment / training. Figure 17 shows that being excluded from a group of friends is associated with NEET status.

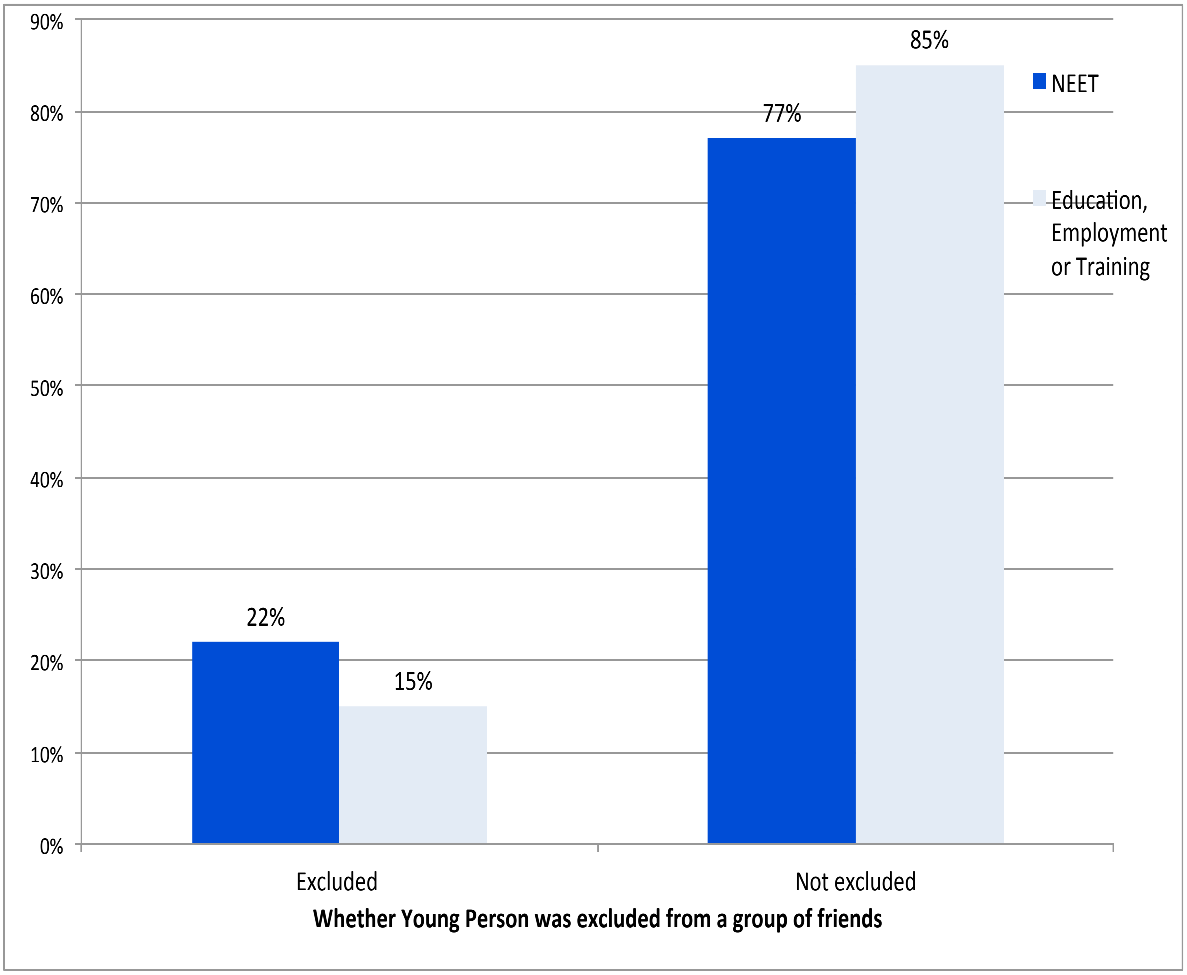


Figure 6.16: NEET by "young person excluded from a group of friends over the last 12 months"

Police got in touch with main parent for something the young person has done

Figure 6.17: 'Police got in touch for something the young person has done' presents the proportion of young people in NEET and those in Education, Employment or Training by whether the police got in touch with the main parent for something the young person had done at Wave 1 (n unweighted = 8,633, n weighted = 4,527). The graph shows that antisocial behaviour, as this is denoted by the police contacting the main parent for their childs behaviour, is associated with NEET status. The proportion of young

people in NEET status, whose parents have been contacted by the police, is very high (29%) compared to those who fall in the Education, Employment or Training category (12%).

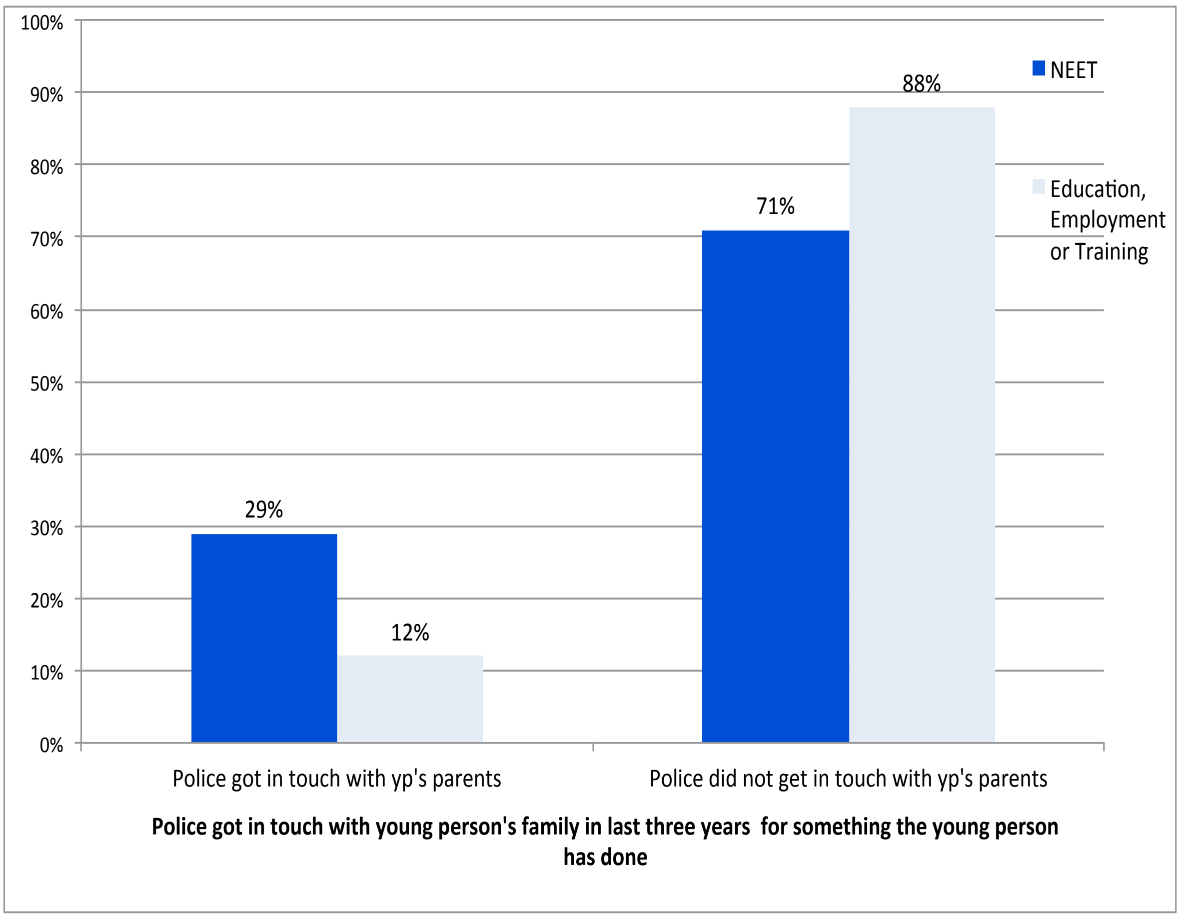


Figure 6.17: NEET by "Police got in touch for something the young person has done"

6.11.1 Peer group and antisocial behaviour; Descriptive statistics

Table 6.14: 'Peer group influence and antisocial behaviour and NEET status' presents descriptive statistics and chi-square tests of association for the two variables to be added to the model. Cross-tabulations present the observed percentages to describe the relationship between NEETs and the two variables added in the analysis. The observed proportions show that young people in NEET status are high in both groups. NEETs constitute the 18% of those who were excluded from a group of friends. The proportion is high (29%) for those young people whose parents have been contacted by the police for their child's behaviour. After initial cross-tabulations additional steps are taken, using the chi-square test, to test the null hypothesis that the categorical variables are independent. From the calculated chi-square value, it is possible to estimate how often in the sample you would expect to see a chi-square value at least as large as the one observed if the independence hypothesis is true in the population. The observed significance is small enough to reject the null hypothesis that the variables are independent for both variables tested.

Table 6.14: Peer group influence and antisocial behaviour and NEET status (source: LSYPE, weighted count)

Control Variables - Chi Square Exact Tests				
		Education/Employment/Training (%)	**NEET** (%)	**Significance**
Bullying	Whether the young person has been excluded from a group of friends over the last 12 months	82%	18%	0.000***
Antisocial behaviour	Whether the police has got in touch because of something the young person has done	71%	29%	0.000***
$^{*}p < 0.5$, $^{**}p < 0.01$, $^{***}p < 0.001$				

6.11.2 Predicting NEET status; The mediating effect of peer group and antisocial behaviour

Further analysis is carried out to explore the probability that a young person will be NEET, or not, using a multivariate logistic regression model. Table 6.15: 'Estimated coefficients for a multiple logistic regression model using NEET, Crime Score, family, individual, school and peer group characteristics' presents the estimated coefficients for the final multiple logistic regression model that controls for all the covariates addressed in the Compositional Model of Neighbourhood effects. The total sample size is 3,601 people (weighted counts) which is reduced in comparison to the previous model (sample size 4,009) after the introduction of new variables in the model. The model assessment begins by looking at the significance of the covariates in the model and the P-value associated with each one of them. The variables that remain significant for $P < 0.001$ is low educational attainment at key stage 2. Variables that remain significant for $P < 0.01$ are the first quartile of Crime Deprivation Score, parents who sometimes monitor young people when they go out at night, ethnicity of young person being "Indian", young people who played truant in the last twelve months and young people who strongly agree that in a lesson they count minutes until it ends. Finally, for $P < 0.05$ variables that remain significant are parents who have no qualifications, families who claim benefits for low income, young people who feel that they are not good at maths, families that have been contacted by the police for their childs behaviour, and a young person that has been excluded from a group of friends over the last 12 months. The observed values in the level of significance show that all the variables from the previous model remain significant.

In comparison to the previous model, the significance of the Crime Deprivation Score increases after the addition of new variables in the model (0.018 compared to 0.027). As is the case of previous models, low educational attainment remains a highly significant variable in predicting the probability of being NEET ($p = 0.001$). The ethnic group

Table 6.15: Estimated coefficients for a multiple logistic regression model using NEET, Crime Score, family, individual, school and peer group characteristics

NEET	B	Standard Error	Significance	Exp(B)
Crime Deprivation 1st quart	0.469	0.197	0.018	1.598
Crime Deprivation 2nd quart	0.198	0.198	0.319	1.219
Crime Deprivation 3rd quart	−0.006	0.213	0.978	0.994
Highest qualification of main parent: No qualification	0.352	0.156	0.024	1.422
Benefit claimants	0.291	0.147	0.049	1.337
Mother birth age under 20	0.417	0.235	0.076	1.517
Single parent family	0.443	0.152	0.004	1.557
Parenting monitoring: Sometimes	0.975	0.399	0.015	2.650
Parental aspirations: Full-time education	−0.239	0.151	0.114	0.787
KS2 1st quart (low attainment)	0.462	0.135	0.001	1.587
Mixed Ethnicity	−0.015	0.237	0.949	0.985
Indian	−0.887	0.342	0.010	0.412
Pakistani	−0.445	0.364	0.221	0.641
Bangladeshi	−0.093	0.336	0.782	0.911
Black Carribean	−0.408	0.414	0.325	0.665
Black African	−0.647	0.435	0.138	0.524
Other Ethnicity	−0.413	0.497	0.407	0.662
Young person played truant	0.457	0.157	0.004	1.579
In a lesson count minutes till it ends	0.452	0.162	0.005	1.572
Young person feels not very good at maths	0.379	0.172	0.028	1.460
Police got in touch with main parent for young person's behaviour	0.439	0.213	0.040	1.551
Young person was excluded from a group of friends	0.320	0.146	0.029	1.377
Cox and Snell: 0.064				
Nagelkerke: 0.12				
$p < 0.5$, $^{**}p < 0.01$, $^{***}p < 0.001$				

that remains significantly associated with NEET status is only Indian in this model. Black African which was associated with NEET status in previous models, is no longer significantly associated. Attitudes to school remain significant variables for $P < 0.01$. The new variables included in the model that denote peer group influence and antisocial behaviour are significantly associated with NEET status at $P < 0.05$. Finally, the observed coefficients show that the Nagelkerke R^2 has slightly increased in comparison to the previous model. The Nagelkerke R^2 is now 0.120 compared to 0.107 in the previous model. This suggests that the new model specification fits the data in a better way than the previous model.

Figure 6.18: 'Possible risk factors for NEET status' presents graphically the odds ratios of the fitted multiple logistic regression model. The bars on the horizontal line show the odds ratio (B coefficient) linking risk factors to NEET status. Dark blue shaded bars show statistically significant relations whereas light blue bars show statistically insignificant relations. The odds of being NEET (as this is denoted by a positive B coefficient / a bar greater than 0) are increased for young people who live in areas with high Crime Score, their parents have no educational qualifications, they belong to a family that claims benefits for low income, their mother was under 20 when she gave birth to the young person, they belong to single parent families, their parents monitor them only sometimes when they go out at night, they have low educational attainment, they played truant over the last 12 months, they believe they have low educational attainment, they count minutes in a lesson until it ends and they have been excluded from a group of friends over the last 12 months, and the police has got in touch with their parents for their behaviour. Bars in Figure 6.18 that are less than 0 (negative B coefficient) indicate that the odds ratio is less than 1, which means that the odds of being NEET are decreased for the following two factors. The main parent would like the young person to continue to full time education after 16 and they are of Indian ethnic origin.

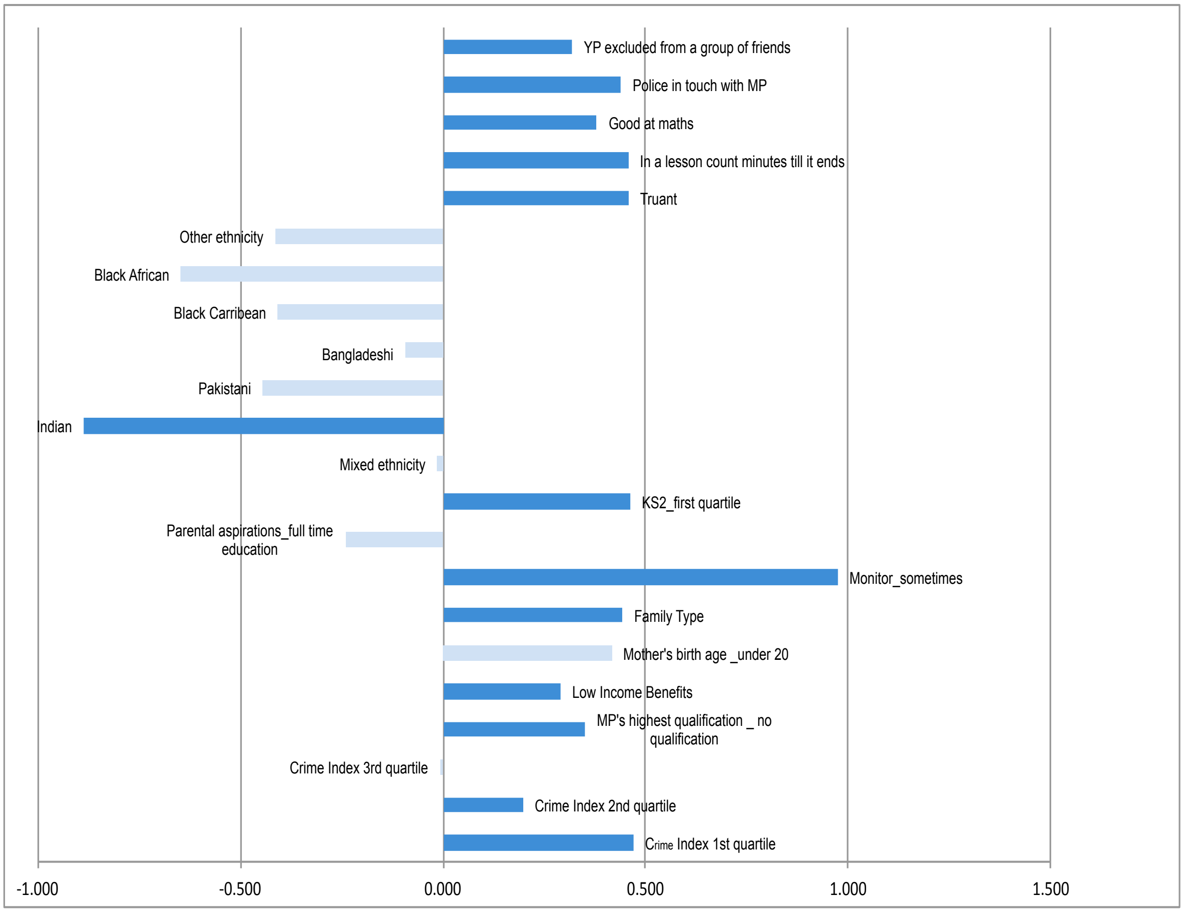


Figure 6.18: Model V, Possible risk factors for NEET status (source: LSYPE)

6.12 Discussion and conclusions

This chapter addressed the first five research questions of this study by building a multivariate logistic regression model to address neighbourhood effects on individual outcomes and especially the effects on young people. More specifically, this study focused on the effect of living in an area characterised by high crime on young people becoming NEET at the ages $18-19$. The method of analysis selected was to build a logistic regression model because the outcome variable of interest was binary. The outcome variable was NEET at $18-19$ and the key independent variable was area deprivation. A set of covariates were chosen to investigate the Compositional model of

Neighbourhood Effects that is put forward in this thesis (Section 3.4).The analysis involved five models, each one addressing a research question in this study. The analysis started by addressing the first research question and investigating the effect of living in an area characterised by high deprivation on young people becoming NEETs. A bivariate logistic regression model was fitted to test the effect of the overall IMD and its seven sub-indices separately on young people becoming NEET. The indices were splitted in quartiles (first quartile =highest deprivation, fourth quartile = lowest deprivation). After fitting the model, the regression coefficients showed that high area deprivation, the independent variable in the bivariate model, was significantly related to the outcome variable, NEET at $18-19$. This evidence suggested that the number of young people in NEET status were higher in areas characterised by high deprivation compared to low deprivation areas. Additionally, logistic regression coefficients showed that living in a highly deprived area increases the probability of a young person becoming NEET at the age $18-19$.

In a similar way to linear regression, the strength of a modelling technique lies in its ability to model many variables. Therefore, subsequent research questions were addressed by generalising the univariate logistic model to the case of more than one independent variables. A multivariate modelling technique was used and in each step a set of covariates were introduced in the model to address each research question. Both descriptive statistics and logistic regression analysis were employed to investigate each part of the model. Model II addressed the second research question and tested the effect of Crime deprivation on young people becoming NEETs after controlling for family demographics, parental practices and parental aspirations. Model III added individual characteristics in the analysis. In model IV young person's attitudes to and experiences of school were added in the analysis. Model V included the effect of peer group influence and antisocial behaviour on young people becoming NEETs after controlling for all the covariates of the model.

The final multivariate logistic regression model showed a number of covariates that remained significant in the analysis and increased the probability of a young person becoming NEET at $18-19$. It is important that high area deprivation as this is denoted by the first quartile of Crime Score remains significant in the analysis (for$P < 0.01$) after the addition of all the covariates in the model. The demographic characteristics that increase the odds of young person becoming NEET is belonging to a single parent family. Parental socio-economic characteristics that increase the probability of becoming NEET are parents with no qualifications and families that claim benefits for low income. Parental practices involve parents who sometimes know where the young person is when they go out at night. The odds of a young person being NEET decrease when the parents aspire their child to continue to full time education after the age of 16. The analysis shows that belonging to a minority ethnic group does not increase the probability of being NEET, Being of Indian origin is a significant variable in the individual demographics category associated with NEET status although it decreases the odds of being NEET at $18 - 19$. Low educational attainment at key stage 2 is a highly significant variable in the analysis (for $P < 0.001$) as young people with the lowest educational attainment face the greatest risk of becoming NEET. Negative attitudes to school, as these are expressed by the young person playing truant and the young person counting minutes in a lesson until it ends, are significant variables that increase the odds of being NEET. The same holds for negative perceptions for educational attainment; Young people who strongly agree at $13-14$ that they are not good at maths face a higher risk of being NEET at $18 - 19$. Antisocial behaviour, as this is expressed by the police getting in touch with the young persons parents for their behaviour, is a significant predictor of becoming NEET. Finally, being excluded from the peer group at $13 - 14$ remains significant in the analysis and increases the odds of being NEET.

This chapter employed multivariate logistic regression analysis to estimate the effect of crime score on young people becoming NEETs after controlling for a set of covariates in five models that were introduced by the Compositional Model of Neighbourhood

Effects. As it has been discussed in Chapter 3, research on neighbourhood effects using observational data has been restricted by the selection bias problem. Individuals who live in deprived areas have different characteristics from people who live in affluent areas. The neighbourhood context is not allocated randomly, rather it is guided by personal characteristics and preferences. A common modelling approach to studying neighbourhood effects using observational data has been to use standard regression models including a wide range of statistical controls for covariates. The same approach was followed in this chapter. A wide range of individual and family variables have been included in the multivariate logistic regression model such as demographics, family composition, parental education, income and ethnicity. The modelling approach attempted to control statistically for a range of family and individual characteristics that affect both neighbourhood choice and young people's outcomes in order to avoid the omitted variables or selection bias problems which can cause over or under estimates of neighbourhood effects.

Establishing causal relations using observational data has been challenging in social science research. The next chapter employs the counterfactual model for causal analysis of observational data, which imitates randomised experimental designs. Under the counterfactual framework, all young people in the population of interest could be exposed to two states, a high and a low crime area, for a binary outcome, being NEET or not. The analysis will further proceed by using sensitivity analysis to estimate the magnitude of hidden biases which might arise from unobserved characteristics and which might alter the conclusions drawn by the analysis.

Chapter 7

Counterfactual Models of Neighbourhood Effects

7.1 Introduction

Chapter 6 explored the effect of living in an area characterised by a high Crime Score on young people becoming NEETs controlling for family, individual, school and peer group characteristics. It investigated the first five research questions of the Compositional model of neighbourhood effects. The modeling approach aimed to control statistically for a range of family and individual characteristics that affect both neighbourhood choice and young people's outcomes and thus to reduce the selection bias problem which is associated with studying neighbourhood effects using non-randomised data. Although randomised data are considered to be the gold standard in research design, true experimental designs are often not possible, practical or ethical in social sciences. Given that this study employs observational data, a relatively new method useful for evaluating causal effects when using observational data will be employed in Chapter 7, propensity score analysis.

The aim of this chapter will be to investigate research question 6, whether the effect of area crime score is different for young people who live in high deprivation compared to low deprivation areas. Section 7.2 challenges the tradition of randomised tests as a gold standard in studying neighbourhood effects by providing a critique on social experiments. The critique questions whether randomised experiments provide unbiased results and robust estimates to inform future policy and sets the ground for an econometric approach to reduce bias and achieve causal attribution in observational studies, the counterfactual causal framework. Section 7.3 sets "the fundamental problem of causal inference" under which a single subject cannot be observed under the control and treatment condition simultaneously. It also describes the counterfactual framework, a model that uses the logic of experiments to investigate the potential outcome if one individual lived in both a high and low Crime Score area and to establish causality using observational data. Section 7.4 explains the theoretical framework developed by Rosenbaum and Rubin [155] (1983) that forms the basis of propensity score matching method. In Section 7.5 propensity score matching is applied to investigate the counterfactual: What would be the potential educational and employment outcomes for people who live in areas characterised by high Crime Score if they lived in areas with low Crime Score.

The analysis will begin by selecting a vector of conditioning variables and estimating the propensity scores. Propensity scores are the predicted probability of receiving a treatment (living in a high Crime Score area). Thereafter, a treatment and a control group will be constructed using propensity scores under the Nearest Neighbour without replacement without caliper algorithm. This method (Rubin [156]) matches the control to the treated group and drops control cases that are not selected as matches employing a tolerance level on the maximum propensity score distance to avoid bad matches in case the closest neighbour is found far away. Multivariate analysis will follow based on the matched sample. Propensity score analysis results are conditional on observed characteristics only. To control for unobserved characteristics that could cause hidden bias and alter the inferences or the propensity score analysis results, Section 7.6

introduces Sensitivity Analysis. Section 7.7 introduces the theoretical background of Sensitivity Analysis introduced by Rosenbaum [153] (2002) as a complimentary analysis after propensity score matching. The Mantel-Haenszel bounds methodology will be described in Section 7.8. Thereafter, the counterfactual model results will be evaluated using sensitivity analysis. The results will be analysed to test if the estimated propensity score analysis results are overestimated or underestimated and if the statistical associations observed imply causality by stating the magnitude of hidden bias that would need to be present to explain the observed associations.

7.2 Randomised experiments or observational studies?

Two types of studies have been employed to estimate the effect of neighbourhood deprivation on young people: experimental and observational studies. Experimental studies assign randomly individuals to deprived and non-deprived areas and have been considered the gold approach in estimating causal effects and reducing selection bias in neighbourhood effects research. There has been considerable critique on experimental studies in terms of the quality of the data they provide, the selection process of individuals to be assigned in poor and non-poor neighbourhoods and the experimental evidence provided by US mobility programmes to inform policy interventions. The critiques on experimental research gave rise to the counterfactual framework as an approach to reduce selection bias and to study causal relations in neighbourhood effects research.

The tradition of randomised experiments has been established in studying programme evaluations and neighbourhood effects. Randomised design has been considered the gold standard in social science in assessing treatment effects in program evaluation and drawing causal associations (see Chapter 3). In the case of studying neighbourhood effects, various experimental designs have been conducted that involved randomly assigning families to reside in particular types of neighbourhoods to estimate area effects on its residents. An example of such a programme was the Moving to Opportunity (MTO) Programme in which poor families were relocated from public houses to other housing in less poor neighbourhoods. Random assignment was ensured as families could not chose the area they would relocate to, rather they were chosen randomly by the programme. Experimental designs, such as the MTO programme, offer a number of advantages compared to observational studies. Randomised experiments permit examination of how a change in neighbourhood context can influence young people and their families. Additionally, it allows researchers to examine potential neighbourhood mechanisms and how neighbourhood effects are transmitted and in this way research is protected from biases and robustness of inferences can be ensured. The key advantage is that experiments allow researchers to establish causal attribution as opposed to drawing inferences based on non-randomised data (Sprott and Farewell [181], 1993).

More precisely, a key issue in studying causal relations in neighbourhood research is that it is not possible to observe the same person at two different states simultaneously. If one person was observed in both a poor and rich neighbourhood, it would be possible to compare the two states and thus draw causal conclusions. Randomised neighbourhood mobility experiments offer a solution to this problem by generating two groups of people that can be compared; an experimental treatment group of people who move to a less poor area and an experimental control group of people who would have participated in a relocation programme but were randomly denied access to the programme. The control group provides a counterfactual whose characteristics and behaviour remains the same and can be compared with families and young people who move to better areas. By comparing outcomes for two groups of people randomly assigned in poor and better areas respectively, it is considered that experimental designs remove selection bias and allow causal relations to be tested.

Despite the advantages offered by randomised experiments, there has been also criticism on this approach. Heckman and Smith [84] (1995) propose that experimental methods can induce biases of their own and criticise the arguments commonly used in support of experimental designs. The first criticism refers to the data offered by experimental studies. It is considered that experimental designs offer limited data, which consequently affect findings and evaluations. A rich dataset is required in order to create a treatment group virtually identical to the control group in an experiment and to allow outcome evaluation. However, this is not often possible in experiments and may result in selection bias because of missing data on the factors that affect participation to the programme and outcomes. Additionally, experimental data are often available for a single year and therefore estimators based on longitudinal structure cannot be used. Finally, because of practical difficulties, experimental data provide answers to specific policy questions of interest but they do not control for extended numbers of covariates which could be available in observational studies.

The second argument in favour of experimental studies challenged by Heckman and Smith [84] (1995) refers to the assumption that randomisation offers a valid method to assign treatment and control groups in which treated and control participants share the same characteristics under the condition of non-treatment. This is a problem encountered in both experimental and observational studies; that one person cannot be observed simultaneously in the treated and control group. In experimental designs the counterfactual is given by random selection of individuals to treated and control groups. In observational studies, assignment to treatment and control groups is achieved by employing econometric approaches. Two assumptions must hold for the outcomes of the experimental design to be consistent with the outcomes that would be obtained if the selected treatment group did not participate in the programme. First, randomisation should not affect the selection process of individuals in a programme. Participants in a programme should be the same as those who would have participated even in the absence of an intervention in order to remove randomisation bias. Randomisation bias results when random assignment causes people who participate in a programme to be different from those who would participate if the programme operated normally. The second assumption refers to substitution bias. Substitution bias refers to the fact that it should not be possible to obtain substitutes for the treatment group. In other words, the control group should consist of people who would not receive the treatment either way, and not of people who wanted to receive the treatment but did not.

The final two arguments refer to experimental evidence on evaluating interventions. It has been argued that experimental evidence on evaluating interventions is easier to explain for policy makers and politicians. However, Heckman and Smith [84] (1995) argue that experiments can be associated with randomisation bias and substitution bias and therefore provide misleading interpretation of interventions and direct policymakers to wrong assumptions. Finally, the fourth point relates to a general opinion that experimental designs offer a clear picture of a programme evaluation in comparison to confusing estimates provided by observational data in evaluating policy interventions. However, the counter-argument is that experimental data are often not publicly available in the academic research community and for this reason their interpretation could not be objective or reliable.

The critiques on the experimental approach have challenged the fundamental assumptions embedded in experimental designs and set the ground for an approach to study causal inferences and to reduce selection bias using observational data, the counterfactual framework. The reasoning of this framework is used in at logical analysis to investigate the hypothesis: "If A were the case, then B would have happened". This framework uses the thought of experiments to define causality. The following section describes why the reasoning of this framework is required to study neighbourhood effects in this thesis as an approach to reduce selection bias and to investigate causal associations.

7.3 The counterfactual causal framework

The aim of the analysis in this Chapter is to investigate a long-standing debate in neighbourhood effects research, whether living in a deprived area has negative consequences on young people's educational and employment outcomes compared to living in an affluent area. The debate on neighbourhood effects centres on the question of whether differences in outcome data (being NEET at the ages $18-19$) between high and low Crime areas are caused and explained by neighbourhood characteristics or are attributable to the characteristics of the population that lives in each area. If the differences in educational and employment outcomes were attributed to area characteristics (crime score), findings would suggest that area characteristics affect young people's outcomes. If the differences were attributed to family, individual, school and peer group characteristics of the population that lives in an area, findings would indicate that specific population characteristics would affect outcomes regardless of whether young people live in an area with high or low crime score. In order to make a comparison between high and low crime score areas possible, it would be necessary to assign study participants with similar characteristics into two groups, those who live in deprived and those who live in affluent areas and then to make a comparison. This would not be possible using observational data because a single individual cannot be observed simultaneously in a high and a low crime score area. Exposure to a causal state, such as area deprivation, could be the outcome of an individual's decision to enter one state or the other, random allocation by a researcher, or a government's decision to allocate individuals to a particular area or a combination of those. The fact that a single subject cannot live simultaneously in a high and low crime score area is referred to as the Fundamental Problem of Causal Inference (FPCI) (Holland [90], 1986). Under the FPCI a single subject can only be observed in one of two potential responses. To overcome this problem researchers have tried to develop improved methods for assessing treatment effects based on observational data. One of these methods is the counterfactual causal framework.

The counterfactual is a conceptual framework with origins in Neyman [134] (1935), Fisher [62] (1935), Cochran and Cox [35] (1950), Kempthorne [103] (1952) and a series of papers by Rubin [156, 157, 158, 159] (1974, 1978, 1980b, 1986). The model is used in social sciences to investigate causality with observational data. In this framework each individual in a population of interest can be exposed to one of two alternative states of a cause. Exposure to each state could affect an outcome of interest. In this study, the population of interest is young people at the ages $18-19$. The two states could be living in a high and a low crime Score area. The outcome is being in NEET status. In this framework the two alternative causal states are referred to as treatment and control. The usage of classic experimental terminology will be incorporated in this observational data analysis and therefore young people in high crime areas will be described as the treated group and those in low crime areas as the control group. Because each individual can only be observed in either the treatment or the control group, a researcher can never calculate individual-level causal effects using the counterfactual framework. Additionally, a key premise in the model is that each individual has a potential outcome in both causal states even though each individual can be observed only in either the treatment or the control state at any point in time. The focus on potential outcomes allows the researcher to conceptualise observational studies as if they were experimental designs. In this way the framework uses the logic and language of experiments to study causal relations.

A causal effect is the difference in outcome between a situation in which a subject receives a treatment and a counterfactual situation in which the same subject does not receive this treatment. The aim of this study is to investigate whether the difference observed in outcomes (NEET status) between young people who live in high crime areas (treated group) and low crime score areas (control group) is attributable to area characteristics (intervention) ceteris paribus. To explore a potential outcome, what would have happened, if a person was observed in both the control and treatment group, in both a deprived and non-deprived area. For a participant in a control condition, the counterfactual is the treatment condition. For a participant in the treatment condition, the counterfactual is the control condition. Thus, for a young person who lives in an area characterised by high crime score the counterfactual is a young person who lives in an area characterised by low crime score and vice versa. The counterfactual is not observed in the data, it is a missing value. For an evaluation of a programme or an intervention to be realised the missing value for a hypothetical outcome needs to be imputed. In other words, because a single subject cannot be observed simultaneously in the treatment and control groups, additional data is required to create a counterfactual and get the necessary information for a comparison to be realised.

The statistical application of the framework that will be employed in the analysis is based on the evaluation proposed by Rosenbaum and Rubin [155] (1983). The authors developed and extended the theoretical framework proposed by Neyman (1923) to address more complicated situations and thus developed propensity score analysis which will be employed in this thesis. The next section describes the theoretical background of propensity score analysis.

7.4 The Evaluation Framework and Matching

7.4.1 Theoretical background

This chapter employs propensity score matching (Rubin and Rosenbaum [155], 1983) as a method to study causal effects and remove selection bias using an observational study, the LSYPE. Several matching methods have been developed in the past (see for example Rubin [156, 157], 1974, 1979) prior to Rubin and Rosenbaum [155] (1983) who introduced the propensity score method. First generation matching methods paired observations based on either a single variable or weighting several variables. As matching methods became more widely used in social science research using observational studies, the computational complexity of implementing such methods increased substantially. Rubin and Rosenbaum [155] (1983) proposed a matching method that uses a binary representation of matching scores, thus reducing the computational complexity of previous methods.

The theoretical framework of propensity score matching starts with the Fundamental Problem of Causal Inference (FPCI) (Holland, 1986) that was briefly introduced in the previous section. The FPCI states that a key problem in identifying causal effects is that a treatment effect can be observed under either the treatment or control condition but not simultaneously. The theory behind the fundamental causal problem is described in this section.

Suppose that we have a population of size N and i index the population under consideration. We write Y_{i1} for the value of a binary variable of interest when unit i is subject to treatment 1 and Y_{i0} when unit i is subject to treatment 0. The treatment effect for a single unit of our population is defined as the difference $\tau = Y_{i1} - Y_{i0}$.

The purpose of PSM is to estimate the average treatment effect of some sample population of size N. We write

$$\begin{aligned} T|_{\tau=1} &= E(\tau_i \mid T = 1) \\ &= E(Y_{i1} \mid T_i = 1) \end{aligned}$$

where $T_i = 1$ if the ith unit was assigned to treatment and $T_i = 0$ if the the i-th unit was assigned to control group. The main problem in such an estimation is that by choosing a subset K of the given population of size N, the average treatment effect can be observed only when the chosen subset K is assigned either to treatment or to control group. More explicitly, it is not possible to observe the potential outcome under the treatment state for those in the control group and at the same time it is not possible to observe the potential outcome under the control state for those in the treatment group.

As a result direct comparisons between individuals is not possible in non-randomised experiments such as the observational study employed in this thesis.

7.4.2 Balancing scores and propensity scores

In randomised experiments, the results in the treatment and control groups can be compared because they are likely to be similar. However, in non-randomised experiments, such a comparison could be fallacious since the units exposed to one treatment differ systematically from the units exposed to the other treatment. In order to overcome the non-comparability of outcomes in non-randomised experiments, Rubin and Rosenbaum [155] (1983) introduced the notions of balancing and propensity scores, which allow comparisons between treated and control groups to be meaningful. The authors define balancing scores and propensity score as follows:

Let $x = (x_i, \ldots, x_n)$ be a vector of pretreatment measurements or covariates for a unit Y_i. A balancing score is a function, $b(x)$ of the observed covariates x_k for $k \in \{1, \ldots, n\}$ such that the conditional distribution of x given $b(x)$ is the same for treated (Y_{i1}) and control (Y_{i0}) units. The most trivial balancing score is $b(x) = x$. In general, given the vector x, one may define many functions on x that are balancing scores. The coarsest function of x that is a balancing score is called the *propensity balancing score*. More formally, given a vector x of covariates, let

$$e(x) = \mathrm{pr}(z = 1 \mid x)$$

be the conditional probability of assignment to treatment one, where

$$\mathrm{pr}(z_1, \ldots, z_n \mid x_1, \ldots, x_n) = \prod_{i=1}^{N} e(x_i)^{z_i} \{1 - e(x_i)\}^{1-z_1},$$

where $z_i = 1$ if unit i is assigned to the experimental treatment and $z_i = 0$ if unit i is assigned to the control treatment.

The function $e(x)$ is called the *propensity score*, that is the propensity towards exposure to treatment 1 given the observed covariate vector x.

7.4.3 Ignorable treatment assignment

This section refers to the two main differences between randomised and non-randomised experiments in relation to treatment assignment.

Randomised and non-randomised experiments differ in the conditional probability $e(x)$ of assigning one unit to a treatment. In randomised trials, the propensity score is a known function that exists for one accepted specification of $e(x)$. In a non-randomised experiment, the propensity score function is unknown which means that there is not one accepted specification of $e(x)$. In non-randomised experiments the propensity score function can be estimated with the use of a model such as for example a logit model.

In randomised trials, all the covariates that are possibly related to assigning treatments Y_{i1} and Y_{i0} are included in the analysis. This means that in a randomised experiment, treatment assignment z and treatment condition Y_{i1} and Y_{i0} are conditionally independent.

$$(Y_{i1}, Y_{i0}) \perp z \mid x$$

In non-randomised experiments, such as observational data, this condition does not hold. In addition, in randomised experiments, every unit of the population has equal chances of receiving a treatment in contrast to a non-randomised experiment. Rubin and Rosenbaum (1983) propose that treatment assignment is strongly ignorable given a vector of covariates v if

$$(Y_{i1}, Y_{i0}) \perp z \mid v, \quad 0 < \mathrm{pr}(z = 1 \mid v) < 1$$

7.4.4 The theory behind propensity score matching

Rosenbaum and Rubin [155] (1983) presented five theorems which provide the theoretical background of propensity score analysis. The theorems can be summarised as follows:

(1) The propensity score is a balancing score;

(2) Any score that is "finer" than the propensity score is a balancing score; moreover, x is the finest balancing score and the propensity score is the coarsest;

(3) If treatment assignment is strongly ignorable given x, then it is strongly ignorable given any balancing score;

(4) At any value of a balancing score, the difference between the treatment and control means is an unbiased estimate of the average treatment effect at that value of the balancing score if treatment assignment is strongly ignorable. Consequently, with strongly ignorable treatment assignment, pair matching on a balancing score, sub-classification on a balancing score and covariance adjustment on a balancing score can all produce unbiased estimates of treatment effects;

(5) Using sample estimates of balancing scores can produce sample balance on x.

For the purposes of this analysis, we present the theorems that are most relevant. Theorem 1, 2, 3 and 4 and Corollary 4.1.

Theorem 7.4.1. *Treatment assignment and the observed covariates are conditionally independent given the propensity score, that is*

$$x \perp z \mid e(x).$$

Proof. This theorem is a special case of Theorem 7.4.2. □

Theorem 7.4.2. *Let $b(x)$ be a function of x. Then $b(x)$ is a balancing score, that is,*

$$x \perp z \mid b(x),$$

if and only if $b(x)$ is finer than $e(x)$ in the sense that $e(x) = fb(x)$ for some function f.

Proof. See [155] Theorem 2. □

Theorem 7.4.3. *If treatment assignment is strongly ignorable given x, then it is strongly ignorable given any balancing score $b(x)$, that is,*

$$(Y_{i1}, Y_{i0}) \perp z \mid x$$

and

$$0 < \mathrm{pr}(z = 1 \mid x) < 1$$

for all x imply

$$(Y_{i1}, Y_{i0}) \perp z \mid b(x)$$

and

$$0 < \mathrm{pr}\{z = 1 \mid b(x)\} < 1$$

Proof. See [155] Theorem 3. □

Theorem 7.4.4. *Suppose treatment assignment is strongly ignorable and $b(x)$ is a balancing score. Then the expected difference in observed responses to the two treatments at $b(x)$ is equal to the average treatment effect at $b(x)$, that is,*

$$E\{Y_{i1} \mid b(x)\,, z = 1\} - E\{Y_{i0} \mid b(x)\,, z = 0\} = E\{Y_{i1} - Y_{i0} \mid b(x)\}. \tag{7.1}$$

The following Corollary allows direct application of the balancing and propensity score methods in pair-matching techniques which will be the main focus of the analysis.

Corollary 7.4.5. *Pair matching on balancing scores. Suppose treatment assignment is strongly ignorable. Further suppose that a value of a balancing score* $b(x)$ *is randomly sampled from the population of units, and then one treated,* $z = 1$*, unit and one control,* $z = 0$ *unit are sampled with this value of* $b(x)$*. Then the expected difference in response to the two treatments for the units in the matched pair equals the average treatment effect at* $b(x)$*. Moreover, the mean of matched pair differences obtained by this two-step sampling process is unbiased for the average treatment effect, denoted by* $E(Y_{i1}) - E(Y_{i0})$*.*

This section described the theoretical framework and application principles of propensity score matching proposed by Rosenbaum and Rubin (1983). This theoretical framework has served as a basis for new models that were developed in the course of time to refine logistic regression, to estimate propensity scores and to combine propensity scores with conventional statistical methods. The next section will describe the analytic step-by-step process of implementing propensity scores that will be followed in this study and the dataset that will be employed in the analysis. The goal of the analysis will be to estimate the counterfactual; to investigate the potential educational and employment outcomes for people who live in areas characterised by high crime score (treated group) if they lived in areas with low crime score (control group).

7.5 Methodology and Data

The analysis employed in this chapter is going to test a counterfactual model of neighbourhood effects using propensity score matching and employing the dataset introduced by the Compositional Model of Neighbourhood Effects in Chapter 6.

7.5.1 The counterfactual model

The counterfactual model for the purposes of this research could be illustrated as follows. We assume that each young person i could live in a highly deprived area $W_j = 1$ or in a low crime area $W_j = 0$ and become NEET at $18-19$ ($X_{1i} = 1$) or not ($X_{1i} = 0$). Individuals who would be selected in treatment or control groups could have potential outcomes in both states; the one that is observed and the one that is not observed. The counterfactual framework would be expressed with the following model:

$$X_{1i} = W_j \times X_{1i} + (1 - W_j)X_{1i}. \tag{7.2}$$

The hypothesis that will be tested is that a young person i who lives in a high Crime area will become NEET at the ages $18-19$. Let W_j be a dichotomous variable ($W_j = 1$ high Crime Score and $W_j = 0$ low Crime Score). The treatment variable for a young person in a deprived area would be $W_j = 1$. The outcome variable would be $X_{1i} = 1$ if the young person is at NEET status at $18 - 19$ and $X_{1i} = 0$ otherwise. To make a causal inference that living in a highly deprived area ($W_j = 1$) causes NEET status ($X_{1i} = 1$), it would be necessary to examine NEET status (X_{i1}) under the condition of living in a low Crime area ($W_j = 0$) to investigate the potential outcome in the counterfactual condition and then compare the outcome with the treatment condition. For this comparison to take place propensity score matching will be employed so that each treated subject will be matched to one control subject to create two groups identical in observable characteristics prior to treatment. In the next subsection, we describe the methodology of propensity score matching.

7.5.2 Methodology

The *first* step in propensity score matching involves selecting the covariates that could be related to different outcomes in treated and control groups and investigating the probability of receiving a treatment. The selection of covariates considered to influence young people's educational and employment outcomes and the model specification for this analysis were informed by theories on neighbourhood effects and young people's development and by previous research on NEETs (see Section 6.6.3). The selection of covariates was informed by the Compositional model of neighbourhood effects that was tested in Chapter 6. After the selection of covariates, the probability of receiving a treatment needs to be estimated. The estimated predicted probabilities of receiving a treatment are the propensity scores. In the context of this analysis, treated and control participants, sharing a similar propensity score will be compared.

After propensity scores are estimated, the *second* step involves matching treated to control participants to reduce bias by choosing a matching algorithm. The advantage of using a single propensity score is that it allows the researcher to avoid the problem of matching failure that would occur if balancing scores were obtained for each covariate separately. A possible consequence of matching is loss of participants in the study. This could happen because controls can be matched with some treated participants but not with all. Due to the fact that not all controls are matched with treated participants, matching is also described as resampling. The aim of this approach is to create two groups (treated and control) that are going to be as similar as possible in terms of their propensity scores to reduce bias. It is important to note that in propensity score matching, the estimated effects are effects of treatment on the treated and not effects of treatment for a whole population. In particular, for the purposes of this study a propensity score matching approach estimates the effect of living in a deprived area on young people becoming NEETs only for those young people and their families who live in a deprived area and not for any individual who could live in a deprived area. Additionally, not all individuals who receive a treatment are equally affected. The matching approach estimates the average treatment effect and not the effect for each individual.

The PSM matching estimator was stated in Equation (7.1). The role of each matching estimator is to compare the outcome of treated individuals with outcomes of control group individuals. Many algorithms for matching exist which differ in respect to the way the "neighbourhood" for the treated individuals are defined and how the weights are assigned to these "neighbours". The most common used matching algorithms are the Nearest Neighbour, Caliper and Radius, Stratification and Interval, Kernel and Local Linear, and Weighting. Choosing a specific matching algorithm can be very important in small samples (Heckman, Ichimura, and Todd [83], 1997). However, as the sample size grows bigger, all PSM estimators should provide the same results because all the estimators are closer to comparing only exact matches (Smith, [176] 2000; Caliendo and Kopeinig [30], 2008). This study follows the Nearest Neighbour (NN) without replacement without caliper matching approach and additionally tests for the Nearest Neighbour with replacement, the Mahalanobis and the Kernel approaches. The Nearest Neighbour matching method (Rubin [156]) is considered effective when individuals are studied in follow-up studies. This method matches the control to the treated group and drops control cases that are not selected as matches. Let's assume that P_i and P_j are the propensity scores for treated and control participants respectively. The treated group is I_i and the control group is I_j. A neighbourhood $C(P_i)$ contains a control participant j as a match for a treated participant i if the absolute difference of propensity scores is the smallest among all possible pairs of propensity scores between i and j. Once j is found to match i, j is removed from I_0 without replacement. If for each i there is only one j found in the $C(P_i)$ then the matching is nearest neighbour matching or $1-1$ matching. If for each i there are n participants in the $C(P_i)$, then the matching is 1 to n matching.

Matching can be used with or without caliper. Caliper is a tolerance level on the maximum propensity score distance employed to avoid bad matches in case the closest neighbour is found far away. More specifically, using a caliper means that an individual from the control group is chosen to match an individual from the treated group that lies within the caliper and is closest in terms of the propensity score. A caliper has similar properties to matching with replacement. It allows bad matches to be avoided and therefore it is considered a tool that improves matching quality. However, employing a caliper also means that fewer matches are performed which consequently increases the variance of the estimates. Additionally, another disadvantage of employing a caliper is that it is not easy to estimate the propensity range that denotes the appropriate level of tolerance to be imposed (Smith and Todd [177], 2005).

One potential drawback raised by critiques of the counterfactual framework, which applies especially to the Nearest Neighbour matching approach, is that it is not always feasible to match treatment cases to controls. Because of this, it is only possible to estimate treatment effects for the treated cases that are matched which could cause a reduction in the final sample size; see [155, Corollary 4.1]. The counter-argument provided by Cohen [36] (1988) is that in a two sample comparison of means, smaller group sizes allow higher accuracy in comparisons. Additionally, the statistical power increases when similar groups are compared as they are more analogous and comparable because of the reduced extrapolation (Snedecor and Cochran [178], 1980). In a similar way, Wacholder and Weinberg [192] (1982) claim that higher precision is obtained in comparing matched pairs in randomised experiments. In other words, estimating treatment effects only for some of the treatment group may result in more robust results compared to estimating effects for the entire group.

The *third* step in the analysis involves estimating first the probability of being NEET if one individual is in the treatment and non-treatment group and second average treatment effects. Average treatment effects are estimated as the difference between the mean scores of participants in treatment and control conditions. This is necessary because of the restrictions imposed by the fundamental causal inference problem. More explicitly, since it is not possible to observe outcomes for treated and non-treated at the individual level, group averages are used to investigate counterfactuals.

Having presented briefly the methodology that will be followed using Propensity Score Matching, the next section describes in detail the statistical analysis. The analysis will be implemented using Stata. Software packages do not offer established operations for implementing propensity score matching. There are limited algorithms developed by users of propensity score analysis such as **psmatch2** in Stata that was created by Leuven and Sianesi [109] (2003); **boost** in Stata that was developed by Schonlau [168] (2005); **optmatch** in R developed by Hansen [79] (2007). For the purposes of this research, the **psmatch2** algorithm was employed to match treated to control participants under the Nearest Neighbour matching approach.

7.6 Analysis and results

7.6.1 Covariate selection and balancing score

The first step involves selecting the vector of covariates that will be included in the analysis and estimating the propensity score that will be used to balance the observed covariates and to match treated and control groups.

Data

The counterfactual model of neighbourhood effects will be estimated by employing the data introduced in the Compositional Model of Neighbourhood effects that was tested in Chapter 6 and the hypothesized pathways of neighbourhood effect in Section 3.4. Logistic regression analysis was the methodology selected to build the model in a sequential process that involved five steps. Initially, the relationship between living in an area characterised by high crime and NEET status was tested using a bivariate logistic regression model. Thereafter, multivariate logistic regression was employed. Variables were added in the model sequentially to investigate the effect of living in an area characterised by high crime on the probability of young people becoming NEETs after controlling for family, individual, school and peer group characteristics. The final multiple logistic regression model controlled for all the covariates addressed in the Compositional Model of Neighbourhood effects. The vector of covariates employed in the final model that was tested in Section 6.11 will be used to estimate the counterfactual in the analysis in this chapter. The propensity score approach requires the treatment variables to be binary, since the propensity score states by definition the probability of being in either the treatment or the control state, either living in a high crime area or in a low Crime area. More specifically, the dependent variable will be a binary variable denoting young people either in NEET status or in Education, Employment and Training at the ages $18-19$. The key independent variable will be high and low Crime Score. The analysis involves only high and low crime score areas omitting areas characterised by middle crime levels to imitate an experiment as close as possible. The vector of independent variables will introduce family characteristics including the main parent having no qualification, parents being claimants of benefits for people in low income, mother birth age under 20, and whether the young person belonged in a single parent family. Parental practices in the model will be described by parental monitoring when the young person goes out at night and parental aspirations for future outcomes of the young person. Individual characteristics will be denoted by educational attainment of young people and ethnicity. Attitudes of the young person to school will be investigated by variables that describe attitudes to schooling and perceptions of educational attainment. Finally, peer group effects and antisocial behaviour will be investigated by whether the young person was excluded from a group of friends and whether the police has got in touch with the young persons parents for their behaviour.

It is important to stress that in propensity score matching only observed characteristics are balanced in the treatment and control group under comparison. Conversely, in random experiments both observed and unobserved characteristics are balanced in the treatment and control groups. Observed characteristics refer to covariates that can be measured and are considered to affect the outcome. For example, in neighbourhood research, parental socioeconomic status is an observed characteristic that could influence the decision to live in a high or low crime area and subsequently have an effect on young people's outcomes. Unobserved characteristics refer to covariates that could influence young people's outcomes but cannot be measured and included in the analysis such as for example individual motivation and ability. Although the results of this analysis are conditional only on the observed covariates, attention has been paid to include as many of the covariates as possible that are considered to be related to living in a high crime area in the model. Measuring a wide range of covariates related to the treatment assignment can increase confidence about producing unbiased estimates for the treatment effect.

The propensity score

After the vector of covariates that will be included in the analysis is specified, the propensity score needs to be estimated. Matching pairs design was chosen in this study as it offers the advantage that the analysis is less affected by biases. The matching is usually based on subject characteristics relevant to each study such as for example age and gender. In this study, matching will be based on the Crime Score of the subject's area of residence that will be employed to estimate the propensity score. Propensity score is the probability that one individual will participate in the treatment or control group, a high or low crime score area. To estimate the propensity score, logistic regression analysis was employed of the binary category (treatment / control) on the chosen observed covariates. The propensity score is estimated in terms of the observed covariates even when there are concerns about hidden biases due to unobserved covariates. The role of the propensity score, when matching to one variable is selected, is to balance all of the observed covariates; see [155, Theorems $1-4$].

Table 7.1: 'Estimating Regression Coefficients for the Propensity Score' presents the regression coefficients in estimating the propensity score. The results show that young

people have a higher probability to live in a high crime area if their parents have no qualification (0.17***); if their parents claim benefits for low income (0.16***); if their mother was at the age of 20 when she gave birth to the young child (0.14***); if they live in a single parent family compared to living in a family with two parents (0.09***); if their parents monitor them sometimes when they go out at night (0.07); if have low educational attainment in KS2 (0.06***); if they belong to a minority ethnic group (mixed ethnicity: 0.23***, Indian: 0.37***, Pakistani: 0.54***, Bangladeshi: 0.45***, Black Carribean: 0.58***, Black African: 0.47***, other ethnicity: 0.46***); if the young person played truant in the last twelve months (0.10***), and; if the police got in touch with their parents for their behaviour (0.05); if a young person strongly agreed that they count minutes until a lesson ends (0.01) and; if the young person feels that they are not good at maths (0.01). In contrast, young people have a lower probability to live in a high crime area if their parents aspire their children to continue to full time education after compulsory education (-0.03*); and; if a young person was excluded from a group of friends over the last twelve months (-0.02). The z test is the test statistic for the null hypothesis that an individual predictor's (living in a high Crime area) regression coefficient is zero. The z value follows the normal distribution which is used to test against a two-sided alternative hypothesis that the regression coefficient is not zero.In particular the z-statistic is the ratio of the coefficient to the standard error of the respective predictor. The probability that a particular z test statistic is extreme or larger than what has been observed under the null hypothesis is defined by $P > |z|$.

Table 7.1: Estimating Regression Coefficients for the Propensity Score

Variable name	Effect	Standard Error	z	P > |z|
Highest qualification of main parent: No qualification	0.17	0.02	8.67	0.000***
Benefit claimants	0.16	0.02	10.39	0.000***
Mother birth age under 20	0.14	0.03	4.82	0.000***
Single parent family	0.09	0.02	5.12	0.000***
Parenting monitoring: Sometimes	0.07	0.05	1.31	0.000***
Parental aspirations: Full-time education	−0.03	0.02	−1.97	0.048*
KS2 1st quart (low attainment)	0.06	0.02	3.69	0.000***
Mixed Ethnicity	0.23	0.03	7.50	0.000***
Indian	0.37	0.03	7.50	0.000***
Pakistani	0.54	0.05	9.85	0.000***
Bangladeshi	0.45	0.06	7.00	0.000***
Black Carribean	0.58	0.05	11.54	0.000***
Black African	0.47	0.04	9.85	0.000***
Other Ethnicity	0.26	0.04	7.00	0.000***
Young person played truant	0.10	0.02	9.70	0.000***
In a lesson count minutes till it ends	0.01	0.03	9.75	0.894
Young person feels not very good at maths	0.01	0.02	5.95	0.861
Police got in touch with main parent for young person's behaviour	0.05	0.03	4.77	0.083
Young person was excluded from a group of friends	−0.02	0.02	0.13	0.268
Number of observations	5436			
LR chi2	1371.64			
Pseudo R2	0.196			
Log Likelihood	−2811.7499			
$p < 0.5$, $^{**}p < 0.01$, $^{***}p < 0.001$				

Matching estimators based on the propensity score

After estimating the propensity score to identify the probability that a young person did live in a high or low Crime Score area, a matching algorithm will be employed to match individuals to treatment and control groups. As already explained in Section 7.5.2 several matching algorithms exist from which the Nearest Neighbour (NN) without replacement without caliper is chosen for this study. The treated subjects were randomly ordered before running psmatch2 to match data. Random ordering of data is required before matching treated and control groups to avoid getting observations with identical propensity score values. Random sorting was achieved by creating a random variable and sorting data on it. It is important to note that even sorting data in a random order does not guarantee that there will not be observations with identical propensity score values. This happens because random sorting does not alter the fact that some observations have the same propensity scores often because the scores are based primarily on categorical variables. After sorting the data, the logit of the propensity score presented in the previous section was used in a 1 to 1 matching approach in which a single untreated subject was matched to each treated subject. Each treated subject was matched to a control subject whose propensity score was closest to that of the treated subject. Matching was employed without replacement and therefore subjects from the control group that were matched to the treated group were not available to be used as matches again. Additionally, matching without caliper was employed which means that there was not a pre-specified maximum distance imposed, and therefore a sufficient number of unmatched subjects was available for each treated subject. The matching after psmatch2 was employed generated 1,337 untreated individuals and 2,068 treated individuals. The total sample in the analysis included 3,405 individuals.

The propensity score, as a function of the observed covariates, was employed to achieve a similar conditional distribution for the treated and control groups [1].

[1]The analysis is also conducted using the Nearest Neighbour with replacement, the Mahalanobis and the Kernel matching estimators. All the PSM estimators generate the same results. This can be

The propensity score balanced the covariates in the two groups and therefore it reduced bias. Table 7.2: 'Selection bias before and after matching' presents bias before and after matching individuals in treated and untreated groups conditional on the individual's covariate values. Before matching the t-statistic is significant because it shows a big difference between treated and control groups. After matching, bias is reduced based on covariate values. In most cases bias is reduced at roughly 100% after matching. A high percentage in bias reduction suggests that the two groups become identical after matching. The t-statistic tended to 0 after matching which is also indicative of having two identical groups. The bias reduction was lower for the covariate denoting antisocial behaviour (police got in touch with parents for something the young person had done: 46.5%). A small reduction in bias was observed in attitudes to schooling (the young person counts minutes until a lesson ends: 13.2%) and no bias reduction was observed on young person's perception of educational attainment (young person feels not very good at maths: −184%).

explained because the sample size in the analysis is big. As already noted, using different matching estimators with large scale data should produce the same results regardless of the method employed because they achieve comparing exact matches (Smith, [176] 2000).

Table 7.2: Selection bias before and after matching

		Mean		%Reduction		t-test	
Variable name	**Sample**	**Treated**	**Control**	**%bias**	—bias—	t	$P > \|t\|$
Highest qualification of Main Parent: No qualification	Unmatched	1.94	1.76	50.4		13.63	0
	Matched	1.93	1.93	0.4	91.1	0.16	0.874
Benefit claimants	Unmatched	1.77	1.5	59.1		16.55	0
	Matched	1.77	1.76	1.3	97.8	0.37	0.714
Mother birth age under 20	Unmatched	1.97	1.92	22.6		6.14	0
	Matched	1.97	1.97	-1.3	94	-0.48	0.628
Single parent family	Unmatched	1.89	1.75	36.3		10.03	0
	Matched	1.89	1.89	-1.6	95.7	-0.49	0.622
Parental monitoring: Sometimes	Unmatched	1.99	1.98	13.6		3.67	0
	Matched	1.98	1.99	-1.9	86.4	-0.78	0.437
Parental aspirations: Full time education	Unmatched	1.17	1.19	-6.7		-1.89	0.059
	Matched	1.17	1.17	0.6	91.2	0.16	0.876
KS2 1st quartile (low attainment)	Unmatched	1.86	1.74	29.6		8.23	0
	Matched	1.86	1.86	0.2	99.4	0.06	0.956
Mixed Ethnicity	Unmatched	1.97	1.93	14.2		3.93	0
	Matched	1.97	1.96	1	92.7	0.32	0.752
Indian	Unmatched	1.97	1.9	30.4		8.17	0
	Matched	1.97	1.98	-1.6	94.8	-0.65	0.517
Pakistani	Unmatched	2	1.93	34.2		8.93	0
	Matched	2	1.99	0.4	98.8	0.3	0.763
Bangladeshi	Unmatched	2	1.9	26.2		6.88	0
	Matched	2	2	0.5	100	0	1
Black Carribean	Unmatched	2	1.94	30.8		8.05	0
	Matched	2	2	0	100	0	1
Black African	Unmatched	1.99	1.96	25.2		6.65	0
	Matched	1.99	1.99	0	100	0	1
Other Ethnicity	Unmatched	1.99	1.97	17.2		4.64	0
	Matched	1.99	1.99	0	100	0	1
Young person played truant	Unmatched	1.91	1.84	21.6		6	0
	Matched	1.91	1.9	1.8	91.5	0.54	0.587
In a lesson count minutes till it ends	Unmatched	1.89	1.87	5.3		1.51	0.131
	Matched	1.89	1.9	-4.6	13.2	-1.28	0.202
Young person feels not very good at maths	Unmatched	1.88	1.88	0.9		0.26	0.795
	Matched	1.88	1.9	-2.6	-184.1	-0.68	0.493
Police got in touch with main parent for young person's behaviour	Unmatched	1.96	1.94	8		2.24	0.025
	Matched	1.96	1.97	-4.3	46.5	-1.3	0.193
Young person was excluded from a group of friends	Unmatched	1.83	1.83	2.2		-0.64	0.524
	Matched	1.83	1.83	-0.4	82.1	-0.1	0.918
Pseudo R2	Unmatched	0.188					
	Matched	0.002					
LR chi2	Unmatched	857.42					
	Matched	6.67					
$P > chi2$	Unmatched	0					
	Matched	0.996					

$*p < 0.5$, $**p < .01$, $***p < 0.001$

Table 7.3: Treatment Effects

Variable	Sample	Treated	Controls	Difference	S.E	T-stat
NEET	**Unmatched**	0.091	0.156	−0.065	0.016	−5.55
	Average Treatment on the Treated (ATT)	0.091	0.132	−0.042	0.014	−3.01
	Average Treatment on the Untreated (ATU)	0.156	0.133	−0.023		
	Average Treatment Effect (ATE)			−0.030		

Note: S.E. does not take into account that the propensity score is estimated

After employing the propensity score to match groups and observing the reduction in bias, the next step involves estimating the average treatment effect and the conditional probability of being NEET. The average treatment effect (ATE) is usually employed in randomized experiments to compare mean outcomes between treated and untreated units. Observational studies also employ ATE to compare the mean outcomes for treated and control groups. The results in Table 7.3: 'Treatment Effects' suggest that after comparing treated and control groups, young people in Education, Employment or Training are less likely to live in high Crime Score areas. In particular, the ATE shows that the probability for young people in Education, Employment or Training to live in low Crime Score neighbourhoods is −0.030 lower compared to the probability for young people in NEET status. This result answers the initial question posed in this chapter; "What would be the educational and employment outcomes for people who live in high crime areas if they lived in low crime areas". The analysis indicates that there is a 3% higher probability for young people in high Crime areas to be in NEET status. The number is small but confirms the initial hypothesis that young people who live in areas characterized by high crime are more likely to be in NEET status compared to those who live in areas with low crime score areas.

After estimating the ATE, a probit regression is run to estimate the probability of being NEET for young people in the treated group (areas with high Crime Score) conditional on observed covariates. Probit regression is selected because the outcome variable is binary. Table 7.4: 'Estimating Regression Coefficients for Propensity Score Analysis' presents probit analysis results. *Effect* in Table 7.4 refers to the estimated probability of being NEET for young people in the treated group. The results indicate that the probability of being NEET in the treated group is higher for young people when the main parent has no qualification ($0.54***$); the main parent claims benefits for low income ($0.50***$); mother's age at birth of the young person was under 20 ($0.36**$); they were in a single parent family ($0.23**$); the main parent knows sometimes (versus always or never) where the young person is when they go out at night ($0.56*$); the young person has low educational attainment; the young person belongs to an ethnic minority group in comparison to being white; and the young person played truant over the last twelve months ($0.30***$). Covariates that increase the probability of being NEET in the treated group but are not significant are counting minutes in a lesson until it ends (0.04) and if the police got in touch with the young persons parents for something the young person had done (0.04). The covariate parental aspirations to continue to full time education decreases the probability of being NEET for young people in the treated group. Additionally, negative perceptions about math attainment and being excluded from a group of friends marginally decrease the probability of being NEET even though they are not significant.

Table 7.4: Estimating Regression Coefficients for Propensity Score Analysis

Variable name	Effect	Standard Error	z	P > |z|
Highest qualification of main parent: No qualification	0.54	0.08	7.03	0.000***
Benefit claimants	0.50	0.05	8.99	0.000***
Mother birth age under 20	0.36	0.11	3.10	0.002**
Single parent family	0.23	0.07	3.40	0.001**
Parenting monitoring: Sometimes	0.56	0.22	2.50	0.012*
Parental aspirations: Full-time education	−0.05	0.06	−0.86	0.388
KS2 1st quart (low attainment)	0.18	0.06	2.91	0.004**
Mixed Ethnicity	0.60	0.11	5.19	0.000***
Indian	1.05	0.11	9.46	0.000***
Pakistani	1.66	0.21	7.78	0.000***
Bangladeshi	1.29	0.23	5.59	0.000***
Black Carribean	1.63	0.22	7.51	0.000***
Black African	1.40	0.20	7.04	0.000***
Other Ethnicity	0.98	0.18	5.43	0.000***
Young person played truant	0.30	0.08	3.96	0.000***
In a lesson count minutes till it ends	0.04	0.07	0.49	0.625
Young person feels not very good at maths	−0.04	0.07	−0.48	0.634
Police got in touch with main parent for young person's behaviour	0.04	0.12	0.31	0.758
Young person was excluded from a group of friends	−0.03	0.06	−0.50	0.616
Number of observations	3405			
LR chi2	857.42			
Pseudo R2	0.188			
Log Likelihood	−1852.3763			
$p < 0.5$, $^{**}p < 0.01$, $^{***}p < 0.001$				

The results of the probit regression used to find the probability of being NEET for the treated and the untreated group in this analysis can be compared with the logistic regression analysis results found in Chapter 6. It is notable that both analyses find similar results with regards to the effect of living in a neighbourhood characterized by high Crime Score. The logistic regression analysis showed that living in a top quartile crime score area increases the probability of being NEET at $18-19$ after controlling for a vector of covariates in five subsequent models that were introduced by the Compositional Model of Neighbourhood Effects. Propensity score matching also shows that individuals that receive a certain treatment (living in a high crime score area) conditional on the vector of covariates introduced by the Compositional Model of Neighbourhood Effects have a higher probability of being NEET at $18-19$ compared to individuals in the control group (living in a low crime score area). Apart from the effect of the neighbourhood context, the effect of the observed covariates is also similar in both logistic regression and propensity score matching analyses. Parental educational qualifications, income, mothers age at birth and family composition are significant predictors of being NEET at $18-19$. The same holds with parental practices, educational attainment, attitudes to schooling and perceptions of educational attainment. The only differences between comparing the results from the two analyses is that all ethnic minorities appear to be significant predictors of NEET status in PSM whereas in the logistic regression analysis only the Indian group remained significant in the final model. Additionally, young people's perception of schooling ability and being excluded from a group of friends had a significant positive effect on NEET status in logistic regression but they appear to have a small negative effect when PSM is employed. Overall, the findings are similar in both analyses. The logistic regression model estimated that the probability of being NEET is higher for young people in high Crime Score areas. Further in-depth analysis was carried out employing a propensity score matching approach in an attempt to balance the covariates in two groups, treatment and control, and thus to reduce bias. The analysis showed that the conditional probability of being NEET was higher for young people in the treatment compared to the control group.

This section employed the reasoning of a randomised experiment by comparing a treatment and a control group to investigate in depth the Compositional Framework of Neighbourhood Effects using an observational study. Propensity score matching was the method selected to create the treatment and control groups and to estimate the difference between the potential responses that could be observed under each of the two groups. The aim of the propensity score analysis was to estimate the conditional probability of being NEET for young people in high crime areas based on observed characteristics and thus to reduce bias and to establish causal effects.

7.7 Sensitivity Analysis

Propensity score matching is used in this analysis in an attempt to gain the structure and the strength of an experiment using observational data. Matching is a method to adjust pretreatment differences between a treatment and a control group in observed covariates. Such an adjustment might not control for hidden biases caused by unobserved covariates that could be important predictors in the analysis. Hidden bias is a common problem in observational studies caused because unobserved covariates, which might affect the conclusions of a study, are not included in a statistical analysis. This is not a problem in randomised experiments where subjects are assigned to treatment and control groups at random. Before the treatment occurs in random experiments, the treatment and control groups differ only by chance. Therefore, comparing treatment and control groups after the treatment is possible and a treatment effect can be clearly shown. In successful randomization, the groups of subjects are balanced with respect to all variables except for the variable of interest. The groups under comparison are balanced not only with respect to observed covariates but also with respect to unobserved covariates. In contrast, in non-randomised experiments the researcher can control for observed covariates but it is not possible to establish causal relations because of unobserved covariates that might incur hidden biases and affect the observed associations.

Two approaches are employed to reduce hidden bias caused by unobserved characteristics, elaborate theories and sensitivity analysis. Cochran [34] (1968) suggests that hidden biases due to unobserved covariates can be limited by employing elaborate theories which can help detect hidden biases. Elaborate theories are a useful tool for selecting covariates in the analysis that help create comparable groups and subsequently conduct specific comparisons. In this study, covariate selection was guided by the Compositional Model of Neighbourhood effects that was informed by theories that explain neighbourhood effects and by theories that describe human development within structural, social and cultural contexts. In addition to elaborate theories, sensitivity analysis is employed in observational studies to investigate the magnitude of hidden biases that need to be present in a study to alter the qualitative conclusions of the study. Sensitivity analysis aims to investigate how much hidden bias can be present in an analysis. This type of analysis does not eliminate the effect of unobserved characteristics, it rather clarifies the magnitude of hidden bias and its effect on the research outcomes. Sensitivity analysis explains whether a researcher should proceed to further investigation to draw causal inferences or not in order to explain hidden bias derived by unobserved characteristics.

The first sensitivity analysis using observational data was conducted by Cornfield et al [39] (1959) who provided the original framework for this type of analysis in a study of cigarette smoking as a cause of lung cancer.The authors compared the probability of death from lung cancer for smokers over the probability of death from lung cancer for non-smokers. The aim was to investigate the discussion raised at the time that smoking might not cause lung cancer but rather that smoking might be related to unobserved characteristics such as genetic predisposition. Cornfield et al found that if an unobserved characteristic was related to lung cancer, it would have to be a very good predictor of lung cancer and approximately nine times more common among smokers than non-smokers. In this sense, the authors used sensitivity analysis to investigate the common concern that association does not imply causality. Sensitivity analysis did not reduce the possibility that unobserved characteristics related to lung cancer existed; It stated the magnitude of hidden bias that needed to exist to explain the observed association between smoking and lung cancer.

Matching techniques in conjunction with sensitivity analysis are rarely employed in the literature in social sciences. One of the first studies using this methodological approach was by Aakvik [1] (2001) who employed matching and sensitivity analysis in an evaluation of a Norwegian vocational rehabilitation programme. The study involved a comparison of employment outcomes of people who participated in a training scheme and nonparticipants using observational data. The analysis employed a matching estimator based on the propensity score to calculate the training effect for the treatment and control group. The overall training programme was found to be significant and higher for individuals less likely to participate in a training programme compared to individuals with a high training probability. Further analysis was carried out to investigate whether the results were sensitive to bias caused by the effect of unobserved covariates on an individual's training status. The overall training effect was found to be significant to selection bias. However, the result that showed that the training effect was positive for individuals less likely to participate in training was not sensitive to bias.

Sensitivity analysis as an approach to explore hidden bias was based on the theoretical framework introduced by Rosenbaum [153] (2002) which is described in the following section.

Propensity score matching is a common method to remove selection bias and to investigate causal inferences in the absence of randomised experiments by estimating average treatment effects. A limitation of the matching approach is that this method is based on the conditional independence or unconfoundedness assumption, which states that all covariates that could influence treatment assignment and the average treatment effect should be observed. In real case scenario, it is almost impossible to include and measure all possible covariates that might affect treatment assignment and outcomes. Hence, one may argue that propensity score matching is limited in the sense that it only includes observed covariates. As a result the researcher is restricted because unobserved characteristics which might affect treatment assignment and outcomes are not included in the analysis using propensity score matching. Unobserved characteristics which are not included in the analysis might be the cause of hidden bias and misleading results because the matching estimators are not robust (Rosenbaum [153], 2002).

To address this problem Rosenbaum [153] (2002) proposed a complimentary analysis, called sensitivity analysis. Loosely speaking, Rosenbaum [153] (2002) developed a bounding approach, testing how "sensitive" are the results given by Propensity Score Analysis in relation to unobserved covariates.

7.7.1 Sensitivity analysis model

In this section we establish some notation to describe the theoretical model that checks the sensitivity of estimated treatment effects.

We write

$$P_i = P(x_i, u_i) = P(D_i = 1 \mid x_i, u_i) = F(\beta x_i + \gamma u_i), \tag{7.3}$$

where P_i denotes the probability of an individual participating in either the control or the treatment group, x_i denotes the vector of observed covariates, u_i denotes the vector of unobserved covariates, $D_i = 1$ is the i-th individual in a population D of size $|D| = n$, that participates in the treatment group ($D_i = 0$ if the individual i does not participate in the treatment group). Moreover, we write β for the "possible" scaling factor effect on the vector of observed covariates. Similarly, we write γ for the scaling factors effect on the vector of unobserved covariates. Finally, given a pair of matched individuals i, j, with $i, j \in D$, we assume that the probabilities of treatment assignment follows a logistic distribution. Notice that, such an arbitrary selection of individuals i and j is possible, since the Propensity Score Analysis matches individuals in control and treatment groups with similar characteristics which makes direct comparison between these two groups possible.

Equation (7.3) denotes that the participation probability depends on a vector of observed and unobserved characteristics for individuals i and j. The odds that the individuals i and j are assigned in the treatment group are given by $P_i/(1 - P_i)$ and

$P_j/(1-P_j)$, and the relative odds ratio is given by:

$$\frac{\frac{P_i}{1-P_1}}{\frac{P_j}{1-P_j}} = \frac{P_i(1-P_j)}{P_j(1-P_i)} = \frac{\exp(\beta x_i + \gamma u_i)}{\exp(\beta x_j + \gamma u_j)} \tag{7.4}$$

Recall that due to propensity score matching βx_i and βx_j are matched individuals with identical observed covariates. Therefore, in equation (7.4) βx_i and βx_j cancel out. Hence,

$$\frac{\exp(\beta x_i + \gamma u_i)}{\exp(\beta x_j + \gamma u_j)} = \exp\{\gamma(u_i - u_j)\}. \tag{7.5}$$

Sensitivity analysis measures how a change in the values of $(u_i - u_j)$ and/or γ alters the interpretation of the average treatment effect given by the Propensity Score Analysis. More precisely, if there are no differences in unobserved variables $(u_i = u_j)$ then (7.5) becomes 0 and as a result our analysis depends solely on observed variables measured by the Propensity Score Analysis. On the other hand, if unobserved variables have no influence on the participation probability, i.e. $\gamma = 0$, then Equation (7.5) is equal to one. In both cases, unobserved variables are not a cause of selection bias. If however there are differences in unobserved variables $(u_i \neq u_j)$ and if unobserved variables influence the probability of participating $\gamma \neq 0$, then sensitivity analysis is required to measure the effect of unobserved covariates on average treatment effects. In [153], Rosenbaum shows that Equation (7.4) gives the following bounds for the probability that one individual, for an arbitrary matched pair $i, j \in D$, will receive treatment:

$$\frac{1}{e^{\gamma}} \leq \frac{P_i(1-P_j)}{P_j(1-P_i)} \leq e^{\gamma}. \tag{7.6}$$

Recall from Chapter 5, in this Thesis, the outcome studied is NEETs which is a binary variable (1 denotes a young person in NEET status and 0 denotes a young person in Education, Employment or Training). Following Aakvik [1] (2001), the Mantel and Haenszel test statistic (MH, [123]), is suggested for binary outcomes.

7.7.2 Mantel-Haenszel test-statistic

The Mantel and Haenszel (MH) test statistic (MH, [123]), is employed to compare two groups on a dichotomous outcome. More specifically, for a binary outcome y we could have a treatment and a control group. If the outcome y is not affected by assignment to either treatment or control group, then the treatment has no effect. If however, the outcome y is different for the treatment and control groups, then the treatment y has a positive or a negative effect. To test for the significance of the tretment effect, the MH non-parametric test is employed.

Let N_{1s} and N_{0s} denote the treated and control groups respectively and stratum s, where $N_s = N_{0s} + N_{1s}$. Write Y_{1s} for the number of participants, Y_{0s} for the number of non-participants, and Y_s for the total number of participants in stratum s. The MH test statistic follows assymtotically the standard normal distribution, given by

$$Q_{MH} = \frac{|Y_1 - \sum_{s=1}^{S} E(Y_{1s})| - 0.5}{\sqrt{\sum_{s=1}^{S} \mathrm{Var}(Y_{1s})}} = \frac{|Y_1 - \sum_{s=1}^{S} (\frac{N_{1s} Y_s}{N_s})| - 0.5}{\sqrt{\sum_{s=1}^{S} \frac{N_{1s} N_{0s} Y_s (N_s - Y_s)}{N_s^2 (N_s - 1)}}} \tag{7.7}$$

In [153], Rosenbaum shows that Q_{MH} test statistic is bounded by two known distributions. Clearly, if $e^{\gamma} = 1$, Equation (7.7) equal to 1, meaning that there is no hidden bias. If $e^{\gamma} > 1$, Equation (7.7) $\neq 1$ and hence unobserved characteristics cause selection bias. In such case, there are two possible scenarios. Firstly, Q_{MH}^{+} describes the overestimated treatment effect and Q_{MH}^{-} described the underestimated treatment effect. The two bounds are give by the following equations:

$$Q_{MH}^{+} = \frac{|Y_1 - \sum_{s=1}^{S} \widetilde{E}_s^{+}| - 0.5}{\sqrt{\sum_{s=1}^{S} \mathrm{Var}(\widetilde{E}_s^{+})}} \tag{7.8}$$

and

$$Q_{MH}^{-} = \frac{|Y_1 - \sum_{s=1}^{S} \widetilde{E}_s^{-}| - 0.5}{\sqrt{\sum_{s=1}^{S} \mathrm{Var}(\widetilde{E}_s^{-})}} \tag{7.9}$$

where $\widetilde{E}_s$ and $\mathrm{Var}(\widetilde{E}_s)$ are the large-sample approximations to the expectation and variance of the number of participants when the outcome y is binary and the value of γ is given.

7.8 Sensitivity to hidden bias model

The previous section described sensitivity analysis, the theoretical model developed by Rosenbaum [153] (2002) to check the sensitivity of estimated treatment effects. Treatment effects in this study were estimated using propensity score matching to compare educational and employment outcomes of young people who live in high and low crime score areas conditional on observed characteristics. After estimating treatment effects, sensitivity to hidden bias caused by unobserved characteristics is investigated in this section using Rosenbaum's [153] (2002) bounding approach. The aim is to further explore research question 6 for hidden biases. Research question 6 investigated whether the effect of the area a young person lives is different for young people who live in high crime compared to low crime areas. Now, a further investigation is carried out to answer the question:"How sensitive are neighbourhood effects findings to hidden bias?"

The purpose of this section is to investigate how an unobserved covariate that affects simultaneously neighbourhood location and education and employment outcomes could alter the conclusions drawn about neighbourhood effects. Following Cochran's [34] (1968) proposition that biases can be eliminated by employing Elaborate Theories and previous research on neighbourhood effects, special attention was paid to select and include a wide range of covariates in the analysis to eliminate selection bias. Despite careful selection of covariates, there might still be unobserved covariates that could affect young people's outcomes. An example of such an unobserved covariate could be parental time devoted to children that could affect both the choice of neighbourhood and the educational and employment outcomes. Let's assume that two young people i and j with similar characteristics live in an area characterized by high Crime

Deprivation. The probability that a young person becomes NEET will depend on a vector of observed covariates x_j and a vector of unobserved covariates u_i; see Equation (7.3). If one of the two young people has parents who are more devoted to their children's development compared to the otherwise similar young person who also lives in a high Crime area, then parental commitment could be an unobserved characteristic that could affect the outcome of the analysis. If parental commitment has no influence on the probability of being NEET, then there is no hidden bias. If however parental commitment affects NEET status, then omitting parental commitment from the analysis would bias the estimates of neighbourhood effects. To investigate if unobserved covariates that cause hidden biases could alter the inferences of the propensity score matching analysis, sensitivity analysis is employed.

Data and methodology

The dataset that will be employed in sensitivity analysis includes the vector of covariates informed by the Compositional Framework of Neighbourhood Effects (Section 3.4) and used in estimating the probability of being NEET in Chapter 6 and the counterfactual model of neighbourhood effets in Section 7.1. Sensitivity analysis is confined to binary responses. The dataset was fully described in Section 7.2.

There are various methods of applying sensitivity analysis. The methodology that will be applied to investigate the sensitivity of the propensity score analysis results to hidden biases follows Becker and Caliendo (2007). The MH bounds methodology is selected in which MH bounds are computed to check sensitivity of estimated average treatment effects on the treated. MH bounds can be employed in Stata after psmatch2 that was applied to run the propensity score analysis (see Section 7.6) and is suited for the nearest neighbour without replacement matching approach that was selected for the propensity score analysis. The MH bounds approach specifies the value of γ for which to carry out the sensitivity analysis. It denotes the bounds on inference quantities. The bounds help the researcher determine the significance of the results found in a similar way to p values and confidence intervals.

A key assumption in sensitivity analysis is that individuals are assigned to treatment or control groups independently with unknown probabilities. Two individuals with the same observed covariates may differ in terms of unobserved covariates, so that one individual has an odds of treatment that is $\gamma > 1$ times greater than the odds for another individual. If $\gamma = 1$ both individuals have the same odds of receiving a treatment. However, in case $\gamma = 2$ one individual might be twice as likely to receive a treatment because of unobserved characteristics before the treatment. In other words, sensitivity analysis investigates how large can γ be in order to find how much hidden bias can be present in the analysis. Average treatment effects results are sensitive to hidden bias for values of γ that are barely larger than 1 and insensitive to hidden bias for quite large values of γ.

Analysis and results

Propensity score analysis in Section 7.6 assumed that young people in high and low Crime areas are different because they differ on observed variables in the dataset. However, if young people in high and low Crime Score areas differ on unobserved measures, a positive association between a high Crime Score and young people in NEET status would not imply a causal effect. Although many were selected and included in the analysis, investigating NEET status using observational data can be affected by selection bias due to unobserved characteristics such as for example parental preferences or individual motivation and ability. Propensity score matching has served to adjust for selection bias in the distribution between young people in high and low Crime areas. The goal of the sensitivity analysis will be to investigate whether inferences about the effect of high Crime Score on NEETs could be altered by such factors which are not observed in the data. Given that it is not possible to estimate selection bias caused by observed characteristics using observational data, sensitivity analysis will be employed to calculate the upper and lower bounds on test statistics. The null hypothesis that will be tested is that there are no effects on NEET status for young people who live in high Crime Score areas for different values of unobserved selection bias.

Let's assume that the probability of a young person becoming NEET is determined by a vector of observed covariates for one individual. At the same time, let's assume that there are unobserved variables and that γ is the effect of unobserved characteristics on the probability of being NEET. If we compare two individuals who appear similar on the observed vector of covariates and there are no differences in unobserved characteristics or the unobserved characteristics do not influence the probability of being NEET, the odds ratio in Equation (7.6) is one and therefore there is no unobserved selection bias. In that case, controlling for observed selection would produce unbiased estimates of neighbourhood effects. If however there are unobserved characteristics such as individual ability that could potentially affect NEET status, then the Equation (7.5) would be greater than 1. For example if $e^{\gamma} = 1.6$, then two individuals who appear similar on the vector of observed covariates x, differ in their odds of being NEET by a factor of 1.6. If $e^{\gamma} > 1.6$ and changes the inference about neighbourhood effects on NEET status, then the estimated neighbourhood effects are considered sensitive to selection bias. Sensitivity analysis measures how changing the value of γ can change the inferences about neighbourhood effects on NEET status. The MH test statistic suggests that the test statistics can be bounded by two distributions. If $e^{\gamma} = 1$ the bounds are equal to 1 and there is no hidden selection bias. For $e^{\gamma} > 1$, the bounds move apart denoting uncertainty about the test statistics and therefore selection bias is present. Two possible explanations can be given. If Q^{+}_{MH} (see Equation (7.8)) neighbourhood effects on NEET status are overestimated and if Q^{-}_{MH} (see Equation (7.9)) neighbourhood effects are underestimated.

Table 7.5 shows the sensitivity of the test statistics for bounds of $e^{\gamma} = 1.2$, $e^{\gamma} = 1.4$

, $e^{\gamma} = 1.6$, $e^{\gamma} = 1.8$ and $e^{\gamma} = 2$ and the test statistics for $e^{\gamma} = 1$ that implies no observed selection bias in the model. The bounds given in Table 7.5 for different e^{γ} can be interpreted in the following way. Positive unobserved selection, in terms of young people in high Crime Score areas having higher probability of being NEET, given the same vector x of observed covariates, implies that the estimated neighbourhood effects in Table 7.4 overestimate the true effects. In this case, the reported chi-square statistic is too high and needs to be adjusted downwards. Conversely, negative unobserved selection, in terms of young people in high Crime Score areas having a lower probability of being NEET, given the same vector x of observed covariates, implies that the estimated neighbourhood effects in Table 7.4 are underestimated. In this case, adjustment needs to take place for downward bias.

If we compare two individuals that share the same vector of observed characteristics x for $e^{\gamma} = 1.2$, this implies that they differ in their odds of being NEET by a factor of 1.20 or by 20%. For $e^{\gamma} = 2$ two individuals that have the same vector of observed characteristics x differ in their odds of being NEET by a factor of 2 or 100%. It is important to stress that as the parameter e^{γ} increases in the sensitivity analysis, the results are no longer significant. As Table 7.5: 'Sensitivity Analysis Results' shows, for $e^{\gamma} = 1.2$ the results are significant implying that young people in high and low crime areas do not differ in terms of unobserved characteristics. Even for $e^{\gamma} = 1.4$ or $e^{\gamma} = 1.5$ the sensitivity analysis results are still significant. However, as the e^{γ} increases, the results show downward bias which implies underestimation of treatment effects. These results indicate the possibility of omitted confounding variables, however when interpreting sensitivity analysis results it is important to bear in mind that unobserved selection is taken to the extremes in this type of analysis. Estimates that are sensitive to selection bias indicate that neighbourhood effects can be positive, negative or zero depending on the magnitude of the selection bias. A sensitivity analysis indicates how biases might alter inference about neighbouhood effects on NEET status but it does not indicate if bias is present or the magnitude of bias in the analysis. Sensitivity analysis results represent the worst possible circumstances and therefore they only show how hidden bias might alter inference (DiPrete and Gangl, [48] 2004). As a consequence, it is still reasonable to assume with relative confidence that many of the confounding variables were actually included in the analysis and therefore it is possible to draw conclusions about the determinants of NEET status.

Table 7.5: Sensitivity Analysis Results for $e^{\gamma} = 1$, $e^{\gamma} = 1.2$, $e^{\gamma} = 1.4$, $e^{\gamma} = 1.6$, $e^{\gamma} = 1.8$ and $e^{\gamma} = 2$

γ	Q^{+}_{MH}	Q^{-}_{MH}	p^{+}_{MH}	p^{-}_{MH}
1	5.47017	5.47017	0.000***	0.000***
1.2	3.8163	7.15637	0.000***	0.000***
1.4	2.43488	8.61164	0.007**	0.000***
1.6	1.24681	9.89897	0.106	0.000***
1.8	0.202373	11.058	0.42	0.000***
2	0.6168	12.1157	0.269	0.000***
		$*p < 0.5$, $**p < .01$, $***p < 0.001$		

where

- (γ): odds of differential assignment due to unobserved factors
- $Q_m h^{+}$: Mantel-Haenszel statistic (assumption: overestimation of treatment effect)
- $Q_m h^{-}$: Mantel-Haenszel statistic (assumption: underestimation of treatment effect)
- $p_m h^{+}$: significance level (assumption: overestimation of treatment effect)
- $p_m h^{-}$: significance level (assumption: underestimation of treatment effect)

7.9 Conclusions

Neighbourhood effects research on young people's outcomes is a study of causal relationships. The aim of the analysis in Chapter 7 was to investigate a debate in neighbourhood effects research, whether living in a deprived area causes negative effects on young people's educational and employment outcomes compared to living in a non-deprived area. The question investigated was whether young people's outcomes could be affected by crime score in their area of residence or not and to explore the effect of other factors such as family, individual, school and peer group characteristics. Two methods were adopted in the analysis. The first method entailed propensity score matching and the second sensitivity analysis.

A comparison of outcomes between young people in high and low Crime Score areas would not be possible unless a study was conducted in which participants with similar characteristics were assigned in poor and non-poor areas. To make such a study feasible in the absence of a randomized experiment, a counterfactual model was employed to use the reasoning of experiments in order to remove bias and to define causality using observational data. Under the counterfactual framework, two causal states were possible for young people, treatment and control. Individuals could be observed only in high Crime Score areas (treatment) or low Crime Score areas (control). The statistical method employed to study the counterfactual framework was Propensity Score Matching that was introduced by Rosenbaum and Rubin [155] (1983) for causal analysis in observational studies.

The selection of covariates considered to influence young people's educational and employment outcomes and the model specification were informed by the Compositional Model of Neighbourhood Effects that was based on neighbourhood effects theories and theories on young people's development (Section 3.4). After the vector of covariates to be included in the analysis was selected, propensity scores were computed. Propensity scores which are the estimated predicted probabilities of receiving a treatment (living in a high Crime Score area) were computed conditional on the vector of the selected observed covariates. The estimated regression coefficients of the propensity scores showed that young people had a higher probability of living in a high Crime Score area if their parents had no educational qualifications, were benefit claimants, their mother was at the age of 20 or less when she gave birth to the young person, they came from single parent families and their parents monitored them only sometimes when they went out at night. Additionally, characteristics such as low educational attainment, truancy, negative feelings about school and negative perceptions of educational attainment were related to a higher probability for a young person to live in a high Crime Score area. After estimating the propensity score to identify the probability that a young person would live in a high or low Crime Score area, a matching algorithm was employed to match individuals to treatment and control groups. The Nearest – Neighbour matching algorithm was selected for this study, a method that matches the control to the treated group and drops control cases that are not selected as matches. Matching was applied without caliper (tolerance level on the maximum propensity score distance employed to avoid bad matches) because it is not easy to estimate the appropriate level of tolerance and also because caliper increases variance in estimates.

Matching, using the propensity score as a function of the observed covariates, aimed to adjust pretreatment differences and to balance the covariates in treatment and control groups. A distinctive attribute of the matching method is that it balances data by matching non-treated participants to treated ones on probabilities of receiving treatment (i.e. propensity scores) and reduces bias as it allows analysis that would be performed using data from a randomised experiment. After matching, bias was reduced at a level higher than 90% in most of the observed covariates. A high reduction in bias indicated that the two groups became identical and therefore comparable after matching. Additionally, the propensity score leveraged matching and therefore reduced the dimensionality of many covariates to a one-dimensional score.

After matching, the average treatment effect (ATE) was computed to explore the counterfactual, ie what would be the outcome for young people who live in high crime score areas if they lived in low crime score areas. The estimate of the ATE is the difference between the treatment group mean and the control group mean on the outcome. The results of the ATE indicate that the probability of young people in Education, Employment or Training living in high crime score neighbourhoods is lower compared to the probability of young people in NEET status. More precisely, the ATE shows that there is a 3% higher probability for young people who live in high crime score areas to be in NEET status. The ATE result may be small but indicates that living in high Crime Score areas is associated with higher probability of being NEET at $18-19$ in comparison to living in low Crime Score area. The results are indicative of an effect, implying that high area crime score has an effect on young people's outcomes.

A probit regression is used to estimate the probability of being NEET for young people in treated and control groups given the individual's covariates. Overall, the results of the probit regression are similar to the results of the logistic regression analysis employed in Chapter 6. More specifically, both analyses indicate that living in an area characterized by high Crime Score increases the probability of being NEET at $18-19$ after controlling for the vector of observed covariates introduced by the Compositional Model of Neighbourhoood effects. Additionally, parental educational qualifications, claiming benefits, mother's age at birth of young person and family composition are significant predictors of being NEET at $18-19$ in both analyses. Similar results are also found for parental monitoring, young person's educational attainment and negative attitudes to school. Minor differences are found in results about ethnic minorities as all ethnic minorities appear significant predictors in PSM in comparison to the logistic regression analysis where only the Indian group remained negatively significant in the full model. Finally, perceptions of educational attainment and being excluded from a group of friends have a small negative effect in PSM whereas in logistic regression analysis they appear significant predictors of NEET status.

The second method adopted in this Chapter, sensitivity analysis, involved testing the propensity score matching assumption and examining the sensitivity of the estimates to the specification adopted. In sensitivity analysis, significance levels bounds and confidence intervals are introduced. Upper and lower bounds of the Mantel Haenszel test statistic are used to test the null hypothesis of no treatment effect. The aim of the analysis was to investigate if treatment selection is non-ignorable because selection might have been partly affected by unobserved variables. More precisely, to investigate the extent that possible changes in assumptions caused by unobserved characteristics could change the basic conclusions of the propensity score results.

The sensitivity analysis results remain significant even for values of e^{γ} (the impact of unobserved covariates) as high as 1.4 or 1.5 implying that young people in high and low crime score areas do not differ in terms of observed and unobserved characteristics. Given that sensitivity analysis takes unobserved selection to the extremes and presents the worst possible situation, the sensitivity analysis results indicate that it is possible to draw conclusions from the propensity score matching analysis. Therefore it is possible to assume that most of the confounding variables were included in the propensity score matching analysis and to draw inferences about the determinants of NEET status.

After estimating the propensity score to identify the probability that a young person would live in a high or low Crime Score area, a matching algorithm was employed to match individuals to treatment and control groups. A range of matching estimators were tried in this study such as the Nearest Neighbour (NN) without replacement without caliper, the Nearest Neighbour with replacement, the Mahalanobis and the Kernel approaches. All PSM estimators produced similar results, because with growing sample size all the estimators become closer to comparing only exact matches (Smith [176], 2000; Caliendo and Kopeinig [30], 2008). The Nearest Neighbour Matching algorithm was selected for this study, a method that matches the control to the treated group and drops control cases that are not selected as matches. This method was chosen because it is considered effective when individuals are studied in follow-up studies. Matching was applied without caliper (tolerance level on the maximum propensity score distance employed to avoid bad matches) because it is not easy to estimate the appropriate level of tolerance and also because caliper increases variance in estimates.

Chapter 8

Conclusion and Future Work

The aim of this chapter will be to sum up the key findings of this study in relation to the research objectives and to discuss their implications. Further, it will consider the strengths and limitations of the study and discuss new directions for future research and policy interventions.

8.1 Summary and discussion of conclusions

The goal of this study has been to understand the pathways through which the effects of high crime in an area may impact the educational and employment outcomes of young people. This study posed and investigated a set of research questions the main focus of which could be resumed in the following: "Does crime in the location influence young people's life chances and if so, how?". In other words, what are the unique processes in high crime score areas that adversely affect young people's outcomes. The approach taken to investigate the research questions was as follows. Taking into consideration the implications for young people in NEET status, I approach an enquiry into neighbourhood effects from a thorough review of the existing literature on the processes that impact NEET status and the pathways that explain neighbourhood effects in Chapter 2.

The aim of this study was to investigate why neighbourhood effects exist by exploring particular mechanisms and processes that mediate area characteristics. This study approached the research enquiry adopting a dual strategy that relied first on an extended theoretical framework of neighbourhood effects that provided a basis of potential mediating pathways and second by addressing econometrically selection bias to test causal speculations. The theoretical framework for exploring and understanding neighbourhood effects on young people, introduced in Chapter 3, the "Ecological Model of Neighbourhood Effects", employs crime score and a vector of other characteristics to connect neighbourhood structural characteristics to educational and employment outcomes. This framework extends on and reformulates arguments of the Life Course theory (Elder [54], 1974; Giele and Elder [73], 1998), the Ecological systems framework of development (Bronfenbrenner [23] , 1979) and the neighbourhood effects theory (Jencks and Mayer [95], 1990). The model includes interactions of individuals within a neighbourhood context and suggests four pathways that are hypothesized to mediate neighbourhood effects and to explain young people's outcomes. The pathways identified were: a) individual characteristics and attitudes; b) parental characteristics and relationships; c) school experiences and attitudes to schooling and; d) social epidemics that act as pathways mediating the direct neighbourhood influence on transition outcomes. The extended theoretical model, which is an original contribution to investigating neighbourhood effects, allows causal assumptions about area deprivation effects to be explored by including various aspects of an individual's life influenced by neighbourhood context.

Evidence is obtained in this study using a combination of the extended theoretical model and of statistical methods for causal estimation. While the majority of quantitative neighbourhood effects literature relies on statistical techniques to overcome selection bias, the emphasis of this study is first on setting clear hypotheses and identifying causal mechanisms and then on employing econometric approaches. As Rubin [156] (1974) suggests, a good study design could allow causal relations to be investigated more accurately than a complex statistical modeling technique. For this reason, after identifying clearly the theoretical framework of potential causal pathways which may mediate neighbourhood effects, the enquiry turns to finding robust econometric techniques to test the assumptions of the theoretical model. Chapter 4 reviews the methodological approaches that have been employed in past research in neighbourhood effects and explores the advantages and limitations of each approach. Chapter 5 asks which is the most appropriate longitudinal dataset first to test the pathways of neighbourhood effects and then to link neighbourhood characteristics and young people's educational and employment outcomes, using geographical measures that represent both spatial and social scales over which the hypothesized mechanisms operate. The LSYPE is introduced and described as a rich longitudinal dataset that allows the extended theoretical framework to be matched with data. Two statistical approaches are adopted to investigate the causal pathways. The first approach controls for a wide variety of individual and family characteristics while the second employs a counterfactual to imitate randomized experiments using observational data.

To control for a wide variety of individual and family characteristics, a logistic regression model is employed in Chapter 6 to model the probability that a young person will become NEET or not. Initial descriptive analysis shows that the higher the area deprivation, the higher the number of young people in NEET status. Further, a bivariate logistic regression model is employed, which is by definition restricted to using only one dependent and one independent variable. The goal is to investigate whether there is an association between neighbourhood crime score and NEET status at $18-19$. The results suggest that high area deprivation is significantly associated with NEET status and the association is significant for both the general IMD index as well as its seven sub-indices. Then, multivariate logistic regression analysis is employed to test the four hypothesized pathways of neighbourhood effects introduced in Section 3.4. The first causal pathway controls for the influence of family demographic characteristics, parental practices and aspirations. The analysis continues to address the second causal mechanism of neighbourhood effects proposed by the theoretical framework and to explore whether the correlation between neighbourhood crime score remains significant over and above the effect of individual characteristics and family characteristics. The third pathway investigated introduces attitudes to and experiences of school. Finally, the fourth pathway identifies the links between peer group influences and investigates neighbourhood effects after controlling for family, individual, school and peer group characteristics.

The causal pathways tested are shown to compensate to the corrosive effect of high crime on young people's outcomes. The results show that area deprivation remains significant throughout all of the pathways investigated, as this is denoted by the first quartile of Crime Score remaining significant in the analysis (for $p < 0.01$) after the addition of all the covariates in the model. These findings suggest that the odds of being NEET at $18 - 19$ are higher for young people who live in areas with high Crime Score. In relation to family influences, the probability of being NEET increases for young people when their parents have no educational qualifications (for $p < 0.05$); they belong to a family that claims benefits for low income (for $p < 0.05$); their mother was under 20 when she gave birth (for $p < 0.05$); they belong to single parent families (for $p < 0.01$); and their parents monitor them only sometimes when they go out at night (for $p < 0.05$). High parental aspirations, as these are depicted by parents who want their children to continue to full time education after 16, are associated with decreased odds of a young person becoming NEET. At the individual level, low educational attainment remains a strong significant covariate on young people's outcomes (for $p < 0.001$). Belonging to a minority ethnic group is not associated with higher odds of entry to NEET status. Conversely, the odds of becoming NEET are lower for young people with Indian ethnic origin. Attitudes and experiences to school that remain significant in the model and increase the probability of being NEET are described by young people who played truant over the last 12 months (for $p < 0.001$); believe they have low educational attainment (for $p < 0.05$); and count minutes in a lesson until it ends (for $p < 0.05$). In the peer group sphere of influence, the odds of becoming NEET are higher for young people who have been excluded from a group of friends over the last 12 months (for $p < 0.05$), and when the police got in touch with their parents for their behaviour over the last year (for $p < 0.05$).

The results that are reported in this study using logistic regression analysis, are consistent with those of previous literature. Neighbourhood effects research finds that living in deprived areas has negative effects on people's life chances and reinforces inequalities. Past research finds that neighbourhood deprivation is associated with limited resources (McCulloch, A., and Joshi, H. [126], 2001), families living on benefits (Harden et al [81], 2006), lack of interest in pursuing education (Wilson [198], 1996), low educational attainment (Duncan et al [51], 1993; Kauppinen [99], 2007) and role models and peer relations that foster antisocial behaviour and crime and result in limited labour force participation (Dubow et al, 1997). At the same time, research on NEETs defines specific pathways of entry into NEET status. Family characteristics that are important determinants of NEET status involve socio-economic background, family type, demographics, monitoring and aspirations (Coles [38], 2002; Crawford et al, 2010; Payne [140], 2000; Pearce and Hillman [142], 1998; Rennison et al [148], 2006). In addition, low educational attainment increases the likelihood of being NEET (Bynner and Parsons [28], 2000; Bell and Blanchflower [9], 2010; OECD [137], 2009; Macmillan et al [120], 2012; Britton et al [22], 2011). Attitudes to school such as truancy, negative attitudes, disaffection influence educational and employment outcomes (Raffe [145], 2003; Coles et al [38], 2002; Crawford et al [42], 2011; Rennison et al [148], 2006). And finally, the activities of young people's peer group and involvement in antisocial behaviour are related to NEET status (Spielhofer [180], 2009; Stone et al [183], 2000).

While the first statistical approach employed to investigate the theoretical framework of the current research involved a regression approach with a range of statistical controls, the second step of the analysis aims to further investigate area effects on young people's outcomes. The aim of Chapter 7 is to explore a key debate in neighbourhood effects, whether NEET status is attributed to high Crime Score or whether the characteristics of the people who live in a specific area determine their outcomes. In the absence of experimental data, where it would be possible to assign individuals to treatment and control groups at random, a relatively new approach is adopted, propensity score matching. Given that a single subject cannot be observed under the control and treatment condition simultaneously (a high and low score area), propensity score matching uses the logic of experiments and creates two comparable groups and matches "treated" and "control" variables on the probability of receiving a treatment before assessing treatment effects to investigate neighbourhood effects (Rosenbaum and Rubin [155], 1983). The goal of this analysis is to investigate the counterfactual; what would be the potential educational and employment outcomes for people who live in areas characterized by high Crime Score if they lived in areas with low Crime Score. The counterfactual model of neighbourhood effects was estimated by employing the vector of covariates introduced in the Ecological Model of Neighbourhood effects. The analysis involved: a) estimating the propensity score; b) employing a matching algorithm to match individuals to treatment and control groups, and; c) estimating the average treatment effects. The results of the analysis for treated and control groups provide similar results to the logistic regression analysis results of chapter 6. More specifically, propensity score analysis shows that individuals that receive a certain treatment (living in a high Crime Score area) conditional on the vector of covariates introduced by the theoretical framework have a higher probability of being NEET at $18-19$ compared to individuals in the control group (living in a low Crime Score area). The effect of the observed covariates employed is also similar in both logistic regression and propensity score matching analyses.

Propensity score matching adjusts pretreatment differences between a treatment and a control group in observed covariates. For this reason, hidden biases caused by unobserved covariates that could be important predictors in the analysis are not controlled in propensity score analysis. Unobserved covariates could include for example ability or self-efficacy which cannot be measured and included in the analysis but are likely to affect educational and employment outcomes. Sensitivity analysis is employed in this study to investigate the magnitude of hidden biases that need to be present to change the inferences drawn by the propensity score analysis. The sensitivity analysis results show that despite the fact that young people in high and low Crime Score areas are equally distributed in terms of observed covariates, there is a difference in terms of the unobserved characteristics in the data. The sensitivity analysis results show that despite the fact that young people in high and low Crime Score areas are equally distributed in terms of observed covariates and a large number of variables were included in the analysis, there is a possibility of omitted confounding variables. The results indicate that unobserved characteristics, such as for example motivation or ability, could be a cause of potential downward bias. However, it is important to bear in mind that sensitivity analysis results represent the worst possible circumstances and therefore great attention is required in their interpretation. Additionally, sensitivity analysis results indicate how biases might alter the inferences drawn by propensity score analysis about neighbourhood effects but not if bias is present or the magnitude of bias.

8.2 Strengths and weaknesses of the investigation

8.2.1 Strengths

This study offers a new perspective in the field of neighbourhood effects academic debate and enhances past literature offering new insights in young people's educational and employment outcomes. The vast majority of literature on neighbourhood effects has focused on the negative effect of deprived neighbourhoods on their residents life chances and reported outcomes such as educational attainment, social exclusion, teenage pregnancy and school drop-out rates. At the same time, research on young people in NEET status focuses on a number of factors considered to determine youth unemployment, disengagement from education or training and social exclusion but not on the effects of the residential and social environment. This study enriches prior research by linking for the first time neighbourhood context effects with young people's educational and employment outcomes.

One of the key strengths of this study is that it employs a rich longitudinal dataset, the LSYPE, which allows a thorough investigation of young people and provides information on the factors that are considered significant on young people's development and the trajectories they chose after compulsory education. The LSYPE is a nationally representative dataset that covers the whole England, it is linked to an area deprivation index, focuses on young people and their families and provides detailed histories of young people's main activities for four years after compulsory education. Due to the fact that it is a longitudinal study, it allows the investigation of neighbourhood effects through long-term processes that start in early teenage years and continue until adolescence. The LSYPE is a powerful source of information that allows the investigation of the pathways through which young people move into educational, employment or other roles in their life. In addition, the LSYPE is linked to an area deprivation index, the IMD, and for the current study special permission was granted to gain access to its seven components. The IMD employs the lower Layer Super Output Areas (LSOAs) to delineate neighbourhoods which offer many advantages such as that they have fixed boundaries and more importantly that they are specifically designed to capture both structural boundaries and social aspects of neighbourhoods.

An additional strength of the research that is reported in this study is that it explores the potential causal pathways between neighbourhood context and young people's outcomes. Most research on neighbourhood effects focuses solely on correlations between area characteristics and neighbourhood outcomes identifying associations through econometric techniques. Little attention is paid on understanding the mechanisms that determine the association between neighbourhood particular attributes and individual outcomes. In contrast to past research, this study formulates a solid theoretical framework drawing upon and reformulating the arguments of theories on individual development and neighbourhood effects. The Ecological Model of Neighbourhood Effects that is put forward in the current thesis aims to explain the relationships under investigation and to thoroughly identify causal mechanisms of neighbourhood effects. The goal of this research is not limited in describing the causal mechanisms and pathways responsible for neighbourhood effects but also to examine quantitatively their relative effect on young people's educational and employment outcomes.

Another strength of this study is that is uses a relatively new methods in establishing causal effects, propensity score matching and sensitivity analysis. Given that one of the main problems in neighbourhood effects research is selection bias, special attention is paid to identifying causal pathways between neighbourhood Crime Score and young people's outcomes. The study implements a relatively new method in establishing causal effects within a counterfactual framework. It shows that when two groups of young people with identical observed characteristics at the age of 13/14 experience high and low crime score neighbourhoods respectively, those in high Crime Score areas are more likely to become NEETs at the ages $18 - 19$ compared to those who live in low crime areas. Using sensitivity analysis, these results are found to be robust to upward bias but not to downward bias, thus identifying an area of future research.

8.2.2 Weaknesses

The results of the sensitivity analysis carried out in this study indicate that downward selection bias is present in the propensity score matching analysis which suggests underestimation of treatment effects of young people who live in high Crime Score areas. The most fundamental methodological problem in studies of neighbourhood context effects is the difficulty to remove or reduce selection bias. The majority of studies observes associations between contextual effects and individual outcomes and presents them as causal effects (Small and Feldman [175], 2012). This study has adopted three approaches to overcome the selection bias problem: a) formulated a clear theoretical framework and research hypotheses to explore causal mechanisms, b) tested the theoretical framework using logistic regression and employing a wide vector of covariates that are considered to influence both the neighbourhood selection and individual outcomes, and c) used propensity score matching and sensitivity analysis to use the logic of an experiment with an observational dataset and to control for selection bias from unobserved covariates on neighbourhood estimates. Despite the efforts taken, the results may still be subject to selection bias. This could be an indicator of unobserved characteristics such as for example motivation or self-efficacy which could have a detrimental effect on young people's outcomes but are difficult to measure and to include in the analysis.

Unobserved characteristics that influence neighbourhood context effects could be a limitation of employing a longitudinal research approach in this study and leaving out qualitative research. A qualitative approach would focus more on individuals and context in respect to how individuals and context interact and how people experience the environment where they live. Such an approach would allow in-depth investigation of the experiences of young people in their neighbourhood and of the processes and mechanisms that high crime in an area affects young people's outcomes. In other words, despite the numerous advantages offered by using a rich longitudinal dataset, the study lacks the qualitative approach that would depict how experiences of young people in a high crime area formulate their perspectives over and above their social position or family demographic characteristics. Qualitative research in the form of interviews has shown that young people in high crime areas experience violence, develop strategies for avoiding victimization and are exposed in a cultural framework that influences and determines their physical and social environment (Harding [82], 2010). These experiences in a specific cultural context determine young people's development, decision making processes, involvement in crime and ultimately educational and employment outcomes.

Another limitation of this study is that it has not been possible to match young people and their families based on the postcode of the area where they live. Therefore, it has not been possible to control for the fact that some residents have moved from one neighbourhood to another with possibly different socio-economic characteristics throughout the study which could have an effect on individuals outcomes. While this is an important limitation of the data, it is considered that the large size of the dataset, the low level of geographical units employed in the analysis (SOAs), and the longitudinal nature of the dataset compensate for this problem.

8.3 Implications for Neighbourhood Effects Research

From a methodological perspective, given the difficulties encountered in studying neighbourhood context effects, this study has implications for future research. Following the majority of neighbourhood effects research that employ traditional regression techniques to control for selection bias, this study uses logistic regression analysis controlling for individual and family characteristics. However, unlike other research, this study further explores crime effects on young people by employing a counterfactual model. This study illustrates the importance of using a counterfactual model in the absence of a randomized experiment. Propensity score matching and sensitivity analysis are new methods to estimate the effect of living in a deprived area. Instead of focusing on methods to reduce or to remove selection bias, these methods employ the logic of an experiment and estimate how the selection bias caused by unobserved characteristics would alter the inferences drawn by propensity score analysis. These methods have advantages as well as limitations, however they offer a different point of view in approaching a complex sociological problem in comparison to traditional approaches.

Additional research on neighbourhood effects might proceed by obtaining a clearer understanding of the pathways through which neighbourhoods exert their effects on young people. Taking into consideration that the identification of causal associations is one of the main challenges in neighbourhood effects research, further exploring potential pathways of influence might provide research with useful insights. A lack of clear hypothesis and theoretical framework explaining causal pathways creates what Jencks and Mayer [95] (1990) described as a “black box” of unexplained relationships. While the criticism was formulated twenty four years ago, it remains valid in neighbourhood effects research until today and is often addressed in the neighbourhood scholarship (Leventhal and Brooks-Gunn [110], 2000; Pickett and Pearl [144], 2001; Sellström and Bremberg [169], 2006). The current thesis put special emphasis on developing a clear theoretical framework to identify and explain neighbourhood effects. Future research might further investigate in depth potential mechanisms to establish causal relations.

Future research on neighbourhood effects could also investigate the way that crime is organised in deprived areas to be able to successfully reduce it. Organised crime is often the result of social relations in given neighbourhoods and not just individual incidents of antisocial behaviour. Research could also be directed on the effectiveness of punishment for those who break the law as a means of reducing antisocial behaviour and improving outcomes for young people. It would be interesting to investigate what would be the educational and employment outcomes for young people who move away from high Crime Score areas. Additionally, it might be worth looking at the association between crime and labour market outcomes in wider geographical areas than LSOAs. Research could also focus on educational attainment of young people in deprived areas to understand if those young people value education and if yes why it is difficult for them to structure and follow a pathway that would improve their educational and employment outcomes and thus allow them to achieve their goals.

In the future it will also be interesting to investigate whether repeated spells of unemployment and inactivity have long term unemployment consequences on young people. As LSYPE data is available, it will be worth exploring the trajectories of those who have experienced NEET status to check if eventually NEETs return to post-secondary education or if they manage to enter the labour market and if they face difficulties in their effort to find a job or if they remain inactive for long periods of their working lives. It will also be interesting to investigate why some young people who have been NEETs might be able to enter the labour market after a period of inactivity and whether this could be explained by personal attributes such as for example individual motivation or ability.

Another potential future approach to investigate neighbourhood effects and causal pathways would include mixed methods research (Small and Feldman [175], 2011; Galster [69], 2008). Combining quantitative and qualitative data would allow the researcher to gain useful insights by taking advantage of the benefits of each method. Qualitative data would enable in-depth understanding of how young people think about their neighbourhoods as geographic and social spaces, how they perceive their neighbourhood boundaries and how they interact with the institutions, services and peer group in their area of residence. It would allow the investigation of young people's experiences and perceptions, and offer an explanation about their actions and decision making processes. On the other hand a longitudinal dataset is essential in studying causal mechanisms as it offers large samples, rich information on demographics, family and individual characteristics and allows the researcher to associate neighbourhood characteristics from a previous point in time to current outcomes. Given that causal effects may act in the course of time, neighbourhood effects research requires an investigation of both experiences and perceptions at a specific time through qualitative data and also residential histories and exposure to a wide range of community characteristics through longitudinal studies. A mixed methods approach would be challenging to implement. For example theoretical constructs might be easy to develop and implement under one method, but it may not be possible to investigate them under the other. While both quantitative and qualitative methods have strengths and limitations, a successful mixed methods approach would allow qualitative techniques to further investigate the findings of quantitative analyses.

8.4 Implications for Policy and Practice

The current research is not policy research. That is, it does not evaluate current policies on neighbourhood effects or on young people's trajectories and therefore it cannot evaluate or recommend specific intervention programmes. Rather, the aim of this study is to find the causal mechanisms that explain why young people disengage from mainstream society roles when they live in neighbourhoods characterized by high crime. In this section, the focus lies on how the findings of the current study could inform approaches of policy makers to the social problem of young people in NEET status in order to improve their life chances.

The pathways of neighbourhood effects on young people investigated in the current research help to identify directions and potential entry routes for policy interventions that involve both the neighbourhood and the individual. In the exploration of young people's trajectories, the association between high crime rates and young people in NEET status is a potential area of concern among policy makers. This association raises a number of questions. Why some young people in high crime areas decide to disengage from education and employment and subsequently face social exclusion? How influential are these effects? Which mechanisms reinforce them? Under what conditions are the effects stronger? What are the future outcomes for those young people and for the next generations? Several answers could be explored. NEETs in high crime areas might become part of a culture that places little emphasis on education and employment or have little encouragement from their families to follow mainstream society roles. They might lack the information or informal networks to find a job.

They may apply for a job but be turned away because the employers consider that those young people would not be a good cultural fit as the work environment would not be in congruence with their values and life-style. They might not try to find a job as a result of negative peer influence who instead engage in antisocial or criminal activities.

The role of crime in shaping individual characteristics, family relations, attitudes to schooling and social networks means that successful interventions to improve neighbourhoods and reduce crime will not only increase safety but will also have benefits on other areas such as for example young people's educational and employment outcomes. It is often the case though that because of increased participation, disadvantaged young people who are most in need, may not be able to benefit from social programmes. For this reason, it is essential that future interventions should target and engage young people who are most in danger of following fractured trajectories after compulsory education. Social service providers should also approach young people with increased understanding about the difficulties they face especially as they go through a very significant developmental period of their life, early adolescence. Additionally, intervention programmes should enable and enhance access to the information, institutions and resources which are required for young people to reorient their priorities, to engage in mainstream society and to take advantage of the opportunities available to realize their potential.

The results of the current study encourage policy makers to focus their efforts to provide support to young people in high crime areas or in disadvantaged families. In calculating and comparing the costs and benefits of interventions to improve neighbourhoods and help young people in NEET status, governments should take into account the risk of short and long term unemployment spells and lower wages for young people who experience NEET status, the cost to the national economy because of lost output and benefits and the danger of intergenerational transmission of adverse labour market outcomes for those who live in deprived neighbourhoods. As Bowles et al [15] (2005) note: “When these children grow up, the adverse wage consequences of lower education will cause their own children to once again be consigned to poorer neighbourhoods with the same absence of role models, thus repeating the cycle”.

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Appendix A

Main activity of young people

Tables A.1 – A.4 show the percentage of young people in NEET status per month. The percentage of NEETs is low in years 2006-2007 ranging from 5.47% to 6.40% for the months September to May. The percentage of NEETs is higher during the summer months of 2007 (the first three months after compulsory education) ranging from 10% to 12.10%. The numbers remain high from September 2008 to June 2010, ranging from 10.60% to 14.80%. The numbers increase substantially from July 2010 (16.10% NEETs) to October 2010 when they reach the highest percentage (27.8% NEETs).

Table A1: Main Activity of young people at the age of 16, LSYPE and YCS

Main Activity September 2006 - July 2007*												
	Sep - 06	**Oct -** 06	**Nov -** 06	**Dec -** 06	**Jan -** 07	**Feb -** 07	**Mar -** 07	**Apr -** 07	**May -** 07	**Jun -** 07	**Jul -** 07	**Aug -** 07
Education	82.80%	82.42%	81.87%	81.58%	81.01%	81.43%	80.93%	80.37%	79.61%	77.95%	77.02%	76.02%
Employed	8.07%	8.54%	9.10%	9.25%	9.49%	8.65%	9.04%	9.43%	9.86%	10.62%	11.64%	13.18%
Apprenticeship/Training	3.25%	3.43%	3.56%	3.59%	3.74%	3.88%	4.00%	4.17%	4.27%	4.42%	4.36%	4.24%
Unemployed/Inactive (NEET)	5.88%	5.61%	5.47%	5.59%	5.76%	6.03%	6.03%	6.03%	6.27%	7.01%	6.98%	6.56%
Total (*Young person age: 16)	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

Table A2: Main Activity of young people at the age of 17, LSYPE and YCS

Main Activity September 2007 - July 2008*												
	Sep - 07	**Oct -** 07	**Nov -** 07	**Dec -** 07	**Jan -** 08	**Feb -** 08	**Mar -** 08	**Apr -** 08	**May -** 08	**Jun -** 08	**Jul -** 08	**Aug -** 08
Education	75.90%	74.80%	74.20%	73.70%	72.90%	72.10%	71.60%	70.80%	69.90%	59.70%	55.20%	54.00%
Employed	13.30%	14.30%	14.90%	15.20%	15.60%	16.10%	16.60%	17.20%	17.70%	24.50%	27.50%	29.00%
Apprenticeship/Training	4.90%	5.10%	5.20%	5.20%	5.40%	5.50%	5.50%	5.60%	5.60%	5.70%	5.40%	5.90%
Unemployed/Inactive (NEET)	5.80%	5.80%	5.70%	6.00%	6.10%	6.30%	6.30%	6.40%	6.40%	10.00%	11.90%	12.10%
Total (*Young person age: 17)	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

Table A3: Main Activity of young people at the age of 18, LSYPE and YCS

Main Activity September 2008 - July 2009*												
	Sep - 08	**Oct -** 08	**Nov -** 08	**Dec -** 08	**Jan -** 09	**Feb -** 09	**Mar -** 09	**Apr -** 09	**May -** 09	**Jun -** 09	**Jul -** 09	**Aug -** 09
Education	56.40%	56.10%	55.50%	55.00%	54.30%	53.90%	53.40%	53.00%	52.50%	52.00%	50.20%	49.10%
Employed	27.30%	28.20%	28.60%	28.50%	28.40%	28.20%	28.40%	28.60%	29.00%	29.00%	30.30%	31.10%
Apprenticeship/Training	5.20%	5.20%	5.00%	4.90%	5.00%	5.10%	5.10%	5.30%	5.40%	5.40%	5.10%	4.90%
Unemployed/Inactive (NEET)	11.10%	10.60%	11.00%	11.60%	12.30%	12.80%	13.10%	13.20%	13.10%	13.50%	14.30%	14.80%
Total (*Young person age: 18)	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

Table A4: Main Activity of young people at the age of 19, LSYPE and YCS

Main Activity September 2009 - May 2010*														
	Sep - 09	**Oct -** 09	**Nov -** 09	**Dec -** 09	**Jan -** 10	**Feb -** 10	**Mar -** 10	**Apr -** 10	**May -** 10	**Jun -** 10	**Jul -** 10	**Aug -** 10	**Sep -** 10	**Oct -** 10
Education	50.20%	54.60%	55.00%	54.90%	54.60%	54.50%	54.50%	54.40%	54.30%	49.20%	41.20%	31.10%	30.10%	33.30%
Employed	30.70%	29.10%	29.50%	29.50%	29.60%	29.60%	29.80%	30.00%	30.30%	33.70%	39.10%	43.40%	44.30%	38.90%
Apprenticeship/Training	4.60%	4.40%	4.20%	4.10%	4.00%	3.80%	3.70%	3.60%	3.50%	3.70%	3.70%	3.10%	3.60%	
Unemployed/Inactive (NEET)	14.50%	11.90%	11.30%	11.40%	11.80%	12.00%	12.00%	12.10%	11.90%	13.40%	16.10%	22.40%	22.00%	27.80%
Total (*Young person age: 19)	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%